













# “Smart city rankings and startup ecosystems: An empirical analysis of inverse correlation across 77 smart cities”

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# SMART CITY RANKINGS AND STARTUP ECOSYSTEMS: AN EMPIRICAL ANALYSIS OF INVERSE CORRELATION ACROSS 77 SMART CITIES

## Abstract

As cities increasingly adopt smart technologies and seek to foster innovation-driven economies, it is vital to understand how smart city development relates to the strength of local startup ecosystems. This study investigates whether a statistically significant relationship exists between a city's performance in the smart city ranking and the strength of its startup ecosystem. The study employed available data from the Global Startup Ecosystem Report (by Startup Genome) and the Smart City Index (SCI by the IMD World Competitiveness Center). A balanced panel regression analysis was conducted on a dataset comprising 77 cities across the years 2020, 2021, and 2023 (2022 is excluded as the SCI was not published). The findings reveal that the Random Effects model yielded statistically significant results, indicating a weak ( $R^2 = 25.63\%$ ) but significant inverse relationship between SCI and startup ecosystem development, which means cities that rank higher on smart city metrics tend to show lower levels of startup ecosystem performance. This counterintuitive result challenges the assumption that technologically advanced cities automatically provide fertile ground for entrepreneurial activity. One possible explanation is that smart cities, dominated by large tech players and rigid governance structures, may present entry barriers for emerging startups. High operational costs, regulatory constraints, and a focus on large-scale infrastructure projects may disincentivize startups from localizing their innovations within these environments. Although the  $R^2$  suggests that other variables beyond the smart city ranking influence startup development. This study highlights the need for urban policies that actively integrate startup-supportive mechanisms into smart city strategies.

## Keywords

smart city, Smart City Index, startup, startup ecosystem, panel data analysis

## JEL Classification

L26, O33, O18, H76, C33

## INTRODUCTION

The expert and academic communities are radically divided on the presence or absence of a linear relationship between the trends in the development of smart cities and startup ecosystems. In recent years, the development of smart cities has become a prominent global trend, driven by the increasing integration of digital technologies into urban infrastructure and governance. At the same time, startup ecosystems have emerged as vital engines of innovation, economic growth, and technological advancement. It is, therefore, reasonable to assume that cities that are more advanced in adopting smart technologies – often referred to as “intelligent” or “smart” cities – would also foster more dynamic and well-developed startup environments. This assumption appears intuitive. Smart cities offer advanced infrastructure, access to data, and high-quality digital services and often aim to create innovation-friendly policy environments, all of which should, in theory, support entrepreneurial activity.

Global indices, such as the IMD Smart City Index by the IMD World Competitiveness Center and the Digital Cities Index by Economist Impact, have been developed to evaluate and rank cities based on criteria like infrastructure, digital connectivity, sustainability, and service quality. Simultaneously, reports such as the Global Startup Ecosystem Report by Startup Genome track the performance and maturity of startup ecosystems around the world. The intersection of these two urban development trends – smart city transformation and the growth of startup ecosystems – raises important questions for urban policymakers, investors, and researchers. Understanding whether smart city development indeed supports startup ecosystems is not only relevant but critical for shaping future urban innovation strategies.

Given that startups are traditionally considered the source of the emergence and diffusion of the most advanced innovative solutions in many sectors of the economy, it is logical to assume that digital technologies used in smart cities can originate from startups. Therefore, the existence of a relationship between the development trends of smart cities and startups looks logical. Given the lack of in-depth research on this issue and a coherent point of view in the expert community, continuing scientific research in this area is relevant.

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## 1. LITERATURE REVIEW

The academic community has widely debated the interplay between smart city development and the growth of startup ecosystems. Some scholars argue that smart cities foster entrepreneurship by providing technological infrastructure and policy incentives, while others highlight institutional and regulatory barriers that may inhibit startup growth.

Several studies suggest that smart cities serve as catalysts for startup growth, offering a conducive environment for technological innovation and business expansion. Integrating digital infrastructure, open data policies, and smart governance frameworks enhances business opportunities and facilitates collaboration between governments, corporations, and startups.

For instance, the #PlanTech initiative in the UK enhances interactions between government agencies, digital entrepreneurs, and technology startups in urban planning (Catapult Connected Place, 2020). Similarly, the Taipei Smart City Project Management Office has been instrumental in fostering public-private partnerships that align startups with municipal challenges, thereby improving urban services and making Taipei a more livable city (Lee & Taipei Smart City Project Management Office (TPMO), 2021). A comparable example is observed in Turin, where a strategic focus on smart technologies has contributed to entrepreneurial activity and technological innovation (Dezi et al., 2018).

