Measuring the Future:

Constructing a Dual-Dimension Index of Technology Development Potential and Ecosystem Co-Benefit Capacity for Global Leading Tech Cities

HKUST BUSINESS SCHOOL
香港科大商學院
WORLD CLASS IN ASIA

Center for Technology and Business Ecosystem
技術與商業生態研究中心

Preface

Since the Industrial Revolution, improvements in efficiency driven by technological progress have remained the central force shaping social and urban development. By continually pushing the boundaries of efficiency, humanity has unlocked unprecedented productive capacity. On this foundation, societies have relied on institutional arrangements, public governance, and redistributive mechanisms to gradually return the dividends of technological progress to the broader population. This logic has long constituted the basic operating paradigm of industrial civilization and modern cities: technology generates growth, institutions regulate distribution, and society achieves overall improvement through rising efficiency.

For a considerable historical period, this paradigm functioned effectively.

However, with the rise of the digital economy, this structure has begun to loosen in systematic ways. As technology has driven speed and efficiency toward their extremes, its impact has no longer been confined to individual firms or discrete industries. Technological outcomes increasingly transcend organizational boundaries, permeate entire value chains, reshape the survival conditions of ecosystem partners, alter the value structure of labor, and even reconfigure urban space, social stratification, and patterns of mobility themselves.

In this process, the logic of “winner takes all” has been significantly amplified and has manifested at unprecedented speed. Actors capable of continuously leveraging technology to scale their capabilities and secure stable technological rents are rapidly concentrating at the top of the pyramid; the middle layer is being compressed, weakened, or eroded; and a growing number of firms and individuals are pushed toward conditions of low marginal returns and heightened insecurity. Although average living standards continue to rise, more organizations struggle at the margins of profitability, and more individuals are depleted by sustained high-intensity competition. Gains in efficiency no longer translate automatically into improved social order; instead, in some cities they have evolved into widespread internal competition and structural anxiety.

Redistributive mechanisms can, to some extent, mitigate unequal outcomes, but they are poorly equipped to address the structural ruptures created by the speed of technological change itself. When technological evolution reshapes industrial structures and dissolves established occupations and organizational forms within a decade, or even less, institutional compensation typically lags behind the transformation. By the time support mechanisms are activated, firms and groups that once depended on the old structures often no longer exist.

Yet efficiency and public value are not inherently opposed.

In practice, we also observe an alternative trajectory. Some firms, while creating value for themselves, preserve viable space for upstream and downstream partners; maintain institutional trust during periods of growth; and assume corresponding social and environmental responsibilities as innovation expands. These experiences clearly demonstrate that technology can function either as an amplifier of fragmentation or, under appropriate governance and ecosystem design, as a force for shared benefit.

It is against this backdrop that this report is written.

We move beyond asking merely why technology develops as it does, and instead ask a more fundamental question: what outcomes does technology ultimately produce? Efficiency itself is not the problem; the critical issue lies in its direction. How is the value created by technology distributed? Are technological dividends broadly absorbed by society, or are they increasingly concentrated among a small number of actors? If technological progress comes at the cost of eroding social trust, distorting opportunity structures, or placing sustained pressure on ecological and systemic capacity, the result may not be more resilient prosperity, but rather urban systems that are more efficient, and more fragile.

This tension will be further intensified in the era of artificial intelligence.

Compared with the digital economy, artificial intelligence does not merely enhance efficiency; it reconfigures capability itself. The scale and speed of productive capacity it releases exceed those of any previous technological wave, with deeper, faster, and less reversible impacts on occupational structures, organizational forms, education systems, and public governance. At the same time, while technological frontiers advance rapidly, governance frameworks often respond with delay, meaning that the faster technology evolves, the greater the systemic risks created by institutional gaps.

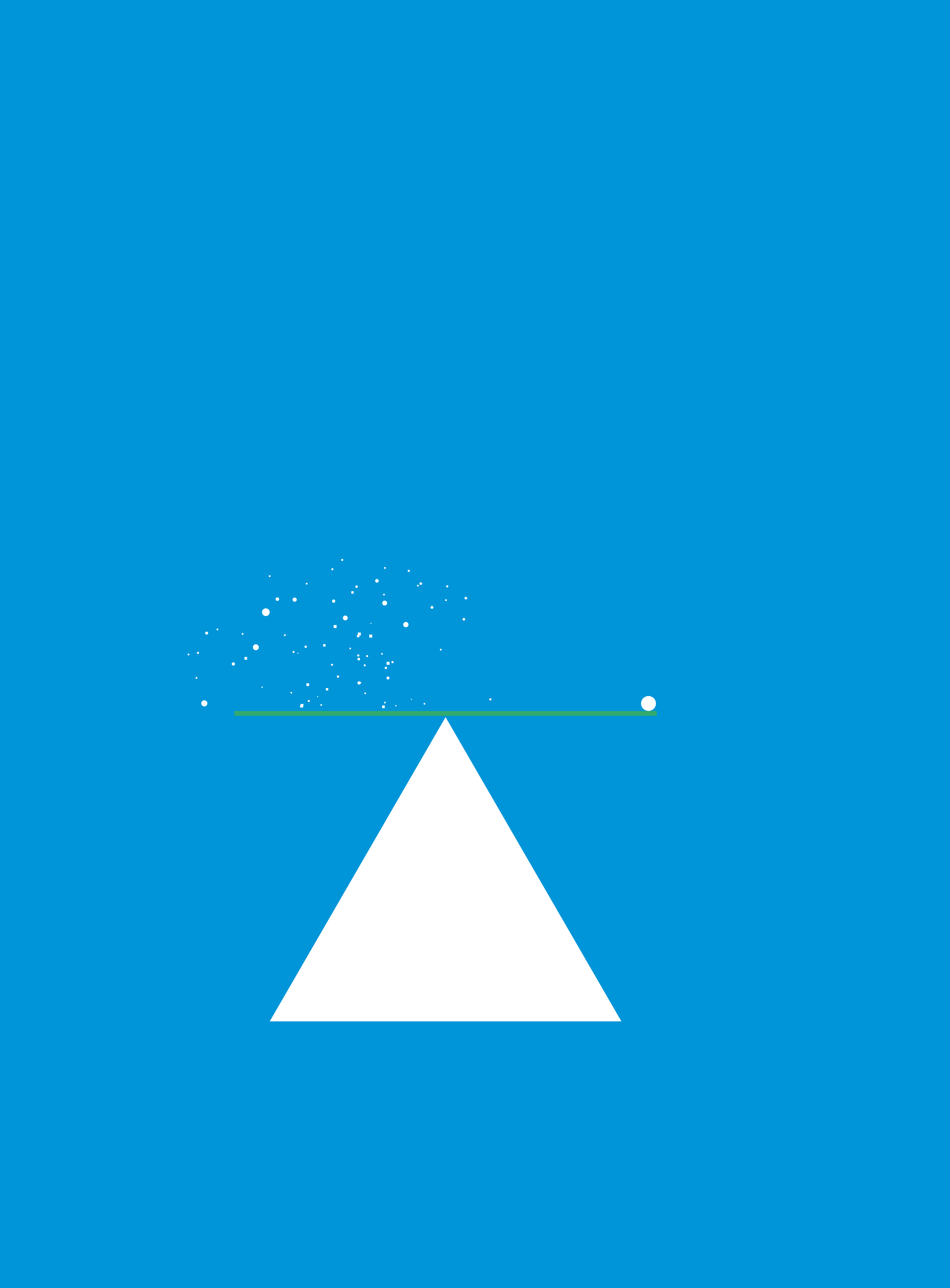
For these reasons, we argue that technology-driven cities have entered a new stage of competition. Differences among cities are no longer determined primarily by who possesses more advanced technology, but by who can consistently translate technological progress into public value.

Based on this premise, the report introduces a dual-dimensional analytical framework centered on Technology Development Potential (TDP) and Ecosystem Co-benefit Capacity (ECB). This framework brings together both the scale of technological capability and the quality of its outcomes within a single evaluative system. It emphasizes that technological development is not merely a process of accumulating technology and capital, but a complex transformation that must be absorbed, regulated, and converted through institutional, industrial, social, and environmental systems.

This report is not intended to produce yet another city ranking. Rather, it seeks to offer a new interpretive coordinate. Ahead of the full arrival of the AI era, this framework helps cities, firms, and policymakers more clearly recognize how technology is reshaping social structures, and how institutional design and ecosystem coordination can guide technological progress toward long-term, sustainable public value.

Kai-Lung Hui

Contents



Executive Summary

From "Technology Development" to "Anxiety over Growth Quality"

Over the past three decades, the main theme of global urban competition has been highly consistent: The future will be won by whoever can gather the most technological resources. R&D investment, engineer density, venture capital, unicorn enterprises, and computing power scale - these indicators have gradually formed the standard profile of a "Technology City" or "Tech City", and have also supported the rapid rise of a number of cities such as San Francisco, Singapore, Shenzhen, and Tel Aviv. For many cities, technology is almost regarded as a "universal solution": as long as technology is strong enough, growth, employment, competitiveness and urban prosperity will eventually follow.

However, in the 2020s, this logic began to show systematic loosening. Among the worldwide most technology-dense cities, the trajectory of development is showing unprecedented divergence: some cities are experiencing rapid increases in living costs, intensifying social divisions, accumulating ecological pressures and amplifying governance tensions while technology continues to expand; Some other cities have been able to maintain technological vitality while simultaneously improving social inclusiveness, governance transparency and environmental sustainability, demonstrating greater long-term resilience.

This is no longer a question of "whether technology has done enough or not", but a more fundamental proposition: How exactly does technology enter urban society and ecosystems? Technology is no longer the answer itself, but a test about the ability to transform.

Core Judgment: What determines a city's long-term success or failure is not the intensity of its technology, but its ability to transform

This study centers on a core judgment: Against the backdrop of technology becoming the core growth engine, the significant difference that determines the long-term development quality of a city does not lie in the potential of Technology development itself, but in whether technology developmentcan be stably and continuously transformed into ecosystem benefits.

To this end, we have constructed a two-dimensional analysis framework, breaking down the development capacity of a tech city into two independent but essential dimensions:

Technology Development Potential (TDP) : measures a city's comprehensive capacity in technology generation, adsorption and transformation, representing the scale, density and industrialization chassis of its science and technology activities.

Ecosystem Co-benefit Capacity (ECB) : measures whether science and technology activities actually translate into broader social inclusion, quality of governance, environmental sustainability and system resilience. In this study, ECB is regarded as a core component and key proxy indicator of "urban development quality", with a focus on the externalities in the social, governance and environmental dimensions brought about by technological growth. It is not the entirety of urban development quality, but it is the most prominent competitive dimension and the concentrated manifestation of systemic risks in the current global tech cities under the background of "growth quality anxiety".

Comprehensive Ranking of the World's Top 10 Tech Cities: A Parallel Comparison of Capacity and Quality with TDP and ECB Rankings

Based on cross-city data from 2018 to 2024, this study conducted a comprehensive assessment of ten representative tech cities worldwide. The rankings of technology development potential (TDP) and ecosystem co-benefit capacity (ECB) are as follows: The leading position of a tech city is no longer determined by the intensity of a single

TDP Ranking

RANKING	CITY	TDP INDEX
1	San Francisco	1.30
2	New York	0.72
3	Beijing	0.62
4	Singapore	0.34
5	Shanghai	0.24
6	Shenzhen	0.12
7	Hong kong	0.10
8	London	0.04
9	Helsinki	-0.11
10	Tel Aviv	-0.26

ECB Ranking

RANKING	CITY	ECB INDEX
1	Helsinki	1.01
2	San Francisco	0.48
3	New York	0.41
4	London	0.28
5	Singapore	0.21
6	Hong kong	0.04
7	Tel Aviv	-0.17
8	Beijing	-0.36
9	Shanghai	-0.51
10	Shenzhen	-0.60

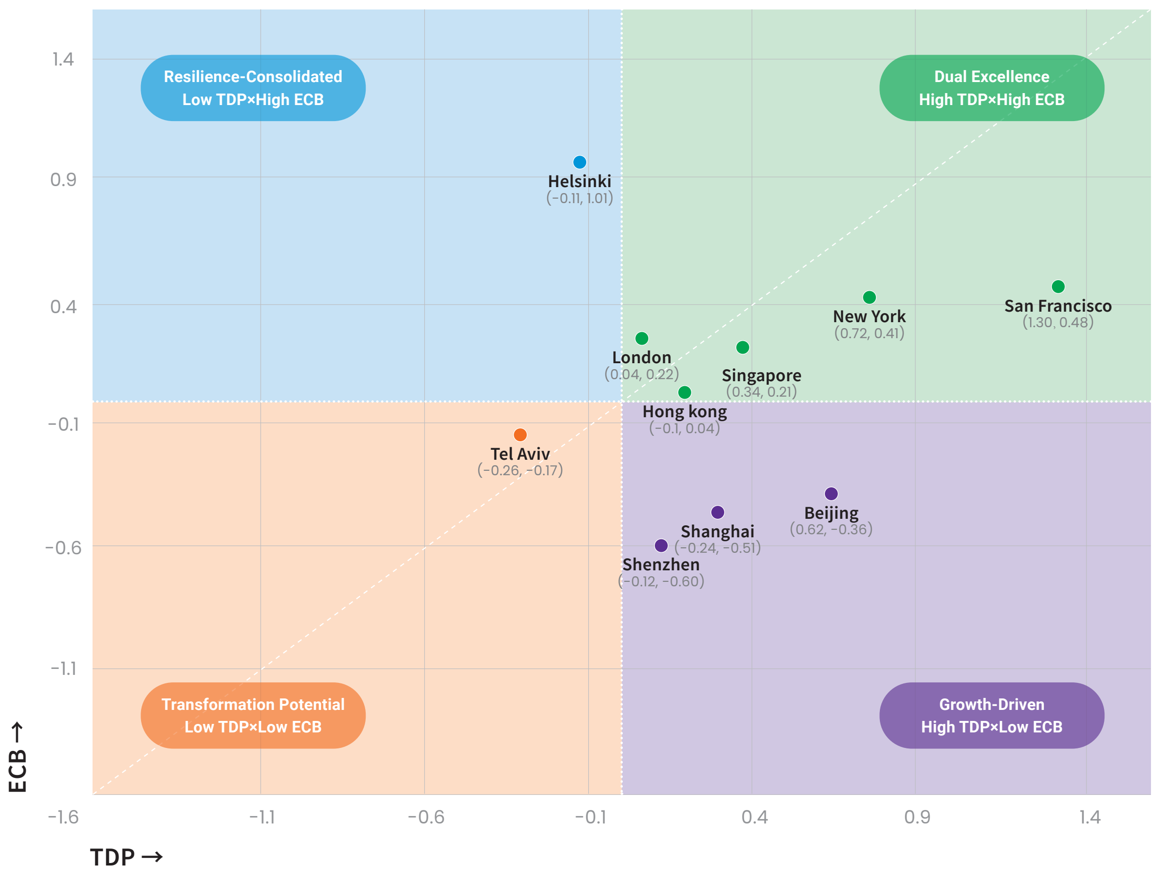
technology. San Francisco, New York and Beijing are at the top with extremely strong technological foundation. Cities like Helsinki and London, although not the largest in terms of technological scale, have relatively outstanding ecosystem co-benefit performance. Meanwhile, in some highly active cities in terms of technology and industry, such as Shanghai and Shenzhen, the co-benefit transformation is relatively insufficient.

TDP× ECB Dual-dimensional Framework

This study proposes a dual-dimensional framework of TDP (Technology Development Potential) × ECB (Ecosystem Co-benefit Capacity), placing technology development and ecosystem co-benefit within the same analytical system, providing new theoretical and empirical tools for understanding the entry of global technology cities into the "Era of Growth Quality".

In the dual-dimensional matrix of TDP× ECB, the ten representative global technology cities do not present a linear distribution of "the stronger the technology, the higher the co-benefit", but are clearly differentiated into four types of structural locations. Each quadrant corresponds to different development paths, constraints and policy priorities.

TDP× ECB dual-dimensional matrix urban distribution map



1. Dual excellence type (high TDP × high ECB), technology - co-beneficial resonance zone
Representative cities: San Francisco, New York, Singapore, London, Hong Kong

Cities in this quadrant possess both a strong technological capability foundation and a smooth mechanism for the transformation of co-benefits. Technological capabilities are enhanced in tandem with social inclusion, governance trust, and environmental performance, and technology is continuously transformed into increments of public value.

From the perspective of the four-quadrant distribution, dual-excellent cities are at a high level in terms of technological vitality and co-benefit performance. Combining mechanism analysis, we infer that they possess stronger system stability and long-term resilience, representing a more sustainable structural form when the competition among technology cities shifts towards the "Quality Era".

2. Growth-driven type (high TDP × low ECB), the co-benefit gap under high-tech density
Representative cities: Beijing, Shanghai, Shenzhen

Cities in this quadrant possess the world's strongest technological infrastructure and capital aggregation capabilities, but their ecosystem co-benefit performance lags significantly behind the pace of technological expansion.

In these cities, technological growth is more reflected in the success at the enterprise and capital levels, while the efficiency of its diffusion to society as a whole is relatively limited, and the carrying capacity of the public system is gradually becoming a constraining factor.

This is not a "failure of technology", but rather an insufficient mechanism for the transformation of technology. The risk of growth-driven cities does not lie in insufficient technological strength, but rather in the fact that during the stage of high technological density, institutional coordination, social inclusiveness and environmental carrying capacity have not been upgraded simultaneously, making it easy to enter the "congestion effect" range.

3. Resilient synergistic type (medium and low TDP × high ECB), a steady-state structure with mutual benefits taking the lead
Representative city: Helsinki

The technological capabilities of such cities are not the most outstanding, but they perform relatively steadily in terms of governance transparency, social inclusiveness and public service systems, thus achieving better results in the ECB dimension.

The advantage of resilient and synergistic cities lies in their shock resistance and system stability. Such cities may not have the strongest technological capabilities, but they maintain a high quality of development with a relatively low technological density by virtue of their institutional, social and environmental advantages. Its long-term appeal is often underestimated, yet it demonstrates greater resilience in an uncertain environment.

The challenge does not lie in "whether to develop science and technology", but in how to further enhance the efficiency of technology transformation without disrupting the existing common benefit structure.

4. **Transformation potential type (low TDP × low ECB), dual-dimensional shortcomings and structural catch-up**
   Representative city: Tel Aviv

The intra-city differences in this quadrant are significant, but the common feature is that the technology or innovation elements have certain advantages, but there is still a structural break point in the co-benefit transformation chain.

The key to transforming potential cities does not lie in "supplement an indicator", but in systematically reconstructing the collaborative relationship among technology, systems, society and the environment. Otherwise, even if local technological breakthroughs are achieved, it will be difficult to form sustainable urban competitiveness.

