China's High-Quality Technology Innovation: Scenario Narrative and Measurement System

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Abstract: *The world today is undergoing disruptive, transformative shifts driven by a new wave of technological revolutions and industrial changes. In this context, a central question for China's innovation-driven development strategy is how to effectively identify and measure high-quality technological innovations. Drawing on the stylized facts and scenario narrative of China's technological landscape, this paper proposes a framework and measurement system for evaluating high-quality technological innovations. While China's top-level design for technological innovation is guided by policy documents, the increasing number of enterprises applying for "high-tech enterprise" status has coincided with a decline in the quality of patent filings. In response, this paper first underscores the challenges and necessity of measuring the quality of technological innovations. Second, we introduce the high-quality technological innovation indicators and employ them to assess the quality of tech innovations at the firm level, utilizing an approach that combines analogical narrative, gene coding, text analysis, semantic logic, and a database of granted invention patents in China. Third, we examine the systematic and individual biases inherent in citation counts, a commonly used indicator, under specific contexts, and employ a granular instrumental variable approach to validate the effectiveness of the indicators. Finally, we develop a "family tree" of the indicators and explore their application scenarios through a combination of established and extended indicators. Our findings provide a theoretical foundation for evaluating China's technological innovation quality, inform policy incentives, and offer insights for academia to apply high-quality technological innovation indicators in different contexts.*

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1. Introduction

Our world is undergoing momentous changes not seen in a century. Disruptive and strategic technologies, particularly artificial intelligence (AI), are driving a sweeping technological revolution and industrial transformation. 5G is rapidly propelling the world into the era of the Internet of Everything

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(IoE), while 6G's integrated space-air-ground network is poised to redefine connectivity, enabling breakthroughs such as millimeter-level positioning for the industrial internet, the creation of human digital twins, and the development of unified intelligent mobile platforms across vehicles, ships, aircraft, and spacecraft. At the same time, the convergence of information technology with fundamental sciences like life sciences and materials science is accelerating, driving progress in cutting-edge fields like quantum science and brain-inspired intelligence. The application of biological principles alongside interdisciplinary knowledge is sparking transformative innovations. AI-powered models for protein structure prediction, intelligent medical solutions for disease diagnosis, and advancements in biological targeting and mass spectrometry are transforming drug discovery and advancing disease diagnostics in unprecedented ways. This new wave of technological and industrial change is disrupting traditional industries and is set to reshape the global division of labor, alter the competitive landscape, and redefine national advantages. While it brings significant opportunities, it also presents considerable challenges.

To strengthen national competitive advantages, it is crucial to understand and fully leverage the operational dynamics and developmental patterns of the new technological revolution. This revolution is defined by three key features: First, the disruptive, transformative, and cutting-edge technological updates and iterations. These innovations are diffusing exponentially, exerting a revolutionary "zeroing effect" (i.e., eliminating outdated practices and technologies) on traditional industries. At the same time, major scientific fields are advancing rapidly, both in depth and breadth, from the microscopic to the macroscopic, ushering in a new era of Big Science. Second, borderless, multi-point, and exponential technological breakthroughs. Technological innovation is increasingly complex and unpredictable, with disruptive technologies emerging rapidly from diverse, global sources and advancing at an unprecedented pace. Third, interdisciplinary, interregional, and cross-sector collaboration. Emerging technologies are driving a cascade of interconnected changes, with technology clusters, interdisciplinary teams, diverse stakeholders, and regions working in synergy to foster mutual progress. The acclaimed ASML lithography systems, for example, resulted from extensive technological and financial collaboration across more than 40 countries, incorporating critical components such as lenses, light sources, wiring, and ultraviolet light exposure units. In summary, disruption, breakthrough, and collaboration are the defining characteristics of this new wave of technological revolution.

How China can effectively seize historical opportunities and overcome the challenges of the industrial and technological revolution is a critical issue in the implementation of its national innovation-driven development strategy. The CPC Central Committee and governments at all levels have long placed great emphasis on scientific and technological innovation, positioning innovation at the heart of China's modernization and adopting an innovation-driven development model as a key national strategy. During the "Three Gatherings of Science and Technology" on May 28, 2021, President Xi Jinping stated: "We have comprehensively deployed reforms in the technological innovation system, introducing a series of major reform initiatives to enhance the overall effectiveness of the national innovation system."[1] However, China's technological innovation is currently hindered by a set of interrelated challenges: weak original innovation, insufficient resource integration, and inefficient resource allocation, all of which impede the development of high-quality technological advancements. A substantial body of literature has explored ways to improve the quality of technological innovation in China, focusing on factors such as policy impacts (Long and Wang, 2015; Shen Yu et al., 2018; Chen et al., 2020) and mechanism design (Zhang and Zheng, 2018; Bai et al., 2019; Chen et al., 2022). These studies consistently highlight issues such as "quantitative growth coupled with qualitative decline" at the macro level and "strategic innovation" at the micro level, offering explanations for these phenomena