Empirical research also highlights the role of multinational corporations in smart city environments. Kanellos and Siokas (2021) analyze the engagement of eight multinational firms in Greek municipalities, demonstrating how sustained corporate investment in R&D enhances economic resilience and urban innovation. This aligns with Chygryn et al. (2023), Sour et al. (2023), Brychko et al. (2023), Kozhushko (2023) and Koibichuk et al. (2023), who underscore the significance of technology transfer in fostering startup growth within smart cities, in energy and health tech domains. Other scholars have examined how digitalization trends – particularly in automation, IoT, and AI – contribute to a more vibrant startup ecosystem (Faisal et al., 2025; Pakhnenko & Pudło, 2023; Graf & Burrell, 2024; Koibichuk et al., 2023; Wright, 2023; Springs, 2024; Strielkowski et al., 2022; Artyukhov et al., 2024). The Russian aggression disrupted smart city development in Ukraine by damaging infrastructure and shifting priorities to wartime needs (Davlikanova et al., 2024; Zámek & Zakharkina, 2024).

Despite the potential advantages offered by smart cities, location selection remains a critical determinant of startup success. Multiple studies emphasize that startups prefer environments where operational costs are lower, and competition for resources is more balanced. Kuzior et al. (2022) and Shaikh et al. (2021) argue that geographical factors play a pivotal role in shaping the trajectory of startups, as regions with underdeveloped ecosystems may offer more incentives to attract en-

trepreneurs. Digel et al. (2022) reinforce this argument, asserting that cities still in the early stages of innovation ecosystem development require more significant efforts to establish smart city infrastructures, which presents an opportunity for startups to enter and influence these markets.

Additionally, Runiewicz-Wardyn and Winogradska (2023), Soumadi (2023) and Lozynskyy et al. (2021) highlight the importance of formal and informal networks in fostering mutual trust and collaboration between urban stakeholders. Their analysis underscores the critical role of educational institutions, accelerators, and business incubators in reinforcing the diffusion of innovation across cities, thereby benefiting both startups and the broader smart city ecosystem. The article by Kuzior et al. (2023) also analyzes various economic, social, political, informational, and technological indicators to assess their impact on e-governance across different clusters of smart cities.

Contrary to the optimistic view that smart cities drive startup growth, several studies argue that the regulatory complexity and institutional structures in smart cities may inadvertently hinder entrepreneurship. AlAstal (2023) suggests that municipalities often lack the agility and capability to engage effectively with startups, leading to missed opportunities for innovation. An investigation of Polish cities (Gdansk, Warsaw, and Wroclaw) by Osowska (2023) finds that smart cities have not fundamentally altered urban policy, raising concerns about the practical implementation of smart city strategies in fostering startup ecosystems.

Further supporting this view, Mitra et al. (2023) analyze smart city strategies in India and conclude that smart city policies do not directly influence long-term startup ecosystem growth. Similarly, Devlin and Coaffee (2021) examine urban policies in Coventry and Leeds (the UK), arguing that while digital technologies have impacted urban planning and governance, their effects remain constrained by existing bureaucratic mechanisms. Činčikaitė et al. (2023) arrive at comparable findings in their analysis of Estonian port cities, where smart city initiatives have not significantly accelerated startup development.

Several studies propose that the relationship between smart city rankings and startup ecosystem growth is not linear. Crowley and Jordan (2021) establish that an increase in the number of startups in urban areas does not directly translate to economic dynamism, suggesting that urban entrepreneurship exhibits diminishing returns in highly developed ecosystems. Similarly, Adler and Florida (2021) explore the geography of urban tech startups, noting that these businesses tend to cluster in either highly specialized technology hubs or major metropolitan areas, which often correspond to high smart city rankings. This implies that startup ecosystems may thrive in different types of urban environments rather than being solely dependent on smart city infrastructure.

The existing literature presents a divergent perspective on the relationship between smart city development and startup ecosystem growth. On the one hand, research highlights the potential synergies between technological infrastructure, public-private partnerships, and innovation ecosystems in smart cities, suggesting that they provide a conducive environment for startup growth. On the other hand, bureaucratic inefficiencies, regulatory burdens, and the preference for large corporate partnerships may limit the opportunities available to startups in highly ranked smart cities.