Proposals of Hong Kong's Development

Hong Kong SAR has entered the "dual excellence" range in the TDP×ECB matrix, but the index value is only slightly above zero, indicating that it has crossed the structural threshold for positive transformation: technological activities have begun to generate certain public value spilt, and advantages such as institutional governance, capital flows, and international connections provide the basic conditions for transformation. However, the core contradiction of Hong Kong does not lie in "whether it has technology development potential", but in "whether the transformation mechanism has entered a stable state". As the density of technological activities rises, the demand for computing power increases, and the engineering and industrialization chains extend, Hong Kong is more likely to be the first to hit the bottleneck of system carrying capacity, resulting in the marginal contribution of technology development potential to ecosystem co-benefit capacity showing unstable and easily peaked characteristics: although it can be transformed, it is difficult to continuously scale up.

What hinders Hong Kong from “critical transformation” to “stable dual excellence” is a set of superimposed structural constraints: the critical scale of the entrepreneurial ecosystem is insufficient (The top layer is visible, but the middle layer of Series B-D is relatively thin, and the ecological cycle is difficult to close); The demand side of the industry is relatively narrow (high financialization makes innovation more inclined towards “embedded optimization”, and the radius of spillover is limited). The chain of technology capital is not closed (financial capital is strong, but the coverage of high-tech VC, growth funds and strategic capital is insufficient. The capital advantage is more like raising the development base rather than forming an amplifier). The talent retention mechanism is insufficient (it can attract financial and professional service talents, but it is difficult to accumulate engineering and scientific research talents in the long term). Therefore, the policy focus of Hong Kong should shift from “expanding S&T” to “consolidating and transforming the structure” : expanding the diffusion radius by opening up the system and scene, strengthening social absorption and talent precipitation by housing and public services, and improving the system carrying capacity in the high-density stage by computing power and hard technology carrier construction, so as to promote Hong Kong from “dual excellence” to “steady state double optimal”.

Key Research Findings

1. Technology does not automatically translate into growth quality

Based on a systematic empirical analysis of ten representative global technology cities from 2018 to 2024, this study finds that: There is no automatic and linear positive relationship between Technology Development Potential (TDP) and Ecosystem Co-benefit Capacity (ECB). Investment in science and technology and the intensity of innovation remain important foundations of a city’s competitiveness, but their role is highly dependent on the collaborative structure of systems, industries, society and ecosystems.

This finding implies that technology is not an automatic guarantee for the high-quality development of cities. Without corresponding institutional support and social absorption mechanisms, scientific and technological activities often only translate into local efficiency or capital gains, and are difficult to continuously generate public values such as social inclusion, governance improvement and ecological sustainability.

2. Four “transformation channels” determine whether technology can become public value

Further mechanism tests have shown that whether technology can be transformed into ecological benefits does not depend on a single factor, but rather on four key but long-underestimated structural channels: institutional thresholds, industrial diffusion, social inclusiveness and system carrying capacity.

The empirical results show that there is a stable and significant positive correlation between the institutional foundation and the ecosystem co-benefit capacity, but the institutional variable has not significantly changed the marginal slope of the ecosystem co-benefit capacity caused by the potential of scientific and technology development. This indicates that the core role of the system does not lie in amplifying the marginal return on technological investment, but in setting the "access conditions" for technology to enter the public system: High-quality systems provide the necessary institutional environment for the social diffusion, public absorption and long-term accumulation of scientific and technological achievements. However, in cities with weak institutional foundations, even if the level of scientific and technological investment is relatively high, their scientific and technological activities are more likely to remain at the level of local efficiency or capital return, and it is difficult to be transformed into stable public value increments.

At the industrial structure level, industrial diversity has significantly enhanced the efficiency of technology spillover. In a highly concentrated industrial structure, technological innovation is more likely to remain at the "frontier bubble" level and is difficult to achieve wide diffusion.

At the social structure level, there is a significant negative correlation between the degree of inequality and the ability of ecosystem co-benefit capacity. Technology does not automatically narrow the gap; instead, it may exacerbate differentiation under the condition of an unbalanced opportunity structure.

At the system carrying level, nonlinear tests show that there is a threshold effect in technological density. When the intensity of technological activities exceeds the absorption capacity of urban society and ecosystems, the co-benefit returns will significantly decline.

Policy Suggestions for the Ecosystem Co-benefit and Technology Development

The governance logic of tech cities is undergoing a profound transformation. If the core proposition of urban competition over the past three decades was "how to enhance technological capabilities", then at the current stage, the more crucial issue has shifted to:

how to continuously transform technological progress into high-quality urban development.

1. The technology strategy is no longer a "single track", but a systematic engineering

Traditional science and technology policies are often regarded as a relatively independent policy track, with their main goals focusing on the scale of R&D investment, the number of innovation entities, or the technological breakthroughs themselves. However, this study indicates that this "isolated technology strategy" is showing obvious structural boundaries. In cities with high technology development potential, what determines whether technology can be transformed into long-term competitiveness is not the technological capabilities themselves, but the degree of coupling between technology and systems, industries, society and ecosystems. This means that if science and technology policies are disconnected from institutional reforms, scientific and technological achievements are more likely to be internalized by a few entities. If technological expansion lacks a social absorption mechanism, it often directly translates into pressure on housing, transportation and public services. If technological growth fails to take into account environmental carrying capacity and spatial structure simultaneously, it may instead magnify systemic risks.

Therefore, for urban administrators, the real challenge does not lie in "whether to continue developing technology", but in how to embed the technology strategy into a set of coordinated institutional, industrial, social and ecological governance systems.

2. When assessing a city's competitiveness, it is necessary to shift from "investment scale" to "transformation chain"

One of the most policy-valuable findings of this study lies in the clear distinction between the capacity for technological investment and the capacity for technological transformation.

For a long time, the assessment of city's competitiveness has highly relied on indicators such as R&D intensity, capital scale, the number of engineers and the number of unicorn enterprises. These indicators are undoubtedly important, but they mainly reflect the front-end capabilities of scientific and technological activities. However, empirical results show that in the stage of high technological density, simply expanding the scale of investment will significantly reduce the marginal contribution to enhancing the ecosystem co-benefit capacity.

This means that the city's competitiveness assessment system itself needs to undergo a shift - from "whether more technology has been done" to "whether technology has truly changed the quality of urban development".

Specifically, urban decision-makers need to systematically question: Have scientific and technological achievements penetrated industrial boundaries and entered public services and traditional industries? Has innovation formed a diffusion path that transcends enterprises, departments and groups? Does technology capital support the entire life cycle of an enterprise's growth rather than just remaining at the early valuation stage?

In other words, what determines a city's long-term competitiveness is not the "height" of technological investment, but the "completeness" of the technological transformation chain.

3. High-tech cities particularly need to attach importance to the pre-governance of "slow variables"

This study further reveals that in cities with a high concentration of technology, the key variables influencing the long-term development quality are often not the "fast variables" that can be rapidly adjusted in the short term, but rather the "slow variables" such as institutional trust, social inclusiveness and environmental carrying capacity.

This study further reveals that in cities with a high concentration of technology, the key variables influencing the long-term development quality are often not the "fast variables" that can be rapidly adjusted in the short term, but rather the "slow variables" such as institutional trust, social inclusiveness and environmental carrying capacity.

These variables share three common features: First, they are difficult to improve rapidly through short-term policy sprints; Second, once there is an imbalance, its negative impact is highly cumulative. Thirdly, it is often underestimated in the early stage of technological expansion but becomes concentrated in the high-density phase. This also explains why some highly successful cities in terms of technology will simultaneously encounter problems such as housing crises, social divisions and rising governance tensions in the later stage.

Therefore, this study puts forward a clear policy judgment: Institutional trust, social inclusiveness and ecological resilience are not the "natural outcomes" of technological growth, but rather the prerequisite conditions for the sustainable expansion of technology. For cities that are already in the stage of high technological density, ignoring these "slow variables" will not accelerate technology development; instead, it may prematurely reach the upper limit of the system.

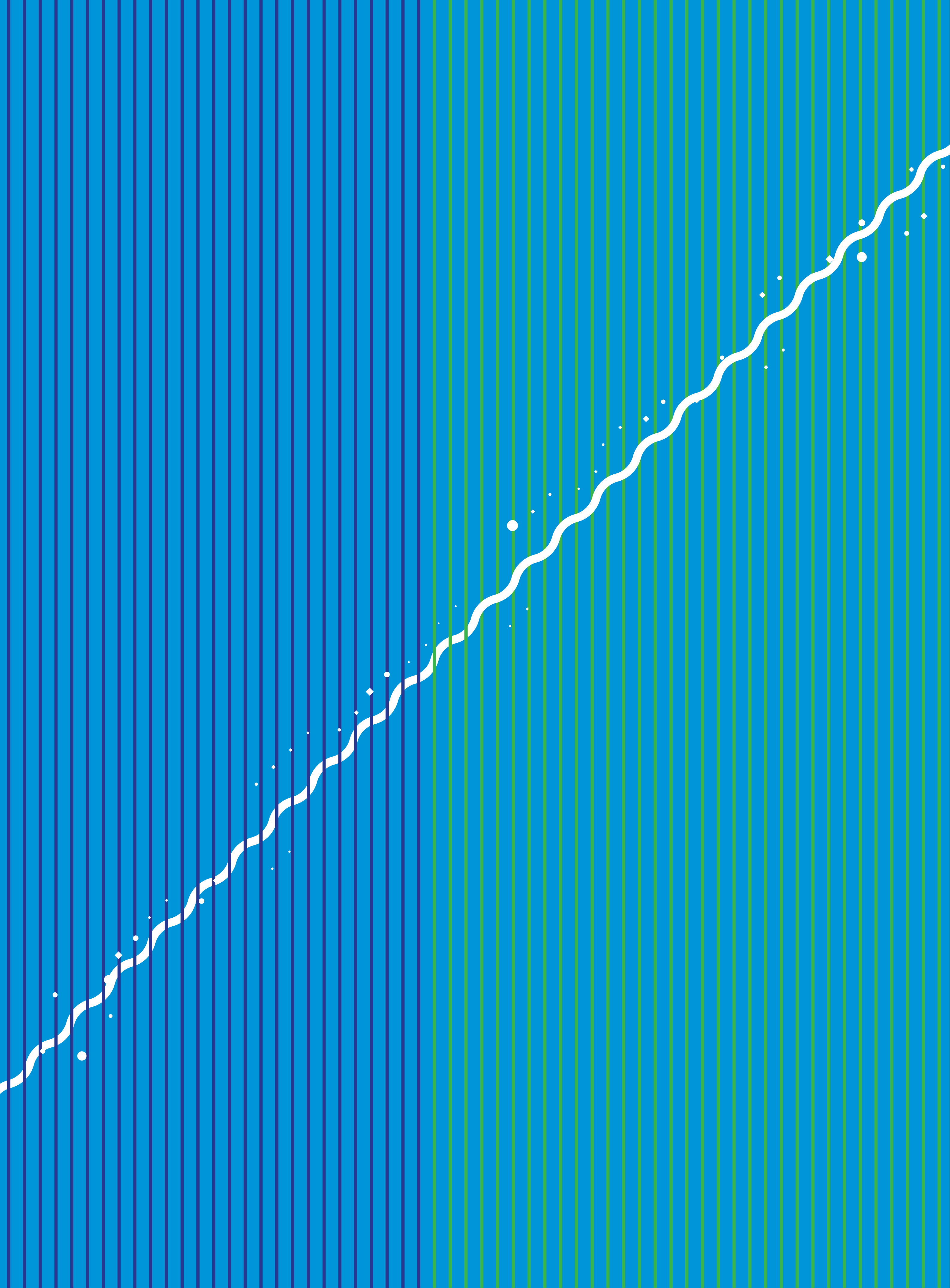
Conclusion: The Competitive Leap from “Tech Cities” to “Regenerative Cities”

The comprehensive ranking analysis, matrix placeholder comparison and empirical test results all point to a clear and consistent conclusion: technology does not automatically bring about high-quality growth. What truly determines a city’s long-term competitiveness is not the strength of technology itself, but whether the city has the systematic capacity to digest, regulate and redistribute the impact of technology.

In this sense, global tech cities have entered a new stage of development: competition no longer mainly occurs in laboratories, capital markets or patent lists, but in the collaborative capabilities among institutions, industries, society and the environment.

This study further proposes a forward-looking judgment: The competitive logic of global tech cities is shifting from “technological competitiveness” to “urban regenerative capacity”. The so-called system regeneration capacity refers to the ability of a city to maintain social inclusiveness, governance stability and ecological sustainability in the face of continuous technological shocks. This ability does not aim for the maximum speed of technological expansion, but rather emphasizes whether technology can be continuously absorbed by the social system, whether the dividends of innovation can be shared by a wider group, and whether the growth process will erode institutional trust and the ecological foundation.

Therefore, a truly leading tech city is no longer merely a “high-tech city”, but a “highly beneficial city” that can maintain social, institutional and ecological stability under conditions of high technological density. The competition among cities in the future, in the final analysis, is a competition about “who can make technology serve public value in the long term”.



Chapter 1

Tech Cities Enter the “Era of Growth Quality”

Over the past three decades, the global technological revolution has reshaped the competitive landscape of cities at an unprecedented speed. Technology density - including the degree of concentration of R&D investment, innovative enterprises, technical talents and digital infrastructure - has gradually become the most intuitive and commonly used measure of a city's competitiveness. From San Francisco, which adheres to a deep innovation system, to Singapore, which adopts a highly institutionalized technology governance model, and then to Shenzhen, which practices a development path renowned for the high coupling of industry, innovation and application, global tech cities together form the most dynamic growth poles in the world economy.

However, a fact that is becoming increasingly clear but has long been overlooked is emerging:

The growth of technology itself is no longer sufficient to explain the long-term prosperity of a city.

When we compare the development trajectories of different tech cities from the global innovation landscape, it is not difficult to find that a structural differentiation is accelerating its emergence. Despite increasing high-level R&D investment, having a highly concentrated pool of scientific and technological talents and globally leading innovative enterprises, and attracting global innovative resources, the social inclusiveness of some cities has been continuously declining, while housing pressure, commuting costs, inequality and ecological load have been constantly rising. While other cities can synchronization improve life quality, governance, transparency and green transformation ability, form a stronger institutional resilience and long-term competitive advantage.

This means that what truly sets tech cities apart is not "how advanced the technology is", but rather how the technology spreads, is absorbed, is constrained within the urban system, and ultimately translates into social and ecological outcomes.

More and more studies have pointed out that if technology development is divorced from institutional quality, social structure and ecological carrying capacity, it will not only fail to bring about lasting prosperity, but may also intensify inequality, increase systemic risks and weaken the long-term governance capacity of cities. The spillover effect of technology in cities has never been linear or neutral. The same scale of technological investment may lead to completely different development outcomes in different cities.

The development logic of a tech city cannot be fully explained by a single theory. It involves complex systems such as institutional framework, innovation ecosystem, industrial evolution, digital platform governance, social behavior and environmental carrying capacity. Although technology is an engine of growth, it can only be transformed into sustainable growth quality through the coordinated action of four systems: institutions, industries, society and the environment.

Whether a city can transform its "technology development potential (TDP)" into a positive coupling among economic vitality, social equity and ecological sustainability - this is becoming a decisive issue for urban development in the technological era. It is precisely against this backdrop that urban development has entered a new stage:

Shift from "who innovates more" to "who grows better".

Growth rate is gradually giving way to growth quality, and the core of growth quality is no longer the technology itself, but whether the technology can form a positive coupling among economic efficiency, social equity and ecological sustainability.

This article summarizes this capability as "ecosystem co-benefits" to propose and systematically construct the "Dual-Dimension Index of Technology Development Potential and Ecosystem Co-Benefit Capacity for Global Leading Tech Cities", thereby answering a long-underestimated but decisive question for urban policy and strategic choices:

Why do cities with the same high density of innovation lead to such different development qualities?

To answer the above questions, a single-disciplinary perspective is clearly insufficient. This study does not attempt to construct an all-encompassing ultimate indicator system for "urban development quality", but rather focuses on a key entry point: in the context where technology has become the core driving force, how can cities transform the potential of technology into positive outcomes for society, governance and the environment (i.e., ecosystem co-benefits). How technology can be transformed into long-term value for cities involves the intersection of multiple fields such as economics, urban studies, institutional theory, innovation ecology, platform strategy, environmental science and behavioral science. **The ECB index constructed in this study is precisely aimed at extracting a set of "development quality" dimensions that are most directly related to the spillover effect of technology from these cross-disciplinary fields.**

Existing research can roughly be summarized into four relatively independent but not yet systematically integrated research threads: Institutional inclusiveness and innovation spillover (such as Acemoglu & Robinson, 2012, 2023) : Emphasizing that institutional quality determines whether technology is universally diffused or seized by a few entities; Innovation

Ecosystem Diffusion and Industrial Diversity (e.g. Feldman & Kogler, 2010): Focusing on how technology generates spillover effects through industrial structure and collaborative networks; Inequality and opportunity absorption (e.g. Stiglitz et al., 2009): It points out that social structure determines whether technological achievements can be widely absorbed; Green transformation and system resilience (such as IPCC, OECD): Emphasizing that the environment and public systems are hard constraints on technological expansion.

These studies each explain "a certain aspect" of the development of tech cities, but lack an integrated framework that can simultaneously explain "why technology leads to different outcomes in different cities". This article precisely attempts to respond to this theoretical gap, with two goals:

First, establish a reproducible and comparable indicator system to simultaneously measure the Technology Development Potential (TDP) and Ecosystem Co-benefit Capacity (ECB) of acity.

Second, through systematic empirical testing, answer a question with more policy implications: Why can some tech cities transform technology into better economic, social and environmental outcomes, while others cannot?

Focusing on the above two goals, this article proposes the following core research questions:

RQ1 (Main Question): *Does the technology development potential (TDP) necessarily enhance a city"s ecosystem co-benefit capacity (ECB)?* This determines whether a "tech city" necessarily equals a "high-quality city".

RQ2 (Mechanism Question): *What key conditions will amplify or block the transformation of TDP to ECB?* This determines the policy priorities: whether to prioritize systems and industrial structures first, or social inclusiveness and environmental carrying capacity first.