This study aims to investigate whether a statistically significant relationship exists between a city's performance in the smart city ranking and the strength of its startup ecosystem.

## 2. METHODOLOGY

To explore this relationship between the development of smart cities and the strength of their startup ecosystems, panel regression analysis on a balanced dataset covering 77 cities across the years 2020, 2021, and 2023 was used. The year 2022 is not included in the analysis because the Smart City Index by the IMD World Competitiveness Center was not published for that year. The dataset includes two key variables: the IMD Smart City Index, which reflects the overall level of smart city development, and an aggregated startup ecosystem indicator (City\_startup), constructed by the authors based on data from the Global Startup Ecosystem Report.

Smart City Index (IMD) is developed by the IMD World Competitiveness Center (IMD, 2023). This index ranks cities based on survey data collected from residents. The survey assesses perceptions of 15 indicators grouped under infrastructure and technological provisions across five domains: health and safety, mobility, activities, opportunities, and governance. Cities are ranked annually according to these dimensions.

City\_startup Indicator measures the development level of each city's startup ecosystem using an aggregate indicator created from the Global Startup Ecosystem Report published by Startup Genome (2023). This report provides data on four normalized factors for each city:

1. Performance.
2. Funding.
3. Market reach.
4. Talent and experience.

To ensure a balanced representation of all components, each factor was given equal weight in the construction of the City Startup Index. This equal-weighted average reflects a city's overall capability to support startup development and success.

The sample of cities used for modeling was formed as follows. First, for all cities presented in The Global Startup Ecosystem Report (Startup Genom), the city\_startup index was calculated using the authors' methodology. Then, the cities for which the Smart City Index was not calculated were excluded from this list. Then, those cities for which there is no information for at least one of the study periods (2020, 2021, and 2023) for one of the indices are excluded from this list.

The input data for the panel sample of the study are presented in Table A1, Appendix A.

To evaluate the relationship between smart city rankings and startup ecosystem development, four regression models were applied using panel data analysis. The models test for potential influence in both directions:

1. Model 1: Smart\_City\_Rank as the dependent variable, City\_startup as the independent variable (Fixed Effects).

2. Model 2: Smart\_City\_Rank as the dependent variable, City\_startup as the independent variable (Random Effects).
3. Model 3: City\_startup as the dependent variable, Smart\_City\_Rank as the independent variable (Fixed Effects).
4. Model 4: City\_startup as the dependent variable, Smart\_City\_Rank as the independent variable (Random Effects).

These models are structured according to the standard panel regression form:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \alpha_i + \varepsilon_{it}, \quad (1)$$

where  $Y_{it}$  – dependent variable (either Smart\_City\_Rank or City\_startup) for the city  $i$  at the time  $t$ ;  $X_{it}$  – the independent variables for the city  $i$  at the time  $t$ ;  $\beta_0$  – the intercept term;  $\beta_1$  – the coefficient estimating the relationship between the two indicators;  $\alpha_i$  – the fixed effect for the city  $i$  (for the model with fixed effect) or  $\alpha_i$  – the individual-specific random effect for the city  $i$  (for the model with random effect);  $\varepsilon_{it}$  – the error term.

The fixed-effects models control for unobserved heterogeneity across cities that remains constant over time, making them suitable when the city-level effects may correlate with the independent variable. The random-effects models assume that individual city effects are uncorrelated with the explanatory variables, offering more efficient estimates when this assumption holds.

By testing both fixed and random effects approaches in both directions, the study ensures a comprehensive analysis of the potential relationship between smart city development and startup ecosystem performance.

### 3. RESULTS

The practical implementation of models with fixed and variable effects describing the relationship between the trends in the development of Smart Cities and startups was carried out in Stata software using the following commands:

- `xtreg Smart_City_rank City_startup, fe` and `xtreg Smart_City_rank City_startup, re`, where `Smart_City_rank` is a dependent variable, and `City_startup` is an influencing variable.
- `xtreg City_startup Smart_City_rank, fe` and `xtreg City_startup Smart_City_rank, re`, where `City_startup` is a dependent variable, and `Smart_City_rank` is an influencing variable.

Table 1 shows the results of applying a regression model with a fixed effect (FE).

Because of within  $R^2 = 0.0116$ , the model explains 1.16% of the variation in `Smart_City_rank` within cities over time (weak explanatory power). Between  $R^2 = 0.3430$  means the model explains 34.3% of the variation between cities. Overall  $R^2 = 0.2563$  allows one to conclude that the model explains 25.63% of the total variation in `Smart_City_rank` (moderate fit).