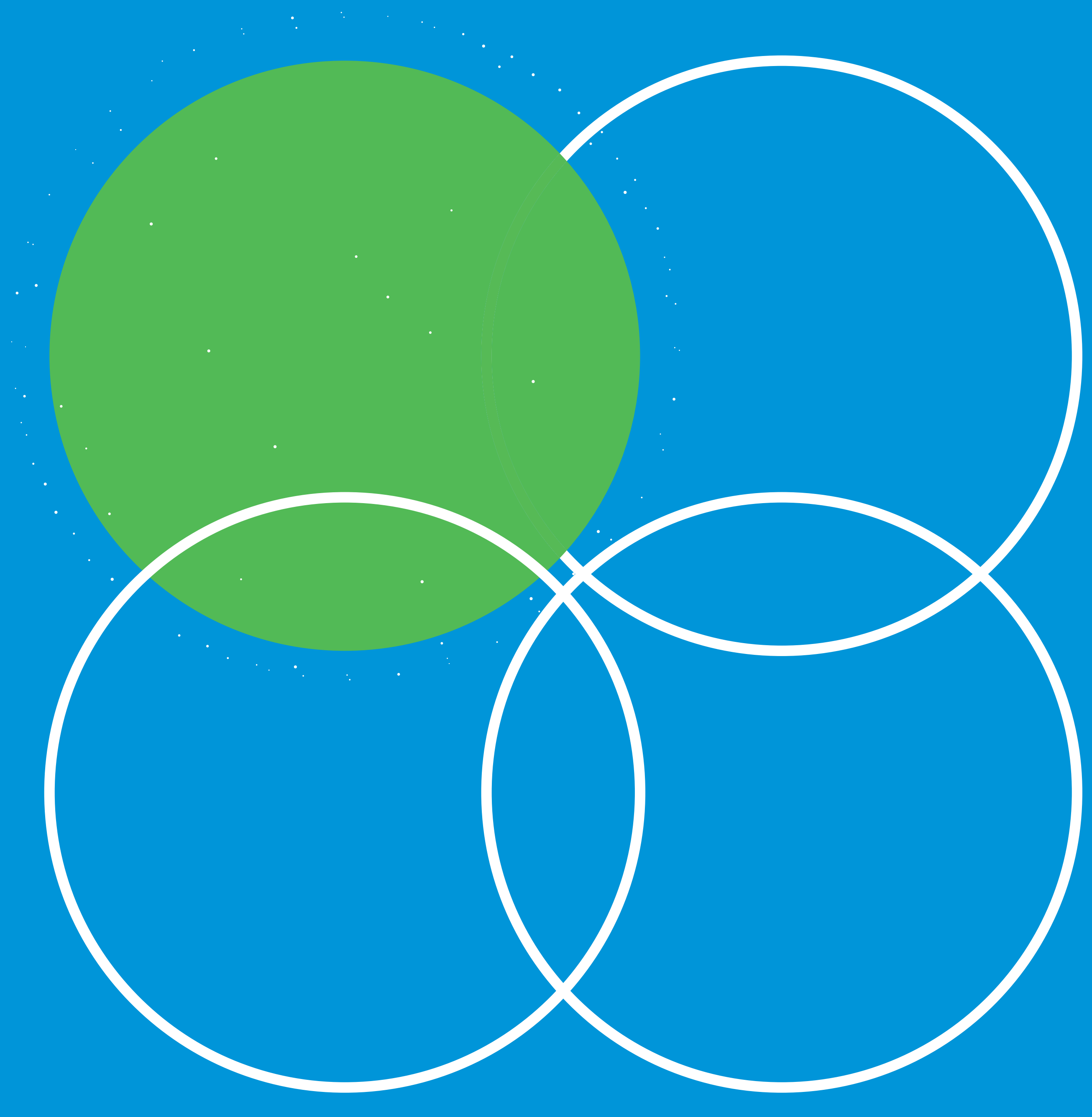
RQ3 (Boundary Question): *Is there a nonlinear or threshold effect between TDP and ECB?* This concerns whether "continuing to increase investment in science and technology" will lead to a decline in marginal returns or even bring about a crowding effect.

RQ4 (City Implementation): *At which link are cities like Hong Kong SAR and Beijing respectively stuck in the technology-benefit transformation chain?* This is related to the differentiated routes of cities and targeted policy tools.

This article holds that the technological capacity of a city is merely the "supply side", while the system, ecosystem, social structure and governance capacity determine how technology is "absorbed, distributed and amplified". Under this framework, a city's long-term competitiveness is not only about how much technology it can create, but also about whether it can truly empower a broader population, a more stable system and a healthier ecosystem with technology.

To explain the differences in city rankings, one cannot merely look at the technological strength itself, but also at how technology is integrated into the urban system.

This article presents a structural chain to explain how the technology potential is transformed into the quality of urban development through multiple mechanisms: The technology development potential (TDP) provides growth momentum, but institutions, industrial networks, social inclusiveness and environmental resilience together constitute the transformation device, determining whether the technology spilspill can enter the public system in a controllable and diffusible manner. The ecosystem co-benefit capacity (ECB) is reflected as the "performance end" of urban development quality and forms feedback to the innovation system through trust, attractiveness and carrying capacity. The real difference among tech cities does not lie in "who is more innovative", but in "who can stably transform innovation into mutual benefit".



Chapter

2

From “Technology-Driven Growth” to “Ecosystem Co-benefit of Science and Technology, Institutions, and Society”

Traditional studies of tech cities often regard technological innovation as the core engine of long-term urban growth. However, technologically leading cities do not necessarily correspond to higher development quality. We believe that greater focus can be placed on whether technological dividends can be effectively translated into public value at the social, governance, environmental, and systemic levels. Building upon existing research perspectives such as institutions, ecosystems, society, and the environment, we aim to explore the integration of technology developments and ecosystem co-benefits within a unified analytical framework, thereby fostering a deeper understanding of the development of global tech cities.

2.1 Core Paradigms of Tech City Research: Technology, Capital and Agglomeration

Research on the competitiveness of tech cities has long been built upon a relatively clear consensus: technological innovation constitutes the core engine of long-term urban growth. Since the advent of endogenous growth theory, a substantial body of literature has emphasized the decisive roles of knowledge accumulation, R&D investment, and human capital in driving regional and urban economic growth (Romer, 1990; Aghion & Howitt, 1992).

At the urban level, this logic has further evolved into an explanatory framework centered on innovation agglomeration. Glaeser (2011) argues that high-density cities derive sustained competitive advantages through knowledge spillovers, labor market matching, and economies of scale, while Florida (2002) emphasizes that the spatial concentration of the "creative class" is a key source of urban innovation capacity and economic vitality. For tech cities, economic density, knowledge spillovers, and industrial diversity position cities as critical sites for the generation and diffusion of innovation.

Within this paradigm, the central question confronting tech cities is:

How to more efficiently generate technology, attract talent, and expand the scale of innovation.

This research tradition provides a solid foundation for understanding inter-urban differences in innovation capacity and also constitutes the theoretical point of departure for what this study conceptualizes as Technology Development Potential (TDP). However, as tech cities enter a more mature stage of development, this paradigm has gradually exhibited limitations in its explanatory power.

2.2 Theoretical Rupture: Why "Stronger Innovation" No Longer Equals "Better Development"

Over the past decade, an increasingly unavoidable reality has emerged: technological leadership in cities does not necessarily correspond to higher development quality. On the one hand, cities and city-regions such as San Francisco, New York, and London continue to maintain globally leading levels of innovation density and technology capital agglomeration; On the other hand, these places simultaneously face challenges including housing crises, widening inequality, rising commuting costs, growing pressures on public governance, and an increasing ecological burden. By contrast, some cities whose scale of innovation is not exceptionally prominent exhibit more balanced performance in terms of quality of life, social stability, and green transition. This phenomenon constitutes a direct theoretical challenge to technological determinism.

In their systematic critique of GDP-based indicators, Joseph Stiglitz, Amartya Sen, and Jean-Paul Fitoussi (2009) argue that conventional measures of economic growth fail to capture distributional structures, equality of opportunity, and sustainability. Within the field of innovation, Acemoglu and Robinson (2012), as well as Acemoglu and Johnson (2023), further emphasize that the interaction between technological trajectories and institutional structures determines whether technology is inclusive or extractive. The same technology may generate entirely opposite social outcomes under different institutional environments.

Urban studies has gradually come to recognize that:

The problem lies not in technology itself, but in the mechanisms through which technology enters social and ecological systems.

2.3 From "Growth Quality" to "Ecosystem Co-benefits": Why High-Quality Development Is Operationalized through ECB

The existing literature widely recognizes high-quality development as a multidimensional concept, encompassing economic structure, social distribution, institutional performance, environmental sustainability, and systemic stability (Stiglitz et al., 2009; OECD, 2021). However, within the study of tech cities, this concept often remains at a normative or conceptual level, lacking operationalized and comparable measurement approaches.

In this study, we deliberately narrow the analytical focus to a more targeted dimension: whether technological dividends are effectively transformed into public value at the social, governance, environmental, and systemic levels.

Based on this premise, this article proposes and employs Ecosystem Co-benefit Capacity (ECB) as an operational definition of development quality in tech cities. ECB is not intended to exhaust all dimensions of high-quality development; Rather, it concentrates on the key outcome dimensions triggered by technology development, namely whether technology improves social inclusion, governance quality, environmental sustainability, and urban resilience in a broader societal context.

This conceptual choice is consistent with the outcome-oriented understanding of development quality found in the Beyond GDP literature, the United Nations Sustainable Development Goals (SDGs), and the OECD Well-being Framework. Social inclusion, governance transparency, environmental sustainability, and system resilience have been widely regarded as core outcome dimensions for evaluating contemporary urban development quality, particularly in high-income, high-technology-density cities.

At the same time, this study acknowledges that ECB cannot fully capture other dimensions of development, such as economic complexity, industrial competitiveness, or cultural vitality. Nevertheless, within the context of tech cities, ECB captures precisely the most salient contemporary form of “quality anxiety”: why technological growth has not been accompanied by more sustainable and inclusive urban outcomes.

2.4 An Institutional Perspective: How Institutional Quality Shapes the Direction of Technological Spillovers

Institutional theory provides the first key analytical lens for understanding heterogeneity in technological spillovers.

Classical institutional economics argues that the rule of law, property rights protection, and regulatory quality shape the incentive structures underlying economic activity (North, 1990). Within innovation studies, this logic has been further developed into the distinction between inclusive institutions and extractive institutions (Acemoglu & Robinson, 2012).

At the urban level, Kaufmann et al. (2010) show that regulatory quality and government effectiveness significantly affect the breadth and equity of technological diffusion, while Mazzucato (2018) emphasizes the mission-oriented role of the public sector in shaping the direction of innovation.

Taken together, these studies demonstrate that institutions are not an exogenous backdrop to innovation, but rather a regulator of the direction of technological spillovers. Institutional quality determines whether technological outcomes are widely absorbed across society or internalized by a limited set of actors. This study conceptualizes this mechanism as the Institutional Valve Mechanism.

2.5 Innovation Ecosystems and Diffusion: From "Invention" to "Systemic Coordination"

Institutions alone are insufficient to explain the spatial heterogeneity of technological spillovers. A second key analytical strand emerges from innovation ecosystem theory.

Feldman and Kogler (2010) argue that innovation is not a single-point activity, but rather a complex networked process involving firms, research institutions, platforms, and the public sector. Industrial diversity has been shown to facilitate cross-domain knowledge recombination, thereby enhancing the adaptability and shock resilience of regional innovation systems (Jacobs, 1969; Frenken et al., 2007).

Research on the platform economy further emphasizes that platform governance structures determine how technologies are organized, allocated, and diffused (Gawer & Cusumano, 2014; Kenney & Zysman, 2016). Open and competitive ecosystems are more likely to embed technologies into a broad range of economic and social contexts, whereas highly closed or monopolistic structures tend to generate "innovation islands."

Taken together, this literature suggests that the key to technological value lies not in who invents the technology, nor in invention per se, but in whether technology can diffuse, coordinate, and be widely absorbed within an ecosystem. Innovation is not a single-point breakthrough, but a multi-actor coordination process involving value chains, platforms, capital, and talent. The higher the level of systemic coordination, the faster the pace of technological commercialization. Industrial diversity, platform governance quality, and the maturity of the entrepreneurial ecosystem jointly determine whether technology remains confined within a small number of firms or diffuses broadly across value chains, the public sector, and everyday urban life.

This set of mechanisms is conceptualized in this study as the Innovation Ecosystem Diffusion Mechanism. Cities, by virtue of their economic density, knowledge spillover effects, and industrial diversity, are often regarded as "innovation machines". However, identical levels of technological output may generate fundamentally different spillover effects across cities. In other words, cities possess distinct innovation ecosystem diffusion mechanisms.

2.6 Social Inclusion and Absorptive Capacity: Why Technology Amplifies or Mitigates Inequality

The third theoretical strand draws on research on inequality and structures of social opportunity.

A large body of empirical research shows that technological progress, in the absence of effective social absorptive mechanisms, often exacerbates income inequality and inequality of opportunity (Autor, 2014; Piketty, 2014). Urban housing markets, education systems, and labor skill structures shape the distributive outcomes generated by technological change: skill-intensive cities are better able to absorb technological dividends, whereas housing supply constraints and skill mismatches limit the inclusive distribution of technological gains (Kline & Moretti, 2014).

Research by the UNDP (2022) and the OECD (2021) further indicates that the digital divide, skill gaps, and housing unaffordability significantly weaken the positive effects of technology on overall well-being. Technology can be transformed into inclusive growth only when supported by education, training, and public service systems.

Taken together, this literature emphasizes that the "last mile" of technological spillovers lies in social structures, rather than in markets alone. Technological spillovers ultimately materialize in people, not merely in indicators. Inequality structures, housing affordability, access to education and skills, and the level of digital inclusion determine whether technological outcomes can benefit the majority of society.

This corresponds to what this study conceptualizes as the Social Inclusion Absorptive Mechanism. The more inclusive a society is, the more likely technology is to translate into inclusive growth; the more fragmented a society becomes, the more likely technology is to turn into "a dividend for the few."

2.7 Environment and Resilience: The Carrying Boundaries of Technological Scale Expansion

The final key theoretical strand draws from environmental economics and urban resilience studies. Recent international approaches to measurement have increasingly focused on regenerative capacity and resilience, that is, whether cities are able to recover rapidly from shocks and emerge stronger through the recovery process.

The co-benefits framework articulated by the IPCC (2022) explicitly points out that while technological progress may reduce emissions intensity, it can simultaneously increase overall environmental pressure through scale effects. As high-density systems, cities' energy structures, infrastructure, and public health capacity determine whether technological expansion translates into systemic risk. Some urban resilience research (Meerow et al., 2016; OECD, 2020) emphasize that responding to climate shocks, public health crises, and digital risks has become a critical dimension of long-term urban competitiveness.

These findings imply that the stronger technology becomes, the higher the demands placed on environmental and resilience capacity. Technology development amplifies urban scale, energy consumption, and system complexity. Energy structure, carbon emissions, green ecological spaces, public health capacity, infrastructure, and digital resilience jointly determine whether cities can withstand the shocks and expansionary pressures generated by technological growth. Where carrying capacity is insufficient, stronger technological capabilities may paradoxically lead to greater systemic risk.

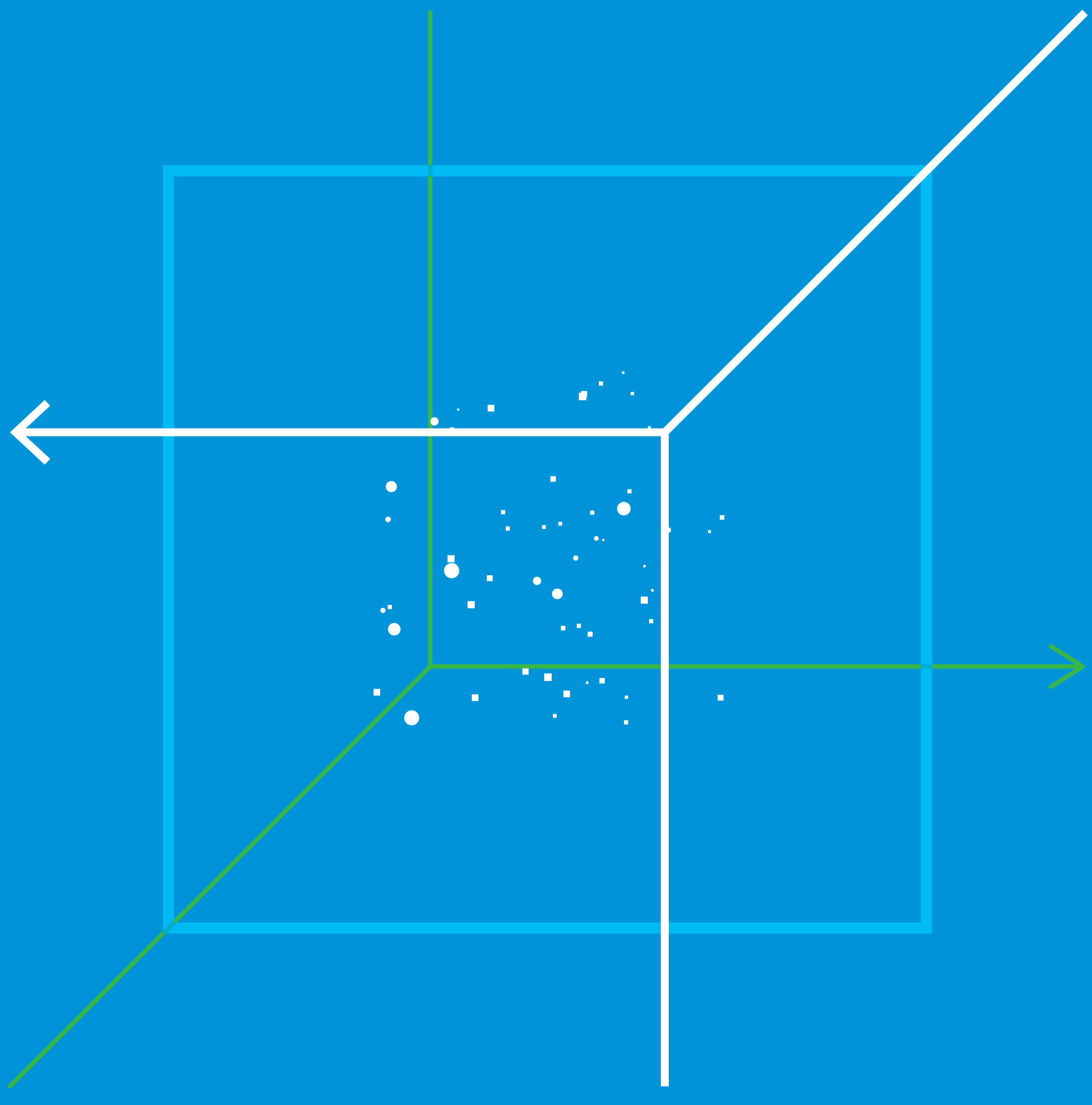
This set of dynamics constitutes what this study terms the Environmental & Resilience Capacity Mechanism. Accordingly, the analysis cannot focus solely on technological intensity, but must also examine how technology affects environmental outcomes, that is, how the environmental–resilience capacity mechanism operates.

2.8 Chapter Summary

In summary, the existing literature offers important insights along four dimensions—institutions, innovation ecosystems, social structures, and environmental–resilience capacity—yet several notable limitations remain. Most studies examine individual mechanisms in isolation, lacking an integrated and systemic analytical framework;

Technological variables are often treated primarily as explanatory inputs, while the outcomes of technological spillovers are rarely measured in a systematic and comprehensive manner; City-level comparative research continues to rely heavily on rankings of innovation intensity, which makes it difficult to explain the structural divergence between high innovation capacity and low development quality.