A 1-unit increase in `City_startup` is associated with a 0.1625 increase in `Smart_City_rank`, controlling for city-specific effects. However, the effect is statistically insignificant ( $p = 0.182$ ).  $T$ -statistic for `City_startup` = 1.34 (not high enough to indicate strong significance). Since  $p$ -value ( $0.182$ ) >  $0.05$ , the effect of `City_startup` on `Smart_City_rank` is not statistically significant.

A significant effect cannot be concluded since the 95% confidence interval  $(-0.077, 0.402)$  includes zero.

$F$ -statistic  $(1,153) = 1.79$  with  $p = 0.1824$  means the overall model is not statistically significant. The negative correlation  $(\text{corr}(u_i, Xb) = -0.5487)$  suggests that unobserved city-level factors influencing `Smart_City_rank` correlate with `City_startup`.

The key takeaways from the analysis are the following:

1. `City_startup` does not have a statistically significant effect on `Smart_City_rank` in this model.
2. Most of the variation (95%) in `Smart_City_rank` comes from differences between cities rather than changes within cities over time.
3. The FE model may not be the best choice if the key variation is across cities rather than within cities.

Next, the study considers a random effects (RE) model (`xtreg ... , re`) if city-level differences dominate (Table 2).

The RE regression assumes that unobserved city-specific factors are not correlated with the independent variable (`City_startup`). The group vari-

**Table 1.** FE regression output for the relationship between `City_startup` (urban startup ecosystem development) and `Smart_City_rank` (Smart City Index)

. xtreg Smart_City_rank City_startup,fe			
Fixed-effects (within) regression		Number of obs	231
Group variable:		ID_City	Number of groups
R-squared:		Obs per group:	
Within	0.0116	min	3
Between	0.3430	avg	3.0
Overall	0.2563	max	3
Corr(u_i, Xb)	-0.5487	F(1, 153)	1.79
		Prob > F	0.1824

Smart_City~k	Coefficient	Std. err.	t	p> t	[95% conf.interval]	
City startup	.1625235	.1213363	1.34	0.182	-.0771874	.4022344
_cons	52.41438	2.624763	19.97	0.000	47.22893	57.59984
sigma_u				37.311882		
sigma_e				8.5465349		
rho				.9501486	(fraction of variance due to u_i)	
F test that all u_i=0:		F(76, 153) = 39.96		Prob > F = 0.0000		

**Table 2.** RE Generalized Least Squares (GLS) regression for the relationship between City\_startup (urban startup ecosystem development) and Smart\_City\_rank (Smart City Index)

<b>. xtreg Smart_City_rank City_startup,re</b>						
Random-Effects Generalized Least Squares (GLS) regression			Number of obs	231		
Group variable:	ID_City		Number of groups	77		
R-squared:			Obs per group:			
Within	0.0116		min	3		
Between	0.3430		avg	3.0		
Overall	0.2563		max	3		
Corr(u_i, X)	0 (assumed)		Wald chi2(1)	0.44		
			Prob > chi2	0.5053		
Smart_City~k	Coefficient	Std. err.	t	p> t	[95% conf.interval]	
City startup	-.082957	.1245383	-0.67	0.505	- .3270476	.1611336
_cons	57.60136	4.511011	12.77	0.000	48.75994	66.44278
sigma_u			29.283444			
sigma_e			8.5465349			
rho			.92150641 (fraction of variance due to u_i)			

able is ID\_City, meaning the panel data structure groups observations by city.

A 1-unit increase in City\_startup is associated with a 0.08296 decrease in Smart\_City\_rank. However, this effect is not statistically significant ( $p = 0.505$ ).  $z$ -statistic for City\_startup =  $-0.67$  is too small to indicate strong significance. Since the  $p$ -value ( $0.505$ )  $> 0.05$ , the effect of City\_startup on Smart\_City\_rank is not statistically significant. Since the 95% confidence interval ( $-0.3270, 0.1611$ ) includes zero, the study cannot conclude a significant effect. Wald  $\chi^2(1) = 0.44$  with  $p = 0.5053$  means that the overall model is not statistically

significant. The RE model assumes ( $\text{corr}(u_i, X) = 0$  (assumed)) that unobserved city-specific effects are uncorrelated with City\_startup. Also, 92.15% of the variance ( $\rho = 0.9215$ ) is due to differences across cities, reinforcing that city-specific factors play a dominant role.

In the next stage, a test of the relationship in the reverse direction, where the influential variable is the city's ranking according to the Smart City Index (IMD), and the dependent variable is the city's ranking according to the City\_startup Index (calculated by the authors based on The Global Startup Ecosystem Report 2023) is provided.

**Table 3.** Fixed-effects regression output for the relationship between Smart\_City\_rank (Smart City Index) and City\_startup (urban startup ecosystem development)

<b>. xtreg City_startup, Smart_City_rank,fe</b>						
Fixed-effects (within) regression			Number of obs	231		
Group variable:	ID_City		Number of groups	77		
R-squared:			Obs per group:			
Within	0.0116		min	3		
Between	0.3430		avg	3.0		
Overall	0.2563		max	3		
Corr(u_i, Xb)	-0.7149		F(1, 153)	1.79		
			Prob > F	0.1824		
Smart_City~k	Coefficient	Std. err.	t	p> t	[95% conf.interval]	
City startup	.0713149	.053242	1.34	0.182	-.0338696	.1764993
_cons	17.14704	2.996728	5.72	0.000	11.22674	23.06735
sigma_u			11.143391			
sigma_e			5.6613757			
rho			.79484142 (fraction of variance due to u_i)			
F test that all u_i=0:			F(76, 153) = 5.68		Prob > F = 0.0000	

The FE regression, which examines the relationship between Smart\_City\_rank (Smart City Index) and City\_startup (urban startup ecosystem development), is shown in Table 3.

The FE regression accounts for city-specific unobserved factors (ID\_City as the grouping variable). However, only 1.16% (Within  $R^2 = 0.0116$ ) of the variation in City\_startup is explained by changes in Smart\_City\_rank within cities, and 34.3% (Between  $R^2 = 0.3430$ ) of the variation in City\_startup between cities is explained. The model explains 25.63% of the total variation in City\_startup.

A 1-unit increase in Smart\_City\_rank is associated with a 0.0713 increase in City\_startup. However, this effect is not statistically significant ( $p = 0.182$ ).  $T$ -statistic for Smart\_City\_rank = 1.34 is too small for significance. Since  $p$ -value (0.182) > 0.05, the relationship between Smart\_City\_rank and City\_startup is not statistically significant. A 95% confidence interval (-0.0339, 0.1765) includes zero, confirming no significant effects.

$F$ -statistic (1, 153) = 1.79,  $p = 0.1824$  means the overall model is not statistically significant. Strong negative correlation (corr(u\_i, Xb) = -0.7149) suggests that unobserved city-specific factors affecting City\_startup negatively correlate with Smart\_City\_rank. The rho (0.7948) means that 79.48% of the variance is due to differences across cities,

reinforcing that city-specific factors dominate the variation in City\_startup.

The key takeaways are the following. Smart\_City\_rank does not significantly influence City\_startup in this model. Second, most of the variance in City\_startup is due to differences between cities rather than changes within cities. Third, the FE model may not be the best choice, given the low within-group  $R^2$  (1.16%) and the high between-group variance (rho = 0.79).

A potential issue is testing RE regression to see if city-level effects are better captured.

The procedure for developing a regression model that describes the impact of a city's ranking according to the Smart City Index (IMD), with the city's ranking according to the City\_startup Index (calculated by the authors based on The Global Startup Ecosystem Report 2023 based on panel data using a regression model with RE) as a dependent variable is shown in Table 4.

Only 1.16% (Within  $R^2 = 0.0116$ ) of the variation in City\_startup is explained by changes in Smart\_City\_rank within cities over time. A 1-unit increase in Smart\_City\_rank is associated with a 0.1134 decrease in City\_startup. This relationship is statistically significant ( $p = 0.000$ ). When Smart\_City\_rank = 0, the expected City\_startup score is 27.4614.