It is precisely in response to these gaps that this study proposes a dual-dimensional framework centered on TDP × ECB, placing technological dynamism and ecosystem co-benefits within a unified analytical system. This framework provides new theoretical and empirical tools for understanding how global tech cities are entering an era characterized by a renewed emphasis on the quality of growth.



Chapter 3

Constructing the Dual-Dimensional Index of "Technology Development Potential × Ecosystem Co-benefit Capacity"

The core competitiveness of technology cities is shifting from ***innovation scale to systemic quality.*** Yet, prevailing global city indices remain heavily reliant on growth-oriented metrics—such as GDP, patent counts, and venture capital inflows—making it difficult to capture the real direction of technological spillovers: Is technology creating broader social welfare, or amplifying inequality and systemic pressures?

The research not only explore ***who develops technology more strongly, but also whether and how technology leads to better economic, social, and environments***. The following sections will explain: **How the indicator framework is designed, How each dimension is constructed, How data are selected and processed, and How statistical and regression analyses are used to test our core mechanistic hypotheses.**

3.1 From Theory to Measurement: Why a New Urban Evaluation Model Is Needed

Over the past several decades, research on technology-driven urban development and ecological sustainability has evolved along two relatively independent, yet neither fully explains the ***transformation mechanism*** between technology and co-benefits:

First, the "dimensional fragmentation" of research perspectives. Existing literature typically focuses on a single dimension—such as institutional quality, innovation ecosystems, social inclusion, or environmental resilience—to examine its impact on urban development. For example: Institutional theory emphasizes how rule of law and regulation shape innovation direction (Acemoglu & Robinson, 2012); Innovation ecosystem studies focus on industrial diversity and knowledge diffusion (Feldman & Kogler, 2010); Social structure analysis highlights how inequality constrains the absorption of technological dividends (Stiglitz et al., 2009); Environmental economics warns that unchecked technological expansion may breach ecological carrying capacity (IPCC, 2022). While these studies illustrate specific aspects of urban development, but lack a systematic framework that integrates **institutional**, **industrial**, **social**, **and environmental dimensions**, thus failing to explain why cities with similar technological intensity often diverge dramatically in development quality.

Second, the "structural disconnect" between technological growth and ecological co-benefits. Although some research acknowledges that technology is not a neutral growth engine, most treat "technology development" and "social/ecological outcomes" as separate analytical domains. Technology evaluation systems (e.g., patent numbers, R&D spending, venture capital) rarely include co-benefit effects. Conversely, sustainability or livability indices often treat technology as an exogenous background factor, not an endogenous driver.

This “measurement separation” has long neglected a critical question:

Does (and under what conditions) Technology Development Potential (TDP) transform into Ecosystem Co-benefit Capacity (ECB)?

Are there linear relationships, threshold effects, or structural constraints between them? Existing studies lack a quantifiable, comparable empirical framework to systematically answer the question.

Therefore, this study constructs the **TDP × ECB Index** to fill these dual theoretical and measurement gap.

Theoretically, this index for the first time places ***technology development potential (TDP) and ecosystem co-benefit capacity (ECB)*** within the same analytical framework, emphasizing their non-causal but systemically coupled relationship—mediated through institutional, industrial, social, and environmental mechanisms.

Methodologically, the index breaks free from the limitations of “single-dimensional rankings” or “isolated indicator stacking.” It establishes a structured, comparable, and reproducible dual-dimensional evaluation system—allowing cities’ positions on both “technological strength” and “co-benefit quality” to be clearly visualized. This provides empirical grounding for identifying transformation bottlenecks and designing differentiated policies.

Through this index, aiming not only to describe who is stronger, but to explain why they are strong—and whether that strength is sustainable. This is precisely the central question that tech cities must answer in the era of growth quality.

3.2 The Dual-Dimensional Framework: TDP × ECB

The core model in this study adopts a two-dimensional structure:

• **X-axis: Technology Development Potential (TDP)**
Measures a city’s ability to generate, attract, and convert technology—serving as the “engine of growth.”

• **Y-axis: Ecosystem Co-benefit Capacity (ECB)**
Assesses the key non-economic or beyond-GDP outcomes triggered by technological expansion—covering social inclusion, institutional trust, environmental sustainability, and

systemic resilience. ECB reflects a specific "quality of growth" perspective: Is growth fair, sustainable, and resilient?

We believe ECB as a crucial yet often overlooked dimension of urban development quality, especially in the current phase of rising "growth quality anxiety."

The two dimensions are not simply causally linked but interact through the four mechanisms outlined earlier—forming non-linear, amplifiable, or obstructable transmission chains. This structure enables tech cities to be clearly classified into four typical development pathways (elaborated in subsequent chapters):

1. **High TDP × High ECB (Dual-Excellence Cities)**
2. **High TDP × Low ECB (Growth-Driven Cities)**
3. **Low TDP × High ECB (Resilience-Consolidated Cities)**
4. **Low TDP × Low ECB (Transformation-Potential Cities)**

3.3 Constructing TDP: Logic and Sub-Dimensions

Technology Development Potential (TDP) is not only a measure of innovation output, but a systemic capacity encompassing knowledge generation, technological foundations, capital support, and institutional environment.

This research decomposes TDP into four sub-dimensions:

TDP-1: Knowledge & Innovation Production

This dimension measures a city's capacity to generate knowledge and applications at both basic research and applied innovation levels—referring to ***where technology comes from***.

Key indicators include: R&D intensity (R&D/GDP); Scientific publication output and impact; Patent applications and grants (especially high-value patents).

A city's core asset is new knowledge. Research outputs, patent quality, and R&D investment collectively determine its "frontier capability." Therefore, this study uses representative indicators such as article share, the number of patent application, and R&D expenditure—reflecting a city's ability to ***produce high-quality knowledge and technology*** (Appendix 1).

TDP-2: Digital & Technological Infrastructure

The World Bank point out that improvements in digital infrastructure significantly promote technology diffusion and innovation, but their effects depend on institutional and human capital conditions (World Bank, 2016). Digital infrastructure serves as the "foundation" for innovation. 5G density, broadband speed, cloud computing nodes, and data center scale directly affect how quickly technology spreads and is adopted.

China Academy of Information and Communications Technology (CAICT, 2023) finds that cities with denser 5G deployment lead in industrial internet integration, providing critical support for industrial digital transformation. Thus, the study uses fixed and mobile broadband speeds, as well as broadband penetration rates, to assess whether a city enables rapid diffusion of technology into real-world applications (Appendix 1).

TDP-3: Technology Capital & Entrepreneurial Ecosystem

Capital and entrepreneurial ecosystems act as the "accelerators" of innovation. Evolutionary economics suggests that industrial agglomeration, knowledge accumulation, and talent structure create path dependence, locking cities into long-term technological trajectories. Risk capital, startup density, and the presence of multinational R&D centers reflect a city's capacity to commercialize technology. Wang Yue (2021) examines how venture capital discovers innovative value within innovation ecosystems. OECD (2023, 2025) highlights that startups play vital roles in economic restructuring, global trade integration, and regional innovation systems, enhancing internationalization and export potential. Chen Ling et al. (2021) systematically introduced the indicator system, evaluation objects, and assessment results of the Global Innovation Hub Index (GIHI), presenting the innovation performance and rankings of 30 international science and technology innovation cities (urban agglomerations) across various dimensions such as scientific centers, innovation hubs, and innovation ecosystems.

This dimension captures the ***commercialization capacity*** of technology—from lab to market—representing a key channel for innovation translation. Key indicators include: venture capital size (VC/GDP); startup density; number of multinational R&D centers and tech company headquarters.

We use the **Technology Capital and Entrepreneurial Ecosystem Composite Index** compiled by StartupBlink to measure city-level innovation vitality. See Appendix 1 for details.

TDP-4: Institutional Readiness for Innovation

This dimension emphasizes that institutions shape the direction and efficiency of innovation—and serve as the "gatekeeper" of innovation diffusion. Rules of law, fair regulation, intellectual property protection, and government openness collectively define technological vitality. For a city, technology development potential only becomes a shared benefit when paired with effective governance and public policy.

Key indicators include: Rule of law index and IP protection; regulatory quality and policy stability; innovation-friendliness.

Empirical studies consistently show that stronger IP protection is linked to higher quality innovation. Luo et al. (2024) and Hu et al. (2023) find that strengthening IP protection improves innovation environments and significantly boosts high-quality outputs. OECD (2022) finds that higher regulatory quality encourages SMEs to invest in R&D and increases innovation activity. These findings support the hypothesis that ***institutional quality amplifies technological spillovers***.

This study uses data on government efficiency, rule of law index, and regulatory quality to examine whether institutional quality enhances the TDP-to-ECB transformation (Appendix 1).

All four sub-dimensions, from TDP-1 to TDP-4 combine to form the overall TDP index. In calculation, each sub-dimension is standardized and aggregated with equal weights.

3.4 Constructing ECB: Logic and Sub-Dimensions

Unlike TDP, which measures ***whether a city grows***, ECB measures ***whether growth generates positive externalities***.

ECB is composed of four structural dimensions, aligning with the four mechanisms outlined in the previous sections:

ECB-1: Social Inclusion & Opportunity Structure

A major risk in tech cities is increasing inequality and housing crises—where technological advancement and industrial upgrading may come at the cost of distributional fairness.

The World Bank (2016) indicates that digital technology and high-tech industries do not automatically deliver inclusive growth. Without strong education and skills systems, technological progress may exacerbate income inequality. However, targeted investments in education and skills can significantly mitigate this effect. Similarly, OECD (2015, 2021) finds that in countries with higher digital literacy, the negative impact of tech expansion on inequality is significantly reduced—or even reversed.

Moreover, talent attraction is not just about salaries. Openness, cultural diversity, affordability, and access to quality education and public services are key factors for high-skilled talent. Glaeser et al. (2023) show that housing affordability is a critical determinant of talent retention: housing supply constraints raise prices and deter high-skilled migration. Florida (2002) argues that high-skilled talent considers openness, cultural vibrancy, and quality of life—not just wages—when choosing cities. Multiple studies confirm that skills structure and city attractiveness are closely linked to skilled migration, with non-wage factors playing a significant role (Glaeser & Mare, 2001).

Another aspect is also critical. Thaler's behavioral economics reminds us that even high digitalization levels do not guarantee inclusivity. Marginalized groups may be "digitally excluded" due to poor interface design, institutional barriers, or behavioral friction. Pew Research Center (2021) finds that despite high overall broadband coverage, low-income groups still lag behind in internet adoption—highlighting persistent digital divides.
This dimension assesses whether technological benefits are widely absorbed—not concentrated among a few.

Key indicators include: income inequality (Gini coefficient, income quantile gaps); housing affordability; access to education and skills; digital inclusion.

The study uses Gini coefficient, housing index, and undergraduate rate and higher education participation rate to complete the following research (Appendix 1).

ECB-2: Governance Transparency & Institutional Trust

This dimension evaluates whether technological governance enhances public trust rather than creating uncertainty. It focuses on transparency and openness as enablers of innovation diffusion.

Key indicators include: The level of government transparency and open government data; integrity and regulatory credibility; citizen participation and institutional responsiveness. Transparent, reliable governance is critical for turning technological spillovers into public benefit, while open data may reduce innovation costs and reduce the time of commercialization cycles (Nesta, 2021).

Cheng Di et al. (2024) compare Toronto's Sidewalk Toronto project and Harbin's Pingfang District: Toronto's project suffered from secrecy, delayed transparency, opaque data governance, and weak oversight—eroding public trust. In contrast, Harbin achieved better outcomes through institutional building and active public engagement.

However, Ripamonti (2024) warns that observational studies may overestimate the positive impact of transparency on trust due to common method bias, while experimental studies yield mixed results.

Thus, the relationship between ***open government data (OGD)*** → ***trust*** → ***governance*** is not always linear: openness helps combat corruption and improve performance—but only if data disclosure is complete and oversight mechanisms are strong.

By using Open Government Index, Corruption Perception Index, Corruption Governance Index, Global Trust Index, and Public Participation Index. Interpretation emphasizes that ***design and implementation quality*** determine whether transparency translates into real co-benefits (See Appendix 1 for details).

ECB-3: Environmental Sustainability & Urban Ecology

Green transition determines whether tech cities can transcend environmental limits and achieve long-term sustainability. Sustainability research consistently views natural capital and environmental quality as foundational to urban competitiveness. Hai Junjiao et al. (2018) identify a research framework centered on "natural capital," with transformation governance and sustainable urban space as emerging hotspots. OECD (2021) argues that green and digital transitions must be pursued in tandem coordinated at the systemic level, not isolated. Empirical studies also show a significant coupling relationship between digitalization and green development in Chinese cities, with dynamic spatiotemporal evolution patterns (Guo, 2022).

This dimension measures whether technological expansion reduces, rather than amplifies, ecological pressure.

Key indicators include: carbon intensity (CO_2/GDP); renewable energy percentage; air quality (PM2.5 concentration); forest covering rate.

The study uses carbon emission intensity per unit GDP, renewable energy percentage, forest coverage, and PM2.5 levels as indicators (See Appendix 1 for details).

ECB-4: Urban Resilience & Systemic Capacity

Resilience is the foundational capacity for long-term urban competitiveness—especially post-pandemic. It refers to a city's ability to withstand, adapt to, and recover from shocks—from pandemics and natural disasters to economic downturns.

Zhao Yu et al. (2024) review research trends from 2000 to 2022, showing that urban resilience has evolved from ecological frameworks into multidimensional models encompassing disaster prevention, economic factors, complex coordination, and dynamic systems. Lü Xiaohuo (2025) emphasizes that lifeline systems are interact with transportation, energy, water, and sanitation. A failure in one can trigger "domino effects." Megacities must combine prevention and response, and optimize spatial structures to enhance systemic risk resistance. UNDRR (2022) finds that systematic risk assessment and early warning systems are key tools for reducing disaster losses and human exposure. Enhanced risk governance significantly reduces economic impacts.

The study uses infrastructure quality index, hospital beds per 10,000 people, disaster risk management index, and public health resilience as indicators—answering whether cities have the environmental and governance foundations to ensure that technological growth does not come at the cost of ecological or systemic stability (See Appendix 1 for details).

All four ECB sub-dimensions—ECB-1 to ECB-4—collectively form the ECB index, capturing cities' real performance in the era of growth quality.

3.5 Index Construction Methods and Design for Comparability

To ensure cross-city, cross-institutional comparability, the study follows these methodological principles:

- **Equal-weight standardization:**

- TDP: Four sub-dimensions with equal weights; each sub-dimension uses Z-score or Min-Max normalization to eliminate unit differences; equal weights or robust weights used within each dimension.
- ECB: Four sub-dimensions with equal weights; includes directional adjustment (e.g., Gini, PM2.5, carbon intensity inverted); Z-score or Min-Max normalization applied; equal weights

used.

- **Hierarchical aggregation structure:**

Indicator → **Sub-dimension** → **Dimension** → **Overall Index**, ensuring each level is interpretable and transparent.

- **Robustness checks:**

Results are tested under alternative weighting schemes, indicator removals, or model variations.

- **Prioritizing data availability and reproducibility:**

All indicators are sourced from publicly available, authoritative databases (e.g., WIPO, World Bank, OECD, UNESCO, WHO, WJP, IQAir, Numbeo, StartupBlink).
The full data collection and index construction rules are documented in Appendix 1.
All indicators undergo the following unified processing:

- Standardization (z-score or Min-Max)
- Directional adjustment for negative indicators (e.g., Gini, PM2.5, carbon intensity)
- Imputation for missing data (based on spatial/temporal proximity or average)
- Clear labeling of data source and cutoff year

3.6 Chapter Summary: From Measurement Tool to Analytical Platform

This index system enables, for the first time, the integration of a city's technology development potential and ecosystem co-benefit capacity within a unified framework. It allows the transformation from ***growth to shared benefit*** to be quantified and visualized—making structural differences and developmental pathways across tech cities clearly visible.

The TDP × ECB framework is not just a ranking tool—it is a **dynamic analytical platform** for understanding how technology becomes a force for inclusive, sustainable, and resilient urban development in the era of quality growth.

Chapter

4

Analysis of Technology Development Potential and Ecosystem Co-benefit Capacity in the World's Top Ten Cities

This chapter examines the cross-city variations in TDP and ECB, presents the structural profiles across eight key dimensions, and identifies which cities exhibit a mismatch between strong technological capacity and weak co-benefit outcomes—i.e., "high TDP but low ECB." Through visual analytics and structural ranking, this chapter systematically reveals the current divergence landscape of global tech cities across the two core dimensions: **Technology Development Potential (TDP) and Ecosystem Co-benefit Capacity (ECB).**

Rather than relying on single-dimensional rankings, this chapter emphasizes the identification of ***structural positions***—aiming to answer: ***Where do different tech cities actually excel or lag? What do these differences reveal about their institutional and governance models?***

4.1 Multidimensional Distribution Patterns of TDP and ECB

Based on the TDP and ECB indicator systems developed in the previous chapter, this chapter conducts a descriptive analysis of the relative positions of the ten global leading tech cities across multiple dimensions. The cities included are: San Francisco, New York, London, Singapore, Beijing, Shanghai, Shenzhen, Hong Kong, Helsinki, and Tel Aviv.

4.1.1 Joint Distribution of TDP and ECB

Figure 4-1 presents the relative positioning of the ten representative tech cities along the two dimensions: **Technology Development Potential (TDP) and Ecosystem Co-benefit Capacity (ECB).**

- **X-axis (Horizontal Axis): Technology Development Potential (TDP)**

Reflects a city's comprehensive capability in knowledge generation, digital and technological infrastructure, technology capital and entrepreneurial ecosystem, and institutional readiness for innovation.

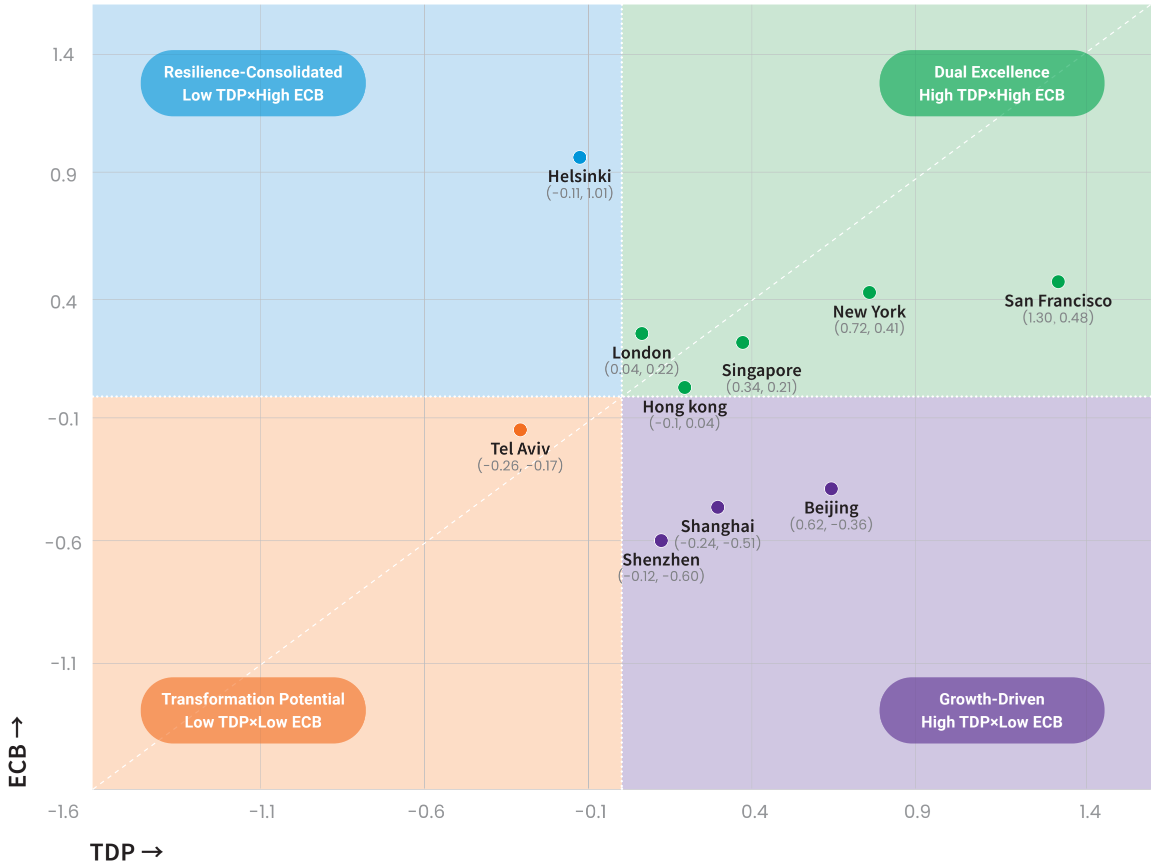
- **Y-axis (Vertical Axis): Ecosystem Co-benefit Capacity (ECB)**

Captures whether technological advancement translates into long-term public value—specifically, social inclusion, governance transparency, environmental sustainability, and urban resilience.

Data Handling Principle:

The analysis primarily uses data from 2024. For indicators with missing values, the most recently available year (typically 2023) is used as a proxy, with clear annotations. Detailed data sources and processing methods are provided in Appendix 1.

Figure 4-1. Scatter Plot of TDP vs. ECB: City Distribution in the Dual-Dimensional Matrix



From the joint distribution of TDP and ECB, it is evident that the world's ten leading tech cities do not align along a single linear axis of "the stronger the technology, the higher the co-benefit." Instead, they form distinct and well-separated clusters across the four quadrants of the dual-dimensional matrix. The scatter plot reveals that some cities exhibit high technology development potential but fail to achieve commensurate levels of ecosystem co-benefit; conversely, other cities demonstrate strong performance in ecological and social outcomes despite not ranking at the top in technological capability.

Three key patterns emerge clearly from the distribution:

1. **No simple one-to-one relationship exists between TDP and ECB**. High technology development potential does not automatically translate into high ecosystem co-benefit capacity. Several cities rank significantly higher on TDP but lag behind on ECB, indicating a breakdown in the transmission mechanism—where technological spillovers are constrained or blocked at the institutional, social, or environmental level.

2. **Cities exhibit clear structural clustering rather than continuous linear progression.** The distribution is not a smooth gradient from low to high across both dimensions, but instead reveals distinct structural groupings. This suggests the existence of different development pathways and governance models, rather than a universal trajectory toward convergence.

3. **The long-term competitive advantage lies in the "dual-high" structure.** Cities located in the upper-right quadrant—high TDP combined with high ECB—possess not only strong capabilities in generating and absorbing technology, but also the systemic capacity to convert technological advancement into high-quality, resilient, and inclusive growth outcomes.

Specifically:

• **San Francisco** and N**ew York** rank among the top in TDP while maintaining positive performance in ECB, placing them firmly in the upper-right quadrant—exemplifying the dual-excellence model.

• **Helsinki** stands out as the top performer in ECB, despite having a relatively lower TDP score, forming a distinct "high ECB, low TDP" profile.

• **London** and **Singapore** rank relatively high on ECB but fall behind the North American hubs in TDP, suggesting a governance model that prioritizes social and environmental outcomes even with moderate technological intensity.

• **Tel Aviv** occupies a unique position, with no other city matching its exact combination of TDP and ECB levels, reflecting the heterogeneity and distinctiveness of its development path.

Among the cities of China:

• **Beijing**, **Shanghai**, and **Shenzhen** all rank in the upper-middle to high range on TDP, yet display notably low ECB scores, clustering prominently in the "high TDP, low ECB" quadrant—indicating a significant structural misalignment.

• **Hong Kong** lies in the central region of the matrix, with neither dimension showing a clear advantage—suggesting a balanced but not dominant performance across both fronts.
In general, the scatter plot clearly demonstrates that **technology development potential and ecosystem co-benefit capacity are not inherently synchronized**. The observed distribution underscores a pronounced structural mismatch—highlighting that future urban competitiveness will depend less on technological scale alone, and more on a city's ability to integrate technological power with institutional, social, and ecological coherence.

4.1.2 Technology Development Potential Ranking (TDP Ranking): Identifying the Core Engines of Innovation

The TDP Ranking answers a clear and focused question:

Which cities are strongest in their ability to generate, attract, and convert technology?

This ranking is based exclusively on the TDP index, without incorporating any social or environmental dimensions. Its purpose is to identify the global epicenters of technological capacity -- free from the potential distortion caused by co-benefit outcomes revealing the true drivers of innovation momentum and technological concentration.

The TDP Ranking reflects the **density of technological activity and the underlying innovation dynamism** of a city, not its overall development quality or sustainability.
The ranking reveals a relatively clear hierarchical structure:

TDP Ranking

RANKING	CITY	TDP INDEX
1	San Francisco	1.30
2	New York	0.72
3	Beijing	0.62
4	Singapore	0.34
5	Shanghai	0.24
6	Shenzhen	0.12
7	Hong kong	0.10
8	London	0.04
9	Helsinki	-0.11
10	Tel Aviv	-0.26

• **San Francisco** and **New York** lead the list, demonstrating a decisive advantage in the aggregation of technological resources, intensity of innovation activities, and efficiency of technology-related resource allocation.

• **Beijing** ranks third, underscoring its outstanding performance in research infrastructure, scientific output, and the scale of technological engagement—reflecting its status as a national and global innovation hub.

• Following closely are **Singapore**, **Shanghai**, and **Shenzhen**, which occupy a mid-to-high tier in TDP. While these cities exhibit strong technological momentum, they still face a noticeable gap compared to the top-tier North American centers, particularly in areas such as venture capital depth, global R&D network integration, and open innovation ecosystems.

• **Hong Kong**, **London**, **Helsinki,** and **Tel Aviv** rank further down in the TDP hierarchy. This reflects a relatively smaller scale of technological resource aggregation and a less dominant position in global innovation networks—though many of these cities maintain niche strengths in specific technological domains.

It is critical to emphasize that this ranking captures **only technology development potential**—a single-dimensional measure. It does not account for how effectively technology is transformed into social, environmental, or governance outcomes. As such, a high TDP score does not imply a high quality of urban development, nor does it guarantee long-term resilience or inclusive growth.

4.1.3 Ecosystem Co-benefit Capacity (ECB) Ranking: Reordering the Metrics of Growth Quality

The ECB Ranking addresses a fundamental question:

Which cities are best at transforming technology growth into shared public value and systemic resilience?

ECB Ranking

RANKING	CITY	ECB INDEX
1	Helsinki	1.01
2	San Francisco	0.48
3	New York	0.41
4	London	0.28
5	Singapore	0.21
6	Hong kong	0.04
7	Tel Aviv	-0.17
8	Beijing	-0.36
9	Shanghai	-0.51
10	Shenzhen	-0.60

This ranking is based on the ECB index, with a focus on four core dimensions:

- Social inclusion and opportunity structure
- Governance transparency and institutional trust
- Environmental sustainability
- Urban resilience and systemic capacity

Unlike the TDP ranking—which reflects technological scale and innovation intensity—the ECB ranking captures **growth quality,** not growth volume. It often reveals a significantly different city hierarchy compared to technology-centric rankings.

In the ECB dimension, city rankings undergo a notable shift.

- **Helsinki** ranks first, demonstrating outstanding performance in growth quality, systemic coordination, and sustainable development.

- **San Francisco** and **New York** maintain positive scores in ECB, though their relative positions are lower than in the TDP ranking, indicating a gap between technological strength and co-benefit outcomes.

- **London** and **Singapore** rank in the upper-middle tier, reflecting strong governance and environmental policies.

- **Hong Kong** occupies a mid-tier position, balancing institutional strength with moderate social and environmental performance.

- In contrast, **Beijing**, **Shanghai**, and **Shenzhen** rank relatively low in ECB, revealing persistent challenges in social equity, housing affordability, and ecological sustainability—despite their high TDP scores.

- **Tel Aviv** also ranks among the lower performers in ECB, suggesting that its innovation ecosystem has not yet translated into broad-based social or environmental benefits.

This reordering underscores a critical insight: **ecosystem co-benefit capacity does not follow the same path as technology development potential**. The distribution of ECB scores is structurally independent—cities can excel in one dimension while lagging in the other.

4.2 Policy Implications by Four Typologies of Tech City Development Pathways

Based on scatter plots and cross-city comparisons, the descriptive analysis systematically reveals the relative positioning of the ten global tech cities across the **TDP** × **ECB** matrix. Cities with high TDP do not necessarily perform well on ECB, and vice versa. There is no simple one-to-one correspondence between technology development potential and ecosystem co-benefit capacity.

To move beyond a "ranking mindset" and toward a more nuanced, structural understanding, this study classifies the ten cities into four distinct development typologies based on their TDP and ECB levels (see Table 4-3):

Table 4.3 The development pathways of Four typologies of tech city

Typologies	Structural Features	Key Risks	Policy Implications
Dual-Excellence (High TDP × High ECB)	Strong Technology, Advanced co-benefit ecosystem	Complex innovation governance	Global leader[1]: Prevent structural lock-in through adaptive governance
Growth-Driven (High TDP × Low ECB)	Innovation-Driven but Inclusive Growth Lagging	Inequality, housing affordability, and ecological pressure	Prioritize governance, inclusion, and environmental sustainability
Resilience-Consolidated (Low TDP × High ECB)	Advanced co-benefit ecosystem, lack of the technology	Weak innovation momentum	Achieve leapfrogging through technological upgrading
Transformation-Potential (Low TDP × Low ECB)	Dual Constrain	Systemic Lagging	Require systemic restructuring of institutions and industries

The four typologies emphasize a fundamental insight:

Urban challenges are Not a problem of scale — but of structure

For technology-driven cities, the policy focus should no longer be on "investing more on technology," but on repairing the institutional, social, and environmental links in the

1 This table classifies cities into four types based on the observed distribution of TDP and ECB, and derives corresponding policy implications. The "Dual-Excellence" type, as a high-performing category identified in the data. Subsequent chapters will examine the underlying mechanisms that explain the emergence and sustainability of this high-performing pattern.

technology spillover chain—where innovation fails to translate into shared public value. Moreover, there is no one-size-fits-all "best practice." What works for one city may exacerbate systemic risks in another. Simply copying the model of a high-performing city can deepen structural imbalances rather than resolve them.

4.3 Chapter Summary

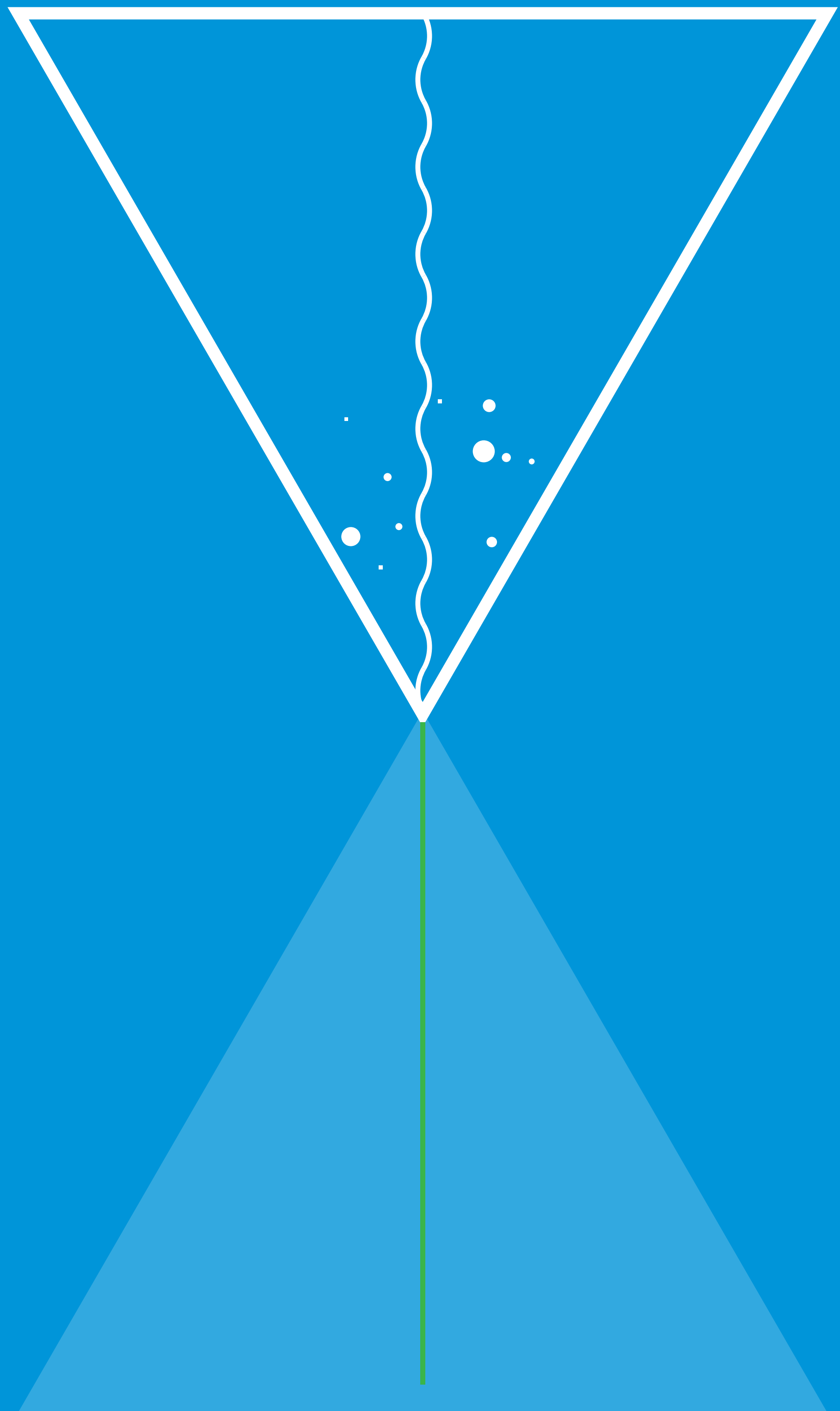
The descriptive analysis above presented following findings:
The differences between cities are not merely about technological strength, but about transformation efficiency. The same technology development potential can yield vastly different outcomes depending on the institutional, industrial, and social context in which it is embedded.

According to these findings, the subsequent chapters will operationalize the key structural differences observed in this chapter—such as institutional quality, the quality of the technology capital environment, levels of social inequality, and conditions of environmental sustainability and resilience—into measurable mechanism variables. A panel regression approach will be employed to systematically test these relationships.

Through F-tests and other econometric diagnostics, the analysis will examine whether these structural factors statistically constitute binding constraints on the transformation of technology development potential (TDP) into ecosystem co-benefit capacity (ECB).

Moreover, acknowledging the inherent limitations of the sample size, data granularity, and city heterogeneity, the study recognizes that some mechanisms may not achieve statistical significance. Therefore, the regression analysis does not focus solely on results. Instead, it also systematically discusses the implications of non-significant findings—avoiding the misinterpretation of empirical identification challenges as evidence of mechanism absence. By incorporating interaction terms, non-linear specifications, and supplementary structural tests, this study aims to answer a central question:

Under the control of time effects, whether these structural factors serve as statistically significant constraints on the TDP–ECB relationship.



Chapter

5

How to transform the Technology Development Potential into the Ecosystem Co-benefit Capacity

Based on panel data covering 10 major global tech cities from 2018 to 2024, this chapter systematically examines whether and under what conditions Technology Development Potential (TDP) can be transformed into Ecosystem Co-benefit Capacity (ECB) at the city level. Focusing on the three core research questions (RQ1 – RQ3), this chapter combines empirical results with theoretical explanations to discuss the internal mechanism of "growth quality differentiation" in tech cities. The regression model and regression results can be found in Appendix 2 and Appendix 3.

5.1 Does Technology Development Potential necessarily enhance Ecosystem Co-benefit Capacity? (RQ1)

First of all, this paper tests whether the Technology Development Potential itself can significantly improve the city's Ecosystem Co-benefit Capacity without introducing additional institutional variables. The benchmark model uses the ordinary least squares (OLS) method to incorporate annual fixed effects and performs clustering robust standard error correction at the city level to control the impact of cross-city heterogeneity and time trends. The regression results show that there is a significant positive correlation between TDP and ECB under most model settings. In general, cities with a stronger scientific and technological foundation tend to perform better on comprehensive indicators such as social inclusion, governance quality and environmental sustainability. This finding is consistent with the existing research conclusions on innovation and regional development, that is, scientific and technological capabilities are still an important prerequisite for cities to achieve high-quality growth.

However, it should be emphasized that this positive correlation does not mean that the Technology Development Potential will be automatically and unconditionally translated into ecosystem co-benefit capacity. With the gradual introduction of institutional, social structure and environmental variables, the significance and stability of TDP coefficients in different models are significantly different. This shows that the potential of technology development is not a "self-realization" growth engine, and its actual effect is highly dependent on the institutional and structural environment in which the city is located. Therefore, the answer to RQ1 is conditional affirmation: the technology development potential improves the ecosystem co-benefit capacity, but is not sufficient to ensure the results.

5.2 Structural constraints of technology transformation mechanism? (RQ2)

To further identify the key conditions for the transformation of technology development potential into ecosystem co-benefit capacity, this paper introduces a series of institutional, innovative ecological and social structural variables, and tests their moderating effects through the interaction term model.