**Table 4.** RE Generalized Least Squares (GLS) regression for the impact of Smart\_City\_rank (Smart City Index) on City\_startup (urban startup ecosystem development)

. xtreg Smart_City_rank City_startup,re						
Random-Effects Generalized Least Squares (GLS) regression			Number of obs	231		
Group variable:		ID_City	Number of groups	77		
R-squared:			Obs per group:			
Within		0.0116	min	3		
Between		0.3430	avg	3.0		
Overall		0.2563	max	3		
Corr(u_i, X)		0 (assumed)	Wald chi2(1)	24.95		
			Prob > chi2	0.0000		
Smart_City~k	Coefficient	Std. err.	t	p> t	[95% conf.interval]	
City startup	-1133693	.0226983	-4.99	0.000	-1578571	-.0688815
_cons	27.46137	1.555658	17.65	0.000	24.41234	30.51041
sigma_u			6.9594147			
sigma_e			5.6613757			
rho			.60177271 (fraction of variance due to u_i)			

Z-statistic for Smart\_City\_rank =  $-4.99$  is large in magnitude, indicating strong significance. Since  $p$ -value ( $0.000$ )  $< 0.05$ , the effect of Smart\_City\_rank on City\_startup is statistically significant. The entire range is negative (95% confidence interval:  $-0.1579$ ,  $-0.0689$ ), confirming a significant negative effect.

Wald  $\chi^2(1) = 24.95$ ,  $p = 0.0000 \rightarrow$  The overall model is statistically significant. The  $\rho = 0.6018$  means that 60.18% of the variance is due to differences across cities; it could be concluded that city-level characteristics are important.

The study concludes that a higher Smart\_City\_rank is significantly associated with a lower City\_startup score, suggesting a hostile relationship. The model is statistically significant, meaning Smart\_City\_rank has a meaningful effect on City\_startup, and 60.18% of the variance in City\_startup is due to city-level differences, reinforcing that city characteristics play a large role.

Thus, out of all four regression models, only one was significant: the regression model with RE, which confirmed the inverse effect of a city's ranking according to the Smart City Index on its ranking according to the City\_startup Index. A potential interpretation of the negative relationship could be that cities with a higher IMD Smart City Index may focus more on infrastructure, digital governance, and sustainability rather than startup ecosystem growth. The Smart City Index by IMD and the Global Startup Ecosystem Report by Startup Genome evaluate cities through different lenses, focusing on various aspects of urban development and innovation. The Smart City Index assesses cities based on a balanced approach that includes economic/technological factors and "humane dimensions" such as quality of life, environment, and inclusiveness. This comprehensive evaluation aims to determine how "smart" a city is by considering its technological advancements alongside the well-being of its citizens. The Global Startup Ecosystem Report focuses on the performance of cities' startup ecosystems. It evaluates factors such as funding availability, market reach, talent, experience, and knowledge within the ecosystem. The goal is to identify where early-stage

startups have the best success opportunities and understand the dynamics that contribute to thriving startup environments.

There are some commonalities between these indexes. First, both indices consider the economic and technological aspects of cities (the IMD Smart City Index evaluates these in the context of overall city development, while the Global Startup Ecosystem Report specifically examines them within the startup ecosystem). Second, innovation is a key component in both evaluations (the IMD Smart City Index looks at innovation as part of a city's smart initiatives, whereas the Global Startup Ecosystem Report assesses innovation through the lens of startup activities and their success).

In addition, some differences could explain the negative relationship between them. First, the IMD Smart City Index provides a holistic view of a city's development, encompassing infrastructure, environmental factors, and citizen well-being. In contrast, the Global Startup Ecosystem Report narrowly focuses on the startup ecosystem, analyzing factors directly impacting startup growth and success. Second, the IMD Smart City Index emphasizes "humane dimensions," evaluating how smart initiatives improve quality of life, inclusiveness, and environmental sustainability. The Global Startup Ecosystem Report does not explicitly focus on these aspects; instead, it concentrates on metrics related to startup performance. Finally, the IMD Smart City Index combines quantitative data with citizen perceptions to assess city performance, providing a nuanced view of how smart initiatives impact residents. The Global Startup Ecosystem Report relies more heavily on quantitative metrics such as funding levels, exit values, and talent availability to rank startup ecosystems.

Another cause of the negative relationship between the IMD Smart City Index and the Global Startup Ecosystem Index is that high-ranked smart cities may have regulatory frameworks that are not conducive to startup innovation. Thus, high-ranked smart cities often have strict regulatory frameworks to ensure sustainability, data privacy, and security. While beneficial for governance, these regulations can create barriers for startups, especially in industries like fintech, blockchain, and AI. For instance, cities with strong data protection