5.2.1 Institutional quality: structural basis rather than marginal amplifier

Institutional quality variables, such as the level of rule of law and governance transparency, are significantly positively correlated with ECB in all models. This result shows that the institutional environment itself is an important structural basis for cities to achieve ecological common benefits.

However, the interaction between institutional variables and TDP does not show a statistically stable significance. This means that under the current sample and measurement framework, institutional quality does not significantly change the marginal slope of scientific and technology development potential to ecosystem co-benefit capacity.

The results suggest that institutions are more likely to play a role by raising the overall level of development rather than amplifying the marginal effects of technology transformation. In other words, a high-quality system does not necessarily make each unit of science and technology investment "more efficient", but it determines whether a city has the basic conditions to continuously transform scientific and technological achievements into public values.

5.2.2 Innovative capital and entrepreneurial ecology: the role has been endogenously absorbed

This paper further examines whether technology capital and entrepreneurial ecology (using indicators such as venture capital intensity as proxy) will regulate the impact of TDP on the ECB. The empirical results show that the relevant variables and their interaction with TDP do not show stable significance.

This finding does not deny the importance of innovation capital in the technology system, but is more likely to reflect the following reality: in the global sample of major tech cities, technology capital is highly concentrated and largely absorbed by the TDP index. In this case, its marginal role as an independent moderating variable is difficult to be clearly identified.

Therefore, capital is not the core weakness explaining the differentiation of tech cities at the current stage.

5.2.3 Social structure: the direct inhibitory effect of inequality

At the level of social structure, there is a significant negative correlation between income inequality (Gini coefficient) and ECB. The results show that the more unequal a city is, the harder it is to transform the achievements of its technology development potential into ecosystem co-benefit capacity.

It is worth noting that inequality does not significantly change the marginal slope of TDP, but rather works by depressing the overall ECB level. This means that inequality does not affect the quality of development primarily by "reducing the efficiency of science and technology", but by limiting social absorptive capacity, making it difficult for the technology dividend to spread to a wider population.

This finding highlights the binding role of social structure in the technology transformation process.

5.3 The boundary of technology development: nonlinearity and system carrying (RQ3)

After confirming that there is a positive correlation between technology development potential and ecosystem co-benefit capacity, this paper further tests whether the relationship remains linear in the whole science and technology density interval.

By introducing the quadratic term of TDP, the regression results show that the linear term coefficient of TDP is significantly positive, while the quadratic term coefficient is negative, and it reaches the marginal significant level in statistics. This result provides preliminary evidence for the inverted U-shaped relationship between TDP and ECB.

The nonlinear relationship shows that in the low or medium stage of science and technology intensity, science and technology input contributes to the enhancement of the city's ecosystem co-benefit capacity; However, when technology is highly concentrated and the carrying capacity of urban systems fails to increase synchronously, the marginal positive effect begins to decline and may even turn negative.

5.4 Structural differentiation and interpretation of quadrant results

Combined with the TDP-ECB four-quadrant structure analysis, significant differentiation in the development path of different tech cities can be observed:

Cities with high TDP × high ECB are the most resilient in terms of long-term growth quality, quality of life and system resilience.

Cities with high TDP × low ECB are more likely to face housing pressures, social tensions and ecological burdens.

Cities with low TDP × high ECB exhibit resilience and governance oriented development patterns.

Cities with low TDP × low ECB face the dual constraints of insufficient innovation capacity and structural conditions.

These differences show that technology development potential cannot replace institutional coordination, social absorption and environmental carrying capacity.

5.5 Comprehensive discussion: from "scientific and technological intensity" to " transformation ability"

Combining the empirical results of RQ1-RQ3, we can form a highly consistent judgment that the technology development potential is an important starting point for cities to move towards high-quality growth, but not a decisive condition. What really shapes a city's long-term performance is not the scale or input intensity of science and technology itself, but whether cities can continuously embed science and technology into their institutional, industrial, social and environmental systems. The fundamental difference between tech cities is not in "who owns more technology", but in whether technology spillovers can be transformed into a public value that can be diffused, carried and sustainable..

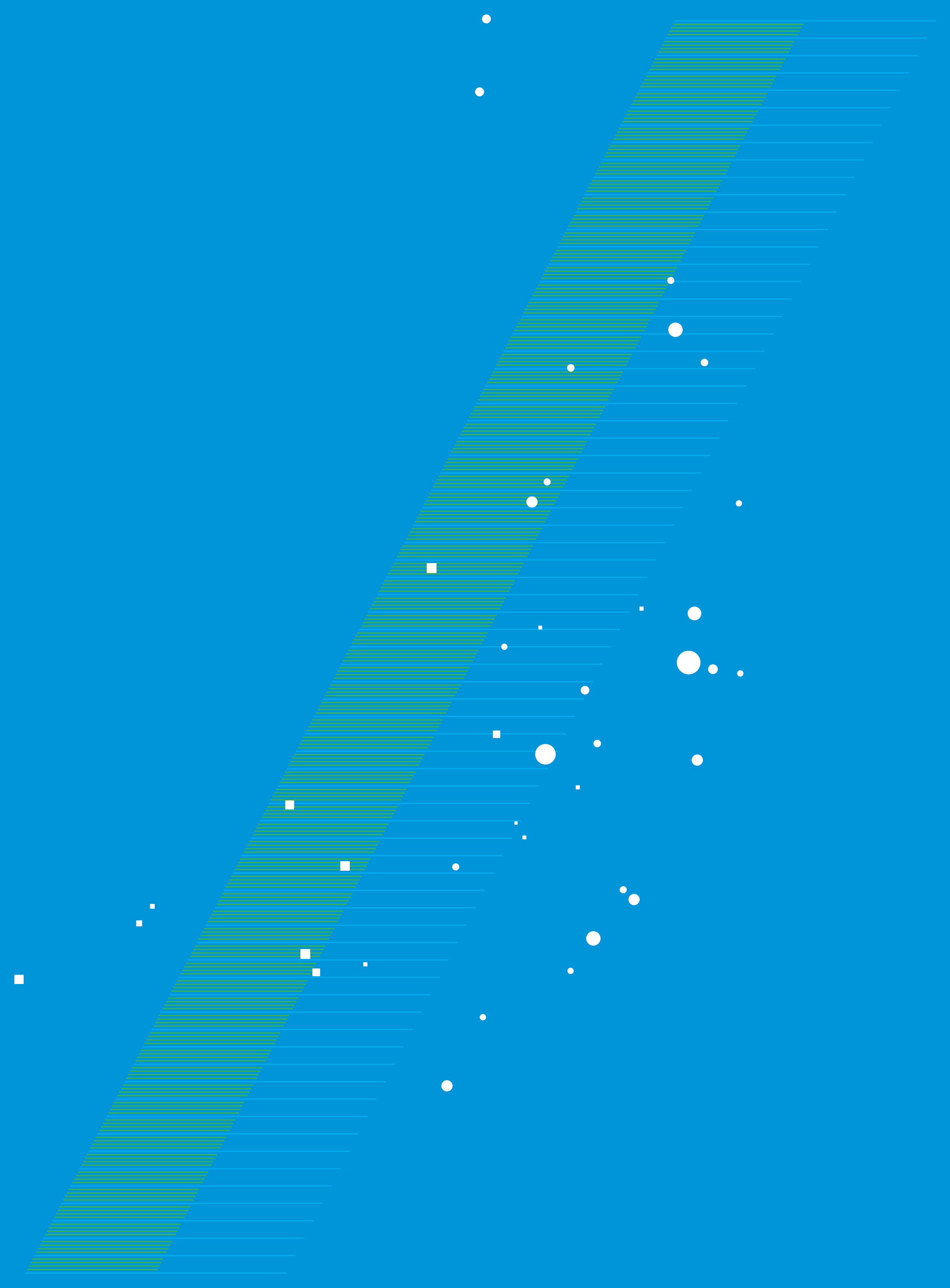
What needs further clarification is that the regression analysis reveals the conditional and non-linear characteristics of the impact of Technology Development Potential (TDP) on Ecosystem Co-benefit Capacity (ECB). The policy proposition of "upgrading TDP and ECB at the same time" is not a direct conclusion of the regression model, but a comprehensive deduction based on the following three aspects. First, the distribution characteristics show that in reality, cities with both TDP and ECB at a high level generally show stronger system resilience and development stability. Second, the mechanism test shows that factors such as institutional quality, social inclusion and environmental carrying capacity significantly affect the efficiency and upper limit of the transformation of science and technology into common benefits; Thirdly, in theory, at the stage of high technology intensity, the ecosystem co-benefit capacity itself constitutes the precondition for the continuous absorption and expansion of science and technology.

Therefore, the policy proposition that TDP and ECB should be promoted at the same time is not a causal law directly proved by the regression results, but a structural strategy judgment based on empirical evidence, mechanism identification and theoretical logic.

5.6 Chapter Summary

Through systematic empirical tests, this chapter shows that the technology development potential will not be automatically transformed into ecological common benefit ability, and its impact is restricted by institutional quality, social structure and system carrying capacity. There are obvious nonlinear and boundary effects in the growth of science and technology. It is difficult to ensure the simultaneous improvement of the quality of urban development by simply relying on continuous investment in science and technology.

These results lay an empirical foundation for the subsequent urban case analysis, and also provide a more explanatory analytical framework for understanding the quality differentiation of global tech city growth.



Chapter
6

The critical transformation of Hong Kong's science and technology ecology: Why is it difficult for a global financial center to become a science and technology center?

In Hong Kong SAR's TDP × ECB matrix, both technology development potential (TDP) and Ecosystem Co-benefit Capacity (ECB) are slightly above zero, which means that Hong Kong has crossed the structural threshold of positive transformation: technology activities begin to generate a certain degree of public value spillover, and the advantages of institutional governance, capital flows and international connectivity do provide a basic foundation for this positive transformation. However, the key issue for Hong Kong is that its transformation mechanism is still in a "borderline but not yet stable" state: in the process of increasing the intensity of scientific and technological activities, increasing the demand for computing power, and extending the links between engineering and industrialization, it is more likely to take the lead in encountering systemic bottlenecks in terms of entrepreneurial hierarchy, industrial demand, capital structure, infrastructure and talent accumulation, Thus, the marginal contribution of science and technology to the ecological community is characterized by obvious instability and peaking.

Therefore, the focus of the analysis in this chapter is not to explain "why Hong Kong lacks technology development potential", but to answer a more diagnostic question: what is preventing Hong Kong from moving from a "critical transition" to a "sustained dual excellence" when it has entered the "double positive quadrant"?

6.1 "The critical size shortfall" in the entrepreneurial ecosystem: the top layer is visible, but the middle layer is not thick enough

In terms of the scale of the entrepreneurial ecosystem, according to data published by StartupBlink, Hong Kong had approximately 798 start-ups and 10 Unicorn companies in 2025. Compared to the start-up base of around 2889 start-ups in Singapore, around 8605 in London and 8977 in New York, the size of Hong Kong's entrepreneurial body is still significantly smaller. This gap is not short-term volatility, but rather reflects the long-term differentiation in the "base size" of innovation players in different cities.

More importantly, Hong Kong's entrepreneurial ecosystem presents a significant "lack of thickness" at the corporate growth level. As shown in Table 6-1, Hong Kong is not lacking in a small number of top-tier companies or individual success stories, but there is a significant shortfall in the number and sense of presence of middle-tier companies in the growth and expansion stage, such as series B-D. In contrast, Singapore and some European and American cities have formed a continuous gradient structure from early start-ups and growth companies to mature technology companies, and Beijing has gradually built a relatively complete growth path driven by policies and industrial agglomeration. Hong Kong is characterized by a "visible top, limited bottom and thin middle tier", which makes it difficult for entrepreneurial activities to form sufficient scale accumulation and ecological self-reinforcement locally.

Table 6-1 scale and structure of Hong Kong's entrepreneurial ecosystem

Ecological hierarchy	Hong Kong situation	Structural characteristics
Top floor (Unicorn enterprise)	10	Not low in volume but highly concentrated in areas such as finance / trading platforms.
Middle tier (Series B–D for growth enterprises)	Thin / insufficient	Key constraints affecting ecological "sustainable scaling up".
Lower middle tier (start up)	798	Relatively few in absolute terms and relatively concentrated in industry distribution.

This structure shows that Hong Kong's entrepreneurial ecosystem can support a certain scale of innovation activities and generate positive spillovers, but when technology activities enter a higher intensity and deeper engineering stage, the insufficient thickness of the middle layer can make it difficult to close the ecological cycle. Even if capital and resources are abundant, it is more difficult to find a sufficient number of "carrying nodes" (sustainable growth enterprises) locally, which makes it difficult for technology capital to reflect as a systematic amplification of technology development potential, but more likely to show as "dot success and unstable chain".

6.2 "The narrow demand side" of the industrial structure: financial advantages can be embedded, but difficult to diffuse

In addition to the entrepreneurial body level, the "demand side absorptive capacity" of the industrial structure to technology activities is key to understanding why Hong Kong is in a critical transition rather than a steady-state duopoly. Hong Kong's economy has long been highly financial, with a consistently high share of the financial and insurance sectors, an active capital market and highly developed financial services, which constitute its core comparative advantage. However, the technology demand side scenario brought about by this structure is relatively narrow: technological innovation is easier to carry out local optimization and efficiency improvement around the existing financial system, while it is more difficult to form a large-scale diffusion across industries and systems.

Based on StartupBlink and related city industry distribution information, it can be observed that Hong Kong's startups are highly concentrated in areas such as fintech, trading platforms and business services, with relatively narrow application boundaries. In contrast, Singapore's technology startups are spread across areas such as artificial intelligence, medical technology, logistics and advanced manufacturing, providing more diverse landing scenarios. Beijing relies on information technology, artificial intelligence and digital platform industries to form a close linkage between R&D and application needs. Shenzhen relies on a sophisticated manufacturing system and a highly integrated supply chain network to enable technology innovation to be quickly embedded in production and application links to form an efficient link between R&D, manufacturing and market demand.

The difference in industrial structure directly determines the "diffusion radius" of technology spillovers. Under the highly financial demand structure, Hong Kong's technology innovation is more like a kind of "high quality embedding", which can form a leading edge in specific areas, but it is more difficult to penetrate into public services, traditional industries and urban operating systems through a diversified industrial network. The result is that technology can generate positive collective benefits (hence the ECB is positive), but it is difficult to generate a wider and more stable systematic increase in collective benefits (hence the ECB is difficult to rise significantly).

6.3 The "structure of science and technology capital is not closed": capital is abundant, but the chain of science and technology capital is insufficient

Hong Kong's capital system is highly developed, but the more prominent contradiction in the technology capital structure is not "insufficient total capital", but that the technology capital has not yet formed a closed structure in terms of scale, hierarchy and functional division. Specifically, the limited size of local technology-oriented VCs, the relative scarcity of growth funds (Series B-D) for the mid and late expansion stages of technology companies, and the insufficient participation of strategic capital and corporate venture capital (CVC) make it difficult for capital to cover the complete financial support chain of "early incubation-scale expansion-industry embedding".

Table 6-2 financing scale of startups in selected cities published by StartupBlink

City	Published funding scale / capital data
San Francisco	Startup Funding (over $109.61B)
New York	Startup Funding (over $40.22B)
Singapore	Ecological growth rate+44.9% (rapid capital ecological expansion)
Hong Kong	Undisclosed city level financing (reflecting insufficient scope and scale of city level technology investment)

San Francisco and New York already have tens of billions of dollars in start-up financing, and Singapore's capital ecosystem is also showing a rapid growth trend. In contrast, Hong Kong remains at a low level in terms of absolute size and growth level coverage of technology capital. As a direct result, some technology start-ups are less able to secure capital support for continuous expansion locally after their early stage of financing, making it easier for them to relocate, merge, or exit early; At the same time, the lack of in-depth participation of mid and late stage capital and strategic capital also limits the systematic embeddedness between technology companies and the industry chain, making it difficult for the entrepreneurial ecosystem to form a self reinforcing recycling mechanism.

From a comparative perspective, Shenzhen has built a stronger industrial capital network through the deep participation of large technology companies and industrial capital; Relying on state-owned industry funds and marketized capital, Shanghai provides continuous support from R&D to large-scale for technology enterprises; Singapore has gradually formed a capital system covering different growth stages by attracting regional headquarters and supporting capital of global technology companies. In contrast, Hong Kong's technology capital is more likely to be represented by a structural separation of "strong financial capital and short technology capital chain", which also explains why capital advantage is more likely to be reflected in an empirical increase in the "development base" rather than a clear marginal amplification effect.

6.4 Infrastructure “high-density stage constraints”: strong speed, but the computing power and engineering carrier is easy to take the lead to reach the top

Hong Kong has significant advantages in digital connectivity and financial infrastructure, but there are still structural weaknesses in key bearer facilities such as computing resources, data center clusters and hard technology industrial parks. The problem is not “total inability to support scientific and technological activities”, but rather that these facilities are more likely to take the lead as constraints in the high intensity phase of scientific and technological activities moving from applied innovation to compute intensive, engineering proven innovation. Hong Kong lacks a sizeable data center cluster and a regional computing hub to carry capacity intensive AI development and large model training activities; Meanwhile, the hard technology oriented industrial park system is relatively weak and has not yet formed a complete spatial carrier covering R&D, engineering verification and industrialization testing. This makes scientific and technological activities at a certain intensity more vulnerable to inadequate computational, spatial and engineering conditions, thereby limiting their further expansion.

The nature of this constraint is more clearly understood than in other cities. Relying on a large number of leading high-tech enterprises, such as Huawei, Tencent and BYD, Shenzhen has formed a hard technology ecosystem covering basic R&D, engineering verification and large-scale manufacturing, enabling innovation to continue to expand within the enterprise and in the upstream and downstream industry chains; Through the collaborative layout of Zhangjiang Science City and the Lingang Special Area, Shanghai has formed a system carrying structure between computing infrastructure, scientific research platform and high-end manufacturing agglomeration; With limited space resources, Singapore has become an important data center and regional hub for several international technology companies in Southeast Asia through a planned layout of data and computing infrastructure.

In contrast, Hong Kong’s greatest weakness is the lack of integrity in Shenzhen’s technology and computing-intensive industry chain. As a result, when scientific and technological activities enter a high-intensity stage, cities are more likely to encounter system load bottlenecks ahead of time, and the marginal contribution of science and technology to the ecological benefits decreases accordingly. This realistic constraint is logically highly consistent with the inverted U-shaped relationship suggested by the previous nonlinear test: when the intensity of scientific and technological activities increases and the carrying conditions are not expanded synchronously, the marginal contribution of science and technology development potential to the collective beneficial capacity will decline earlier.

6.5 The "insufficient retention mechanism" of talent structure: it can attract financial talents, but it is difficult for engineering and scientific research talents to accumulate for a long time

From the perspective of public assessment and industry observation, there is a significant imbalance in the talent inflow structure in Hong Kong. Assessments such as StartupBlink generally point out that Hong Kong has a strong edge in attracting financial, legal and business services talents, but is less attractive to engineers, researchers and technology R&D talents than tech cities such as Singapore, Shenzhen, Beijing and London. This difference is not caused by a single policy or short-term factors, but is closely related to the triple conditions of "job supply growth path cost of living" in the urban ecological structure. First, the high degree of financialization of the industrial structure has a long-term "career crowding out effect" on talent selection. The financial sector generally outperforms local technology companies in terms of salary, stability and social status, which makes talents with a polytechnic background more inclined to move to finance-related positions. Secondly, high living costs and spatial constraints exacerbate the pressure on engineering and scientific talents to drain. Hong Kong has long been one of the world's most expensive cities to live in, and it is difficult for technology companies, especially start-ups, to provide benefits and development certainty that match the financial industry. In the absence of mid-tier growth companies and clear pathways to growth, engineering talents tend to flow to cities with a complete technology ecosystem and a more competitive cost of living.

More importantly, the insufficient computing power and Shenzhen technology industry chain make it difficult for high-end engineering and scientific research posts themselves to form scale. The lack of data center clusters, computing hubs and hard technology industrial parks limits the availability of AI companies, large model R&D teams and engineering verification platforms, thereby weakening the structural demand for engineers and scientific talents. Under such conditions, the "difficulty in retaining" talent is not the lack of attractiveness of the city, but the lack of an ecological carrier that matches its professional competence and accumulates sustainably.

Therefore, the talent challenge in Hong Kong is not simply "insufficient talent attraction", but "insufficient retention mechanism": the city can continue to attract high-end financial and professional services talents, but it is difficult to support engineers and researchers to form long-term accumulation and cross-stage mobility in the technology field. This lack of precipitation further weakens knowledge diffusion and innovation accumulation, making it difficult for science and technology development potential to be continuously and stably translated into a higher level of ecosystem co-benefit capacity through human capital channels.

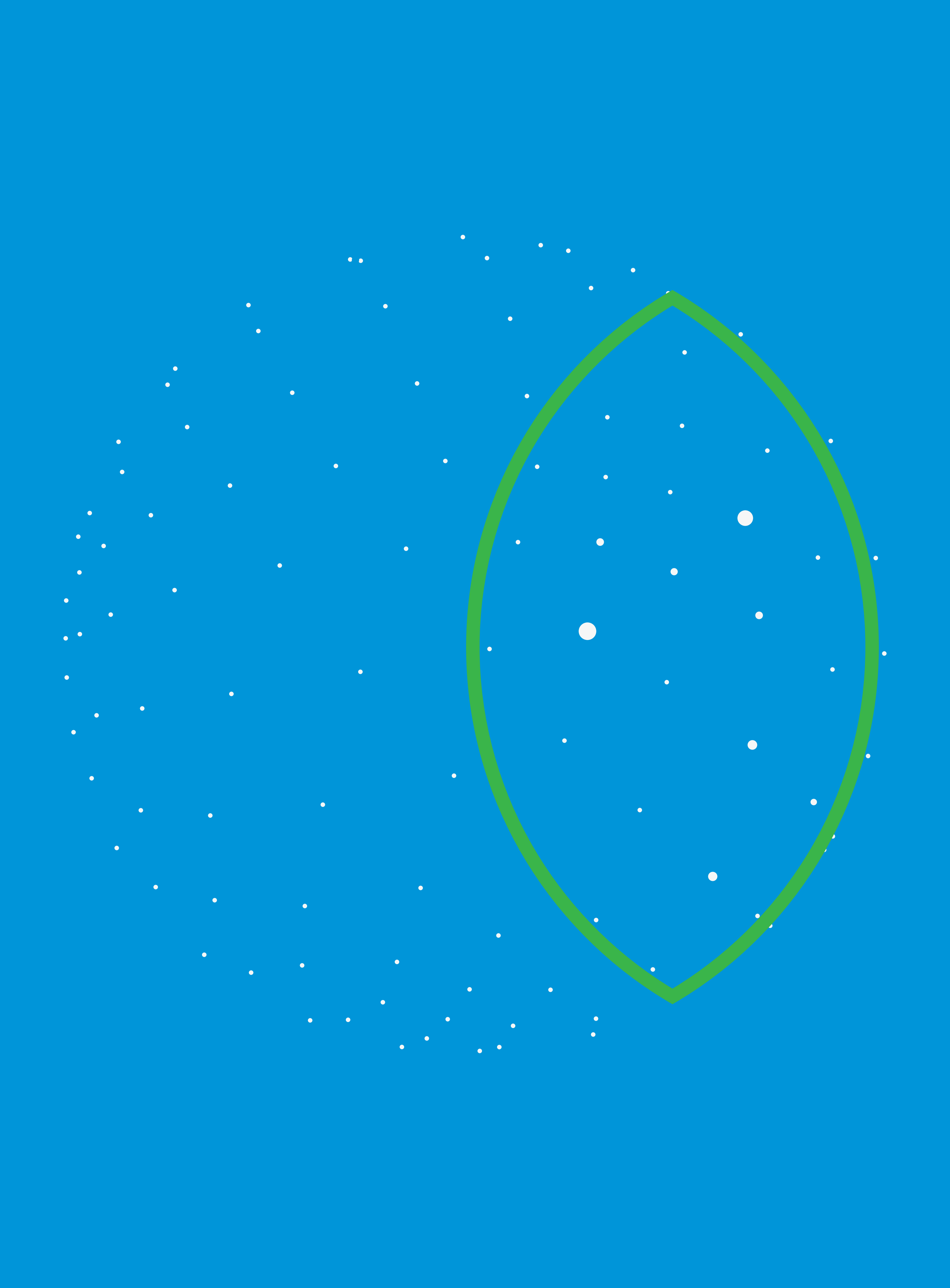
6.6 Chapter Summary: Hong Kong has crossed the threshold but has not yet entered the "steady state double excellence"

From the analysis in this chapter, we can see that Hong Kong has just entered the "double positive quadrant" in the TDP×ECB matrix, which means that Hong Kong is not lacking in institutional foundation, capital flows or international connectivity, and its technology activities have been able to generate a certain degree of positive collective benefit spillover. However, the key contradiction in Hong Kong is not "transformability", but "steady state transformation and continuous amplification".

From the perspective of entrepreneurial ecological structure, Hong Kong has the problem of insufficient middle layer thickness, which makes it difficult to close the ecological cycle; From the perspective of industrial structure, narrow demand side scenarios lead to limited technology spillover radius; From the perspective of technology capital structure, capital advantage is more likely to be reflected in raising the development base rather than forming a closed loop of technology capital covering the whole growth stage; From the perspective of infrastructure and load carrying conditions, computing power and engineered carriers are more likely to be the first constraints in the high-density stage, providing a realistic explanation for the nonlinear relationships identified earlier; In terms of talent structure, Hong Kong can attract financial and professional services talents, but engineering and scientific talents are difficult to settle in the long term, further weakening the sustainability of knowledge diffusion and innovation accumulation.

Based on the above structural diagnosis, a conditional conclusion can be drawn: Hong Kong already has the basic conditions to transform its technology development potential into an ecosystem co-benefit capacity, but its transformation mechanism is still in a critical and unstable stage. As the intensity of scientific and technological activities continues to increase, if the entrepreneurial ecosystem thickness, industry demand diversity, scientific and technological capital closeness and infrastructure carrying capacity are not strengthened synchronously, science and technology development potential will be systematically constrained earlier and its marginal contribution to ecosystem co-benefit capacity will decline.

Therefore, the focus of Hong Kong's policy should not rest on focusing merely on slogans about expanding S&T, but on the systematic project of "consolidating the critical transformation structure and entering sustained dual excellence": first, improve the efficiency of scientific research achievements landing and cross industry diffusion through the opening of systems and scenarios; Second, promoting social inclusion and long-term accumulation of engineering talents through housing, public services and talent accumulation mechanisms; The third is to enhance the urban carrying capacity through the construction of computing power and hard technology carriers so that scientific and technological growth can continue to be translated into sustainable and mutually beneficial outcomes at a higher intensity stage.



Chapter

7

Conclusion and Reflection

Over the past three decades, technological density has reshaped the global urban competitive landscape. Innovation capacity, capital agglomeration, and talent mobility have enabled a select group of cities to rapidly emerge as a milestone in the global economy. However, technological intensity itself is no longer sufficient to explain long-term urban prosperity. In an era of high technological concentration, the true divergence among cities is increasingly unfolding at the level of ***how technology is transformed***.

The empirical findings of this study convey a consistent and clear message:

Technology does not automatically translate into sustained urban competitiveness. What truly determines the difference is ***how technology is absorbed and amplified by institutional, industrial, social, and environmental systems***.

The next stage of competition among technology-driven cities is not just about technology itself, but about whether the benefits of technological advancement can be effectively captured by institutional and societal systems—and transformed into widely shared well-being.

Therefore, the policy focus for tech cities should no longer concentrate on "how to enhance technological strength," but shift toward a more challenging question:

How Technology Development Potential (TDP) systematically improve the transformation capacity to Ecosystem-Co-Benefits capacity (ECB)?

7.1 From "Technological Advantage" to "Structural Advantage": A New Logic of Urban Competition in the Era of Growth Quality

The framework proposed in this research—**Technology Development Potential (TDP)** × **Ecosystem Co-benefit Capacity (ECB)**—aims to provide analytical language and decision-making tools for this new stage. It is not only an index for evaluation, but a cognitive framework for reshaping the relationship between technology, cities, and society. By shifting the focus from "scale comparison" to "mechanism comparison," it offers a mid-level path between macro-level growth theories and micro-level innovation studies.

The research argues that urban competition has moved from a "factor-based" stage to a "structure-based" stage, where the key contributor is no longer development speed, but quality. The future winners will not be those with the most technology, but those that can consistently convert technological advances into public value.

The judgment is not derived solely from result of regression coefficients but synthesized from multiple lines of evidence: the distributional pattern of TDP and ECB across cities, the empirical validation of conditional and nonlinear mechanisms, and comparative analysis of four distinct urban development trajectories.

Technology drives growth, but only through the coordinated integration of institutions, society, and ecological systems can lasting prosperity be sustained. This is precisely the core proposition revealed by the Dual-Dimension Index of Technology Development Potential and Ecosystem Co-Benefit Capacity for Global Leading Tech Cities, and also the shared challenge that all tech cities must confront as they enter the **era of growth quality**.

At present, technology has transitioned from a scarce resource to a fundamental factor. It is no longer the scarcity of technology that matters—but the capacity to transform it. What determines long-term urban competitiveness is not ***whether technology exists, but how its system enables technology to enter and benefit society***.

When institutions are credible, society is inclusive, and ecological capacity is sufficient, technological investment is more likely to diffuse widely, generating sustained productivity gains, reducing social conflict and governance costs, and prolonging the duration of innovation dividends. In contrast, when these conditions are absent, technological growth may lead to imbalance income, rapidly rising living costs, mounting pressure on infrastructure and the environment, and erosion of institutional trust and social consensus.

Based on non-linear tests and case observations, we conclude that simply increasing technological inputs in a linear fashion cannot resolve these structural challenges. Thus, urban governance must undergo a paradigm development: from ***enhancing technological supply to optimizing the pathways of technological transformation***. Ecosystem co-benefit is not a "side effect to be addressed after growth"—it is a ***prerequisite for growth to be sustainable and legitimate***.

7.2 Limitations and Reflexivity of the Research Method

This study employs a multi-layered argumentation framework: **distributional observation** → **mechanism testing** → **case illustration** → **policy inference**, aiming to identify structural differences and long-term constraints in the development of tech cities. It should be noted that the "High TDP × High ECB" path proposed here is not a direct causal output of regression models, but a structural policy judgment derived from cross-city distribution patterns, conditional and non-linear mechanism validation, and comparative case analysis.

Due to limitations in sample size, data availability, and index construction methods, the results are better interpreted as revealing systemic relationships and risk boundaries, rather than precise predictions. Nevertheless, this framework still provides a theoretically grounded and operationally useful foundation for understanding how technology development can be transformed into sustainable public value.

Specifically:

- First, the sample size and data availability limit the granularity of econometric analysis, making results more suitable as structural evidence than as predictive models.

- Second, index construction inevitably involves choices in indicator selection and weight assignment, so conclusions should be further tested and calibrated across different contexts.

- Third, cross-city comparisons inherently struggle to fully capture deep-rooted factors such as historical path dependence, cultural differences, and political institutions, requiring supplementary case studies and institutional analysis for contextual interpretation.

Tech cities are complex systems, any model can only reveal part of their underlying structure. Based on this analysis, future research could pursue three directions:

1. **From cross-sectional comparison to longitudinal evolution:** Use time-series data to study how cities transition from “growth-driven” to “dual-excellence” structures across different developmental stages.

2. **From city-level indices to policy simulation:** Apply the TDP × ECB framework to evaluate the impact of specific policy interventions (e.g., housing, education, platform governance) on technological transformation efficiency.

3. **From urban studies to technology governance research:** Explore whether the spillover mechanisms of AI, platform economies, and green technologies are undergoing structural changes

Appendix

Appendix 1

Data Description

(1) Sample range and data structure

The research sample is 10 global leading tech cities, forming “City x Year” panel data. The current data covers 10 cities from 2018 to 2024 (7 years), with N=70 (10×7=70) observations.

Sample country/region: Chinese Mainland, including Beijing, Shanghai and Shenzhen; Hong Kong, China; United States, including San Francisco and New York; Britain, including London; Finland, including Helsinki; Israel, including Tel Aviv; Singapore. Due to research needs, some mechanism variables are national proxy, which will share the same value in cities in the same country.

(2) Source of data

For overseas data and some domestic data, the data used in this report are derived from international authoritative bodies and public databases, including the World Intellectual Property Organization (WIPO), the World Bank, the Ookla Speedtest Global Index (2017-2024), the Food and Agriculture Organization of the United Nations (FAO), UNESCO, the World Health Organization (WHO), IQAir, NumberoStartupBlink and the World Justice Project.All data are used for non-commercial research purposes, and the original information can be obtained from the official website of the corresponding institution.

The data of Chinese cities involved in this report mainly come from the statistical yearbooks issued by the provincial and municipal statistical bureaus, the seventh national census data, the Statistics Department of the Hong Kong Special Administrative Region Government, the World Bank, the World Justice Project (WJP), CEIC China Economic Database, the Hong Kong Open Data Portal and other authoritative channels.

The data time range mainly covers the period from 2018 to 2024. Some indicators, such as carbon emission intensity per unit GDP, renewable energy percentage and forest coverage, are up to 2023 and 2021 respectively. The infrastructure quality index is updated to 2017. Readers should be aware of the timeliness of the data cited in this article.

A. Knowledge and innovative production

The data of article sharing volume is taken from the official website of Nature Index (Nature Index 2020-2025 Science Cities). Since 2019, the Nature Index has annually published the Leading 200 science cities in the top 200 Article Shares of the previous year, with all 10 cities on this list.

Data on patent applications (per million population) are derived from the World Intellectual Property Organization (WIPO) and integrated by the World Bank in 2025; The calculation is based on the population data in the United Nations World Population Prospects and the total number of patent applications in each country.The number of patent applications per million people in Chinese Mainland is calculated based on the number of permanent residents published in the yearbooks of provinces and cities and the total number of patent applications in that year.

The amount of R&D investment is obtained by collecting R&D expenditure data in the relevant yearbooks of each city or multiplying its R&D intensity data by regional GDP to ensure consistency with macroeconomic caliber.

B. Digital and technology infrastructure

Fixed and mobile broadband speed data is from Ookla's Speedtest Global Index. Broadband network penetration data are derived from the World Telecommunication/ICT Indicators Database of the International Telecommunication Union (ITU) and the Euromonitor platform.

C. Technology capital and entrepreneurial ecosystem

The Global Startup Ecosystem Index is compiled by StartupBlink, and the data are selected as reference indicators to measure the vitality of city-level innovation ecology.

D. Institutional quality and innovation governance

The government efficiency data are taken from the World Bank's Worldwide Governance Indicators (WGI), which are all data at the national or regional level, with the lowest value set at -2.5 (the weakest government efficiency) and the highest value set at+2.5 (the strongest government efficiency). The latest data are as of 2023.

The rule of law index data are also taken from the Worldwide Governance Indicators, and are all data at the national or regional level, with the lowest value set at -2.5 (the weakest rule of law level) and the highest value set at+2.5 (the strongest rule of law level). The latest data are as of 2023.

Regulatory quality data are taken from Worldwide Governance Indicators, too and are all data at the national or regional level. The lowest value is set to -2.5 (the weakest regulatory quality), the highest value is set to+2.5 (the strongest regulatory quality), and the latest data is as of 2023.

E. Social inclusion and opportunity structure

Gini coefficient data are mainly from the World Bank Poverty and Inequality Platform, of which the latest data in the United States, Britain and Finland is 2023, the latest data in China is 2022 and the latest data in Israel is 2021.Singapore’s Gini coefficient data is derived from the Infographic - Key Household Income Trends 2024 document published by the country’s statistics department, which contains annual Gini coefficients for the period 2018-2024. Between 2018 and 2024, Hong Kong only published the Gini coefficient in the Hong Kong 2021 Census - Thematic Report: Household Income Distribution in Hong Kong report. The smaller the Gini coefficient, the more average the income distribution, and the larger the Gini coefficient, the more uneven the income distribution. The World Bank generally considers 0.3-0.4 to be moderate, while above 0.4 it considers inequality to be high.

Housing related indicators (including price-to-income ratio, loan-to-income ratio, price-to-rent ratio, affordability index and housing index) are based on city-level data provided by the Numbero platform, reflecting the housing market situation comprehensively.

The undergraduate rate data, derived from UNESCO UIS, is calculated by dividing the number of people aged 25 years and over who have obtained or completed a bachelor's degree or equivalent by the total number of people in the same age group and multiplying by 100. A number of 0 means zero or the value is so small that it can be rounded to zero. Data are collected by the UNESCO Institute for Statistics and are mainly derived from national censuses, household surveys and labour force surveys. All data are mapped into the International Standard Classification of Education (ISCED) to ensure country-to-country comparability of education programmes. The undergraduate rate data of Chinese Mainland and Hong Kong are differentiated according to different urban statistical standards: Beijing is calculated based on the education structure data of the population aged 15 and above in the statistical yearbook from 2020 to 2024; Shanghai uses the data of the seventh national census in 2020, and divides the number of graduates of master's degree and doctoral degree by the estimated permanent population; Due to the lack of statistics in the yearbook, Shenzhen uses the seventh census data to sum up the number of undergraduate students in all districts of Shenzhen and divide it by the number of permanent residents for estimation; The Hong Kong Special Administrative Region adopts the proportion of people aged 15 and above with a bachelor's degree published by the Hong Kong Bureau of Statistics, which basically corresponds to the mainland standard and is comparable.