laws (e.g., GDPR in Europe) may make it harder for startups dealing with big data, AI, and analytics to access and use data freely for innovation. Research indicates that complex permit processes, zoning laws, and business registration requirements in well-regulated smart cities can discourage new business formation and slow down startup growth. Smart cities often prioritize public-private partnerships (PPPs) with established tech firms (e.g., IBM, Siemens, Huawei) to implement smart infrastructure projects. This preference for large, well-funded corporations may limit opportunities for startups to engage in public procurement contracts or receive government-backed funding. A report by Statista (n.d.) highlights that most smart city initiatives focus on scaling existing technologies through partnerships with big tech firms rather than fostering startup-led disruptive innovation. As a result, startup ecosystems in such cities may struggle to compete for funding, partnerships, and market access. A report by Deloitte (Fishman & Hamilton, 2018) notes that municipalities are increasingly collaborating with private and non-profit sectors to advance their smart city agendas, which can lead to limited opportunities for startups to participate in these projects. This preference can marginalize smaller, innovative firms, making it challenging to contribute to and benefit from smart city developments.

## 4. DISCUSSION

The results reveal a statistically significant but modest inverse relationship between a city's smartness (as measured by the IMD Smart City Index) and the strength of its startup ecosystem. This finding, derived from the Random Effects model, challenges the belief that smart city development inherently supports entrepreneurial growth.

While case studies such as Taipei's Smart City Project (Lee & Taipei Smart City Project Management Office (TPMO), 2021), the #PlanTech initiative in the UK (Catapult Connected Place, 2020), and open innovation efforts in Turin (Dezi et al., 2018) suggest that smart technologies can catalyze startup activity, the current findings align more closely with critical perspectives. AlAstal (2023), Osowska (2023), and Mitra et al. (2023) point to bureaucratic rigidity, high operational costs, and complex regulatory environments as barriers to startup growth in smart cities.

The divergence may stem from the different priorities of the two indices used. While the Smart City Index emphasizes infrastructure, governance, and citizen well-being, the Startup Ecosystem Index focuses on startup-centric metrics such as funding, talent, and scalability. This difference explains why some highly ranked smart cities may not offer favorable conditions for early-stage ventures.

Additionally, established smart cities often favor large, well-funded technology partners in public-private partnerships (Fishman & Hamilton, 2018), limiting access and visibility for startups. As noted by Adler and Florida (2021), innovation often thrives in less saturated environments, not necessarily in the most technologically advanced cities.

Ultimately, this study underscores the need for cities to integrate more startup-supportive policies – such as flexible regulation, inclusive procurement, and early-stage funding – into their smart city strategies. Smart infrastructure alone may not translate into vibrant entrepreneurial ecosystems without intentional alignment.

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## CONCLUSION

This study aimed to examine the relationship between smart city development and the growth of startup ecosystems, specifically testing whether a linear relationship exists between a city's ranking in the IMD Smart City Index and its ranking in the City Startup Ecosystem Index.

The key finding of this study is that only the Random Effects model revealed a significant inverse relationship between smart city rankings and startup ecosystem performance. This suggests that higher smart city rankings may be associated with less favorable startup conditions. Despite the statistical significance, the relationship was modest ( $R^2 = 25.63\%$ ), indicating that other unobserved factors also

shape ecosystem development. A likely explanation is that highly ranked smart cities often have established infrastructures and dominant tech players, which can limit market entry and innovation opportunities for startups. Additionally, high operational costs and rigid regulatory frameworks in these cities may pose barriers to early-stage ventures. These findings challenge the assumption that smart cities inherently foster entrepreneurial growth and suggest that smart city policies and startup ecosystem development do not always align. They highlight the need for cities to adopt more startup-friendly policies to ensure that urban innovation also facilitates entrepreneurial activity.

The results of this study challenge the assumption that smart cities inherently foster entrepreneurial growth. Instead, they suggest that smart city policies and startup ecosystem growth do not always align, and cities need to adopt more startup-friendly policies to encourage entrepreneurial activity.