The data of higher education participation rate (% gross) is national or regional data, which is from UNESCO. In addition to the complete data of Chinese Mainland and Hong Kong (2018-2024), the latest data of Britain, Finland, Israel and Singapore is as of 2023, and the latest data of the United States is as of 2022.

F. Governance Transparency and Institutional Trust

The Open Government Index is published by the World Justice Project to assess government transparency and public engagement.

Corruption Perceptions Index data is from Corruption Perceptions Index released by Transparency International, with a value of 0-100, of which 100 points are extremely clean and 0 points are extremely corrupt.

Corruption governance data are taken from the Worldwide Governance Indicators, which are country-level or regional (such as Hong Kong) data, with the lowest value set at -2.5 (the weakest government performance) and the highest value set at +2.5 (the strongest government performance). The latest data are as of 2023.

The data of the global trust index is taken from the Edelman Trust Barometer released by Edelman, which only counts some sovereign countries, excluding the Hong Kong SAR of

China and Israel. A score of 1-49 is distrust, a score of 50-59 is neutral, and a score of 60-100 is trust.

The public participation index is interviewed and scored by the World Justice Project through a questionnaire, which is released by the World Bank. The index summarizes 463 questions, involving four dimensions of civil and commercial law, criminal law, labor law and public health, and finally integrates into the WJP Public Participation Index. The lowest score of 0 represents almost no citizen participation, and the highest score of 1 represents full citizen participation. The index focuses only on the national level.

G. Environmental sustainability and urban ecology

The carbon emission intensity per unit GDP, the proportion of renewable energy and forest coverage data are all from the World Bank and the Food and Agriculture Organization of the United Nations (FAO), of which the carbon emission and renewable energy data are as of 2023 and 2021, and the forest coverage data are as of 2021.

Air quality PM2.5 concentration data are provided by IQAir and represent annual average levels at the national level.

H. Urban resilience and system carrying capacity

The indicators of IQI (1-7) are derived from the global competitiveness report 2016-2017 published by the World Economic Forum (WEF), with data from the global competitiveness report 2016-2017 being selected as reference indicators on a national statistical basis.

Overseas data on hospital beds per 10000 people, indicators derived from the World Health Organization, where country estimates are based on weighted averages weighted by total population. For domestic beds per 10000 people, the estimate is derived from China's 2018-2024 statistical yearbook by dividing the permanent population (10000 people) at the end of each year by the total number of beds in each city.

Disaster risk management index (1-7). This indicator is derived from the world bank's statistical disaster risk management capacity indicator, which is derived from the Hyogo Framework for action score. The Hyogo Framework for action covers the following aspects: (1) ensuring that disaster risk reduction is a national and local priority and provides a strong institutional foundation for implementation; (2) Identifying, assessing and monitoring disaster risks and enhancing early warning; (3) Harnessing knowledge, innovation and education to build a safe and resilient culture at all levels; (4) Reducing potential risk factors;

(5) Strengthen disaster preparedness for effective response at all levels.

Data on health resilience are collected from the WHO Global Health Observatory. Data for all countries are as of 2022. This column focuses on the domestic general government health expenditure (gghe-d) as a percentage of total general government expenditure (GGE).

(3) Data processing

In this paper, two types of composite indices are used as regression core variables: technology development potential index (TDP) and ecosystem co-benefit capacity index (ECB). Both are constructed by the indicator system and have been standardised across the full sample (10 cities × 2018-2024):

• TDP: four sub dimensions equal weight; Each sub dimension is constructed by the Z-score mean of the indicator; Full sample (10 cities × 2018-2024) standardised

• ECB: four sub dimensions of equal weight; Including directional adjustment (e.g., Gini coefficient /pm2.5/ carbon intensity is reversed); Full sample standardisation

In the process of indicator synthesis and data processing, the indicators are integrated by equal weighting to ensure that all dimensions have the same basic impact in the overall assessment; For indicators with only 1 – 2 years of data, if the time span is short but there is some continuity, the arithmetic mean is adopted to estimate to reflect the relatively stable trend; If an indicator has no data at all in a particular city or region, it will be processed as 0 and indicated in the chart or description to reflect the status of missing data; For indicators that are partially missing but have access to data for two or more consecutive years, priority is given to using the average of the data from the most recent two years as the representative value to balance timeliness and stability, ensure transparent and reproducible analysis logic, and avoid misjudgments caused by missing or incomplete data. Some indicators, such as the Hong Kong Gini coefficient, are only counted every five years and lack continuous data, so they are reasonably supplemented and replaced with reference to country-level trends in the analysis. All data are traceable, verifiable and suitable for regional comparisons and trending.

Here are some notes:

Equal weight approach: each sub-dimension is constructed from the Z-score mean of the indicator; The whole sample was standardised, and the reverse indicators were directionally adjusted (e.g., Gini coefficient /pm2.5/ carbon intensity was reversed) to ensure uniform units and consistent caliber.

In this report, the missing indicators of the original table in the whole sample for 1-2 years are filled with an average, while the remaining missing indicators are filled with the same city/country in the previous and later stages; If it is greater than or equal to 6 years, it will be treated as 0 or missing according to the nature of the indicator.

For those missing at the city level, the report has been replaced with national data and the levels are clearly marked in the table to avoid confusion.

The indicators in this report have different time horizons, with the year-to-date marked in the original data, which should be used with attention to timeliness.

Some of the data in this report (e.g., housing metrics obtained through Numbeo and Ookla, as well as mobile and broadband network speed metrics) are based on customer submissions and market research estimates and may be subject to volatility and are recommended for trend analysis rather than absolute value comparisons.

Appendix 2

Summary of regression models and formulas

(1) Benchmark model: total effect of TDP on ECB (RQ1)

The model is used to answer: does the technology development potential enhance ecosystem co-benefit capacity “in general”?

Regression formula (Model 1:Baseline):

$$ECB_{i,t} = \alpha + \beta_1 TDP_{i,t} + \gamma_t + \varepsilon_{i,t}$$

Description:
- $ECB_{i,t}$: city i’s ecosystem co-benefit capacity index for year t
- $TDP_{i,t}$: technology development potential index
- γ_t: Annual fixed effect
- Standard error: city-level clustering robust standard error

Purpose: to establish if there is a stable average correlation between TDP and ECB

Conclusion correspondence: RQ1 (“conditional affirmation”)

(2) Mechanism regulation model: whether structural conditions change transformation efficiency (RQ2)

The model is used to answer: What conditions can amplify or block TDP → ECB?

Regression formula (Model 2: Interaction Models):

$$ECB_{i,t} = \alpha + \beta_1 TDP_{i,t} + \beta_2 Z_{i,t} + \beta_3 (TDP_{i,t} \times Z_{i,t}) + \gamma_t + \varepsilon_{i,t}$$

Description:

- $Z_{i,t}$ are replaced by:

1. Rule of Law / Open Government
2. Technology capital (VC Index)
3. Social inequality(Gini Coefficient)
4. Renewable Energy Percentage / Disaster Risk Management Index

- key judgments:

β_2: Direct effects of structural variables
β_3: Is there a marginal amplification / blocking effect

Conclusion correspondence: RQ1 ("conditional affirmation")

Conclusion correspondence:

institution/inequality: structural constraints
capital/environment: insufficient statistical identification of regulatory effects

(3) Nonlinear model: is there a "risk of over secrecy" in technology (RQ3)

The model is used to answer: Will there be marginal decline or even reversal in continuous overweight technology?

Regression formula (Model 3: Nonlinear):

$$ECB_{i,t} = \alpha + \beta_1 TDP_{i,t} + \beta_2 TDP_{i,t}^{\ 2} + \gamma_t + \varepsilon_{i,t}$$

Description:

Criteria:
$\beta_1 > 0$
$\beta_2 < 0$

Meaning: inverted U-shaped relationship → system bearing constraints

Conclusion correspondence: RQ3 (borderline)

(4) Structural groupings and threshold models (supplementary)

Used to distinguish between "insufficient potential" and "blocked mechanisms".

Regression formula (Model 4: Threshold / Group):

$$ECB_{i,t} = \alpha + \beta_1 TDP_{i,t} + \beta_2 D_{HighVC,i,t} + \beta_3 (TDP_{i,t} \times D_{HighVC,i,t}) + \gamma_t + \varepsilon_{i,t}$$

Description:

· $D_{HighVC,i,t}$: High tech capital group (vc/gdp upper quartile)

Results: interaction items were not significant → threshold mechanism was weaker than structural constraint.

Appendix 3

Summary of regression results

(1) TDP → ECB benchmark and mechanism verification results (RQ1-RQ2)

Variable	(1) Baseline	(2) Institution	(3) Capital	(4) Inequality	(5) Environment
TDP	0.21*	0.78***	0.68**	−5.49	1.41**
Institutional quality		0.57***			
TDP ×system		Not significant			
VC Index			Not significant		
TDP × VC			Not significant		
Gini				−6.09**	
TDP × Gini				Not significant	
Environmental indicators					Not significant
TDP ×environment					Not significant
yearly FE	Yes	Yes	Yes	Yes	Yes
Urban clustering SE	Yes	Yes	Yes	Yes	Yes
N	70	70	70	70	70
R^2	High	High	Medium	Medium	Medium

(2) Nonlinearity and boundary effect test (RQ3)

Variable	(6) Nonlinear	(7) Path Dependence	(8) Threshold
TDP	0.76***		0.99***
TDP^2	−0.43*		
System (current period)		1.32**	
System (lagging)		Not significant	
High VC			Not significant
TDP × High VC			Not significant
yearly FE	Yes	Yes	Yes
Urban clustering SE	Yes	Yes	Yes
N	70	40	70

Appendix 3

References

[1] Acemoglu, D., & Robinson, J. A. (2012). *Why Nations Fail: The Origins of Power, Prosperity, and Poverty*. Crown Business.

[2] Acemoglu, D., & Johnson, S. (2023).*Power and Progress: Our Thousand-Year Struggle Over Technology and Prosperity*. New York: PublicAffairs.

[3] Aghion, P., & Howitt, P. (1992). A Model of Growth through Creative Destruction. *Econometrica*, 60(2), 323–351.

[4] Frenken K., Van Oort F. and Verburg T. (2007) Related variety, unrelated variety and regional economic growth. *Regional Studies*, 41, 685–697.

[5] Feldman, M. P., & Kogler, D. F. (2010). Stylized Facts in the Geography of Innovation[J]. *Handbook of the Economics of Innovation*, (1), 381-410.

[6] Florida, R. (2002). *The Rise of the Creative Class: And How It's Transforming Work, Leisure, Community and Everyday Life*. New York: Basic Books.

[7] Gawer, A., & Cusumano, M. A. (2014). Industry platforms and ecosystem innovation. *Journal of Product Innovation Management*, 31(3), 417–433. https://doi.org/10.1111/jpim.12105

[8] Glaeser, E. L., & Mare, D. C. (2001). Cities and skills. *Journal of Labor Economics*, 19(2), 316–342.

[9] Glaeser, E. L., & Gyourko, J. (2003). *The Impact of Building Restrictions on Housing Affordability*. Federal Reserve Bank of New York Economic Policy Review.

[10] Glaeser, E. L., & Gottlieb, J. D. (2009). The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States. *Journal of Economic Literature*, 47(4): 983–1028, DOI: 10.1257/jel.47.4.983.

[11] Glaeser, E. L. (2011). *Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier*. New York: Penguin Books.

[12] IPCC. (2022). *Climate Change 2022: Mitigation of Climate Change—WGIII Contribution to the Sixth Assessment Report[R]* (pp. 567-612). Cambridge: Cambridge University Press.

[13] Stiglitz, J. E., Sen, A., & Fitoussi, J.-P. (2009). *Report by the Commission on the Measurement of Economic Performance and Social Progress*. Paris: Commission on the Measurement of Economic Performance and Social Progress.

[14] Ripamonti, J. P. (2024). *Essays on Transparency and Trust in Government* [Doctoral thesis]. Bocconi University.

[15] Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5), 71–102. https://doi.org/10.1086/261725

[16] North DC. (1990), *Institutions, Institutional Change and Economic Performance*. Cambridge University Press.

[17] Mazzucato, M. (2018). Mission-oriented innovation policies: challenges and opportunities. *Industrial and Corporate Change*, 27(5), 803-815.
[18] Kaufmann, D., Kraay, A., & Mastruzzi, M. (2010). "The Worldwide Governance Indicators: Methodology and Analytical Issues", *World Bank Policy Research Working Paper Series* No. 5430.
[19] Jacobs, J. (1969). *The Economy of Cities*. New York: Random House.
[20] Kline, P., & Moretti, E. (2014). People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs. *Annual Review of Economics*, 6, 629–662.
[21] Luo, Q., & Zhao, X. (2024). Intellectual property protection intensity and regional technological innovation structure: Based on the perspective of economic complexity theory. *Heliyon*, 10(21):e39964.
[22] Hu, X., Zhang, Z., & Lv, C. (2023).The impact of technological transformation on basic research outcomes: The moderating role of intellectual property protection. *Journal of Innovation & Knowledge*, 8(3), 100402.
[23] Kenney, M., & Zysman, J. (2016). The Rise of the Platform Economy. *Science and Technology,* 32(3), 61–69.
[24] Autor, D. H. (2014). Skills, Education, and the Rise of Earnings Inequality among the 'Other 99 Percent'. *Science*, 344(6186): 843–851.
[25] Piketty, T. (2014). *Capital in the Twenty-First Century*. Harvard University Press.
[26] UNDP (2022). *Human Development Report 2021/2022: Uncertain Times, Unsettled Lives – Shaping Our Future in a Transforming World*.
[27] OECD. (2015). *In It Together: Why Less Inequality Benefits All*. Paris: OECD Publishing. https://doi.org/10.1787/9789264235120-en
[28] OECD. (2018). *Beyond GDP: Measuring what counts for economic and social performance*. Paris: OECD Publishing. https://doi.org/10.1787/9789264307292-en
[29] OECD. (2020). *Cities in the World: A New Perspective on Urbanisation*. OECD Publishing.
[30] OECD. (2021). *Brick by Brick: Building Better Housing Policies*. https://www.oecd.org/social/brick-by-brick-9789264239845-en.htm
[31] OECD. (2021). *Science, Technology and Innovation Outlook 2021*. OECD Publishing.
[32] OECD. (2021). *OECD Skills Outlook 2021: Learning for Life*. Paris: OECD Publishing. https://doi.org/10.1787/0ae365b4-en
[33] OECD. (2023). *OECD SME and Entrepreneurship Outlook 2023*. Paris: OECD Publishing. https://doi.org/10.1787/342b8564-en
[34] OECD. (2025). *Entrepreneurial Ecosystem Diagnostics*. OECD Studies on SMEs and Entrepreneurship. Paris: OECD Publishing. https://doi.org/10.1787/7096961f-en
[35] UNDRR. (2022). *Global Assessment Report on Disaster Risk Reduction 2022: Our World at Risk*. Geneva: United Nations Office for Disaster Risk Reduction. https://www.undrr.org/publication/global-assessment-report-disaster-risk-reduction-2022
[36] Guo, S., Diao, Y., & Du J. (2022). Coupling Coordination Measurement and Evaluation of Urban Digitalization and Green Development in China. *Int J Environ Res Public Health*, 19(22):15379.
[37] Meerow, S., Newell, J. P., & Stults, M. (2016). Defining urban resilience: A review. *Landscape and Urban Planning*, 147, 38–49.
[38] China Academy of Information and Communications Technology. (2023). *White Paper on the Development of 5G in China and Its Socioeconomic Impact (2023)* [R]. China Academy of Information and Communications Technology.
[39] Pew Research Center. (2021). Digital divide persists even as Americans with lower incomes make gains in tech adoption.

[40] Wang, Y. (2021). *Research on the Mechanism of Venture Capital Industry Innovation Value Discovery from the Perspective of Innovation Ecosystem* [D]. Northeastern University.
[41] Chen, L., & Xue, L. (Eds.). (2021). *Measuring Global Science and Technology Innovation Centers: Indicators, Methods, and Results* [M]. Beijing: Social Sciences Academic Press.
[42] Cheng, D., Rong, Y., & Zhao, Y. (2024). Transparency demands and privacy protection in smart city construction: Governance practices in Toronto and Harbin. *Chinese Public Administration*, (10), 42–52.
[43] Hai, J., Zeng, G., & Zou, L. (2018). A review of urban sustainability research based on main path analysis. *World Regional Studies*, 27(06), 54–64.
[44] Zhao, Y., & Li, C. (2024). A review of research hotspots and trends in urban resilience at home and abroad. *Urban Studies*, 45(05), 1–11.
[45] Lyu, X. (2025). Ideas and suggestions for the planning and construction of resilience in megacities and large cities. *Beijing Planning and Construction*, (01), 34–37.

Steering Committee

HUI Kai-Lung
Associate Provost of the Hong Kong University of Science and Technology
Director of HKUST Center for Technology and Business Ecosystem

HU Yu
Adjunct Professor of HKUST (GZ); Member of the Advisory Committee
HKUST Center for Technology and Business Ecosystem

LIU Sha
Founder of Mingzhu Special Training Camp; President of the HKUST Shanghai Alumni Association
Member of the Advisory Committee, HKUST Center for Technology and Business Ecosystem

LANG Yuanpeng
Managing Partner of JINGTIAN & GONGCHENG

Research Team

MENG Zhaoli
Professor of Business Practice, HKUST
Associate Director of the HKUST Center for Technology and Business Ecosystem

LIN Dongwei
Assistant Manager of HKUST Center for Technology and Business Ecosystem

Introduction to
HKUST Center of Technology and Business Ecosystem

Initiated by the HKUST Business School, HKUST Center of Technology and Business Ecosystem (hereafter CTBE) focuses on how emerging technologies such as artificial intelligence and robotics are reshaping business strategy and ecosystem structures. With 'the evolution of technology and business ecosystems' as its core research theme, the center systematically explores multi-level collaborative mechanisms spanning product design, organizational structure, and platform governance, providing deep insights into the evolving logic and future trends of digital-era business ecosystems.

CTBE is committed to fostering deep collaboration among academia, industry, and policymakers by building an inclusive and innovative research network. The center will actively strengthen strategic connections between Hong Kong, the Greater Bay Area, and Mainland technology enterprises, driving integrated development and coordinated advancement of the regional tech ecosystem, and promoting exemplary models of collaboration.

Grounded in the practices of leading Chinese tech firms and integrated with cutting-edge global theory, CTBE aims to develop forward-looking and actionable strategic frameworks for business ecosystems. It will regularly release insight reports, co-develop case libraries with industry leaders, and conduct cross-sector dialogues on key topics, aspiring to become a globally influential think tank for tech-driven ecosystem studies.
CTBE promotes a research paradigm based on cross-boundary collaboration, systems innovation, and ecological symbiosis, actively exploring pathways to ecological civilization in the digital age. Looking ahead, the center will focus on ecosystem design, new organizational forms, and ecological civilization development, continuously delivering structured theoretical frameworks and strategic guidance to support a technology-driven, sustainable society.