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## APPENDIX A

Table A1. Panel data

No.	City	City ranking positions					
		in Smart City Index ranking (IMD)			in City_startup Index ranking (calculated by the authors based on The Global Startup Ecosystem Report 2023)		
		2020	2021	2023	2020	2021	2023
1	ABU DHABI	14	12	13	23	15	25
2	AMSTERDAM–DELTA	11	13	15	25	34	21
3	BANGKOK	78	86	88	25	19	20
4	BARCELONA	58	70	75	28	29	23
5	BENGALURU–KARNATAKA	96	97	110	26	25	15
6	BERLIN	21	21	33	7	6	7
7	BIRMINGHAM	68	73	74	21	27	26
8	BOGOTA	104	113	129	0	0	10
9	BOSTON	24	22	37	7	9	11
10	BRISBANE	27	40	24	8	10	19
11	BRUSSELS	16	45	35	19	21	10
12	BUCHAREST	76	87	104	0	10	17
13	BUENOS AIRES	93	104	124	16	9	16
14	CAIRO	100	105	108	9	0	19
15	CAPE TOWN	99	106	125	10	9	14
16	CHENGDU	77	84	97	14	14	17
17	CHICAGO	54	56	61	22	25	25
18	COPENHAGEN	3	5	4	37	37	38
19	DELHI	85	94	105	30	25	19
20	DENVER–BOULDER	31	34	53	38	38	31
21	DUBAI	19	14	17	25	22	24
22	DUBLIN, MI	28	44	63	35	36	25
23	ESTONIA	39	24	32	15	16	17
24	GENEVA–LAUSANNE	8	6	9	35	35	27
25	GOTHENBURG	43	46	36	37	34	8
26	GREATER HELSINKI	5	9	8	24	23	32
27	GUANGZHOU	64	66	71	27	25	24
28	HAMBURG	6	8	11	27	30	30
29	HANGZHOU	60	63	70	16	29	24
30	HONG KONG	34	33	19	25	24	25
31	ISTANBUL	80	88	107	11	23	18
32	JAKARTA	81	92	102	15	16	16
33	KUALA LUMPUR	71	80	89	22	22	24
34	LAGOS	105	116	132	12	16	12
35	LISBON	75	81	99	13	19	17
36	LONDON	10	3	6	36	37	37
37	LOS ANGELES	36	30	50	25	26	32
38	LYON	61	62	64	37	31	26
39	MADRID	30	37	37	8	6	6
40	MANCHESTER–LIVERPOOL	57	58	73	19	21	23
41	MANILA	95	100	115	0	10	12
42	MARSEILLE	83	91	101	10	10	19
43	MELBOURNE	33	36	31	40	39	11
44	MEXICO CITY	103	110	121	11	13	11
45	MILAN	70	69	82	31	29	19
46	MONTREAL	52	55	69	29	28	29
47	MUMBAI	89	95	109	19	18	13
48	MUNICH	17	15	20	12	17	22
49	NAIROBI	107	115	131	0	0	14
50	NANJING	59	57	58	31	34	31

**Table A1 (cont.).** Panel data

No.	City	City ranking positions					
		in Smart City Index ranking (IMD)			in City_startup Index ranking (calculated by the authors based on The Global Startup Ecosystem Report 2023)		
		2020	2021	2023	2020	2021	2023
51	NEW YORK CITY	12	19	21	14	17	16
52	OSLO	2	2	2	39	40	40
53	PARIS	47	49	46	37	33	32
54	PHILADELPHIA	79	85	92	18	18	21
55	PHOENIX, AZ	72	77	93	0	0	17
56	PRAGUE	4	10	14	27	26	25
57	RIO DE JANEIRO	109	118	136	0	0	9
58	RIYADH	44	39	30	16	13	9
59	ROME	97	111	122	17	14	10
60	SANTIAGO	102	107	119	12	10	9
61	SAO PAULO	108	117	130	0	10	7
62	SEATTLE	41	38	55	39	37	28
63	SEOUL	20	18	16	21	22	25
64	SHANGHAI	42	32	25	22	20	15
65	SHENZHEN	66	60	66	29	29	23
66	SINGAPORE	7	7	7	39	38	32
67	STOCKHOLM	9	11	10	30	32	30
68	SYDNEY	32	29	18	22	28	25
69	TAIPEI CITY	23	25	29	17	15	15
70	TEL AVIV	55	59	91	21	29	18
71	TOKYO	73	67	72	22	26	23
72	TORONTO–WATERLOO	46	31	48	34	7	35
73	VANCOUVER	40	28	42	15	13	38
74	VIENNA	18	20	28	18	12	13
75	WARSAW	48	41	44	34	36	35
76	WASHINGTON, D.C.	13	26	39	37	29	6
77	ZURICH	1	1	1	1	1	1

*Note:* Smart\_City\_rank is a variable characterizing the rank of the respective city according to the methodology of the IMD World Competitiveness Center; City\_startup is an integrated indicator of startup movement in cities (calculated by the authors based on The Global Startup Ecosystem Report 2023 (Startup Genome, 2023)).