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[1] Xi Jinping. *Speech at the 20th Academician Assembly of the Chinese Academy of Sciences (CAS), the 15th Academician Assembly of the Chinese Academy of Engineering (CASE), and the 10th National Congress of the China Association for Science and Technology* [M]. Beijing: People's Press, 2021.

from historical, theoretical, and practical perspectives. While China's top-level design for technological innovation prioritizes innovation quality, in practice, the focus often shifts to innovation quantity (Chen et al., 2022). This discrepancy is reflected in the reliance on easily measurable quantitative indicators, such as the number of patents and R&D investment, in planning, goal-setting, and evaluation processes.

We believe the gap between policy intentions and actual enforcement arises from a combination of China's innovation incentives and the challenges in assessing innovation quality. The current evaluation system is inadequate, and the difficulty in measuring quality hampers the advancement of China's technological innovation. While invention patents can reflect industry progress and emerging technologies, they often fail to capture the full scope of innovation. For example, patents like the "XXX Flatbread Oven" and the "Eco-Friendly and Efficient Artemisinin and Dihydroartemisinin Extraction Method" may both be categorized as invention patents, yet they differ greatly in terms of originality and impact. This disparity in quality becomes even more evident in contexts such as "innovation championships" or the "year-end sprint", which undermine the focus on high-quality innovation. To address this, it is crucial to overhaul the system to measure technological innovation quality, adopting a more nuanced, scenario-based approach.

To address this question, we develop an identification framework and a measurement system for high-quality technological innovations, grounded in the typical scenario narrative of technological innovation in China. Our approach unfolds in several stages: Stage 1: We analyze the key stylized facts and relevant indicators concerning the quality and quantity of technological innovations in China. Stage 2: We introduce a novel measurement system for assessing the quality of technological innovations in China, inspired by the analogy of gene coding. Stage 3: We leverage licensed invention patent data from 1986 to 2016, alongside textual analysis techniques and semantic reference logic, to estimate the originality, influence, and vitality of technological innovations at the firm level. In addition, we conduct a comprehensive comparison of existing technological innovation quality indicators, revealing both systematic biases stemming from the annual fluctuations in patent applications and individual biases related to underlying patent technology citation data. To address these issues, we employ a granular instrumental variable approach to eliminate the effects of both types of bias, demonstrating the effectiveness of the proposed innovation quality indicators. Lastly, we construct a family tree of technological innovation quality and its application scenarios, incorporating an extended set of indicators developed in this study alongside existing measurement frameworks.

Exploring the scenario narrative and measurement system for high-quality tech innovations in China holds significant research value. This work is crucial for advancing theoretical research on tech innovation quality and supporting China's innovation-driven development strategy. First, we extend the measurement of technological innovation quality from patents to the "innovation genes" embedded in patents, using the analogy of gene coding and text analysis methodology. Our introduction of the "innovation gene" concept offers a new approach to assessing technological innovation quality. Second, we develop a measurement system that accounts for both systematic and individual biases, reducing errors associated with "strategic innovation". Finally, we compare the strengths and weaknesses of existing indicators with our own, create a family tree of tech innovation quality indicators, and examine their application scenarios. Our findings provide valuable guidance for both theoretical research and practical applications in tech innovation.

This paper is structured as follows: Section 2 offers a comprehensive literature review, while Section 3 analyzes stylized facts concerning the quality and quantity of technological innovation in China. Section 4 introduces a genetic analogy framework to conceptualize the quality of innovation, and Section 5 employs text analysis and semantic citation techniques to derive new measures of technological innovation quality. Section 6 provides a comparative and contextual analysis to validate these proposed indicators, and Section 7 extends the indicators by constructing a family tree of technology innovation quality indicators. The paper concludes with a summary of key findings and policy recommendations.

2. Literature Review

Technological innovation is a key driver of both national and regional development. To harness its full potential, it is crucial to first define what constitutes technological innovation and assess its current stage of progress. Addressing these fundamental questions about how technological innovation is measured provides the theoretical framework and critical foundation necessary for implementing effective innovation strategies.

2.1 Early Innovation Measurement: A Quantitative Focus

Earlier research on R&D and innovation output has typically measured the level of technological innovation using three types of indicators: (1) Innovation investment, including R&D expenditure (Feldman, 1994) and venture capital investment (Gompers and Lerner, 2006); (2) Intermediate innovation outputs, such as the number of patents (Griliches, 1990); and (3) New product announcements, drawn from trade, engineering, and technical publications (Acs, 2002). Among these, the patent-based measurement approach stands out as the most widely used by academics, businesses, and government agencies. This approach has gained popularity due to its advantages in providing readily accessible firm-level data, delivering clear and interpretable results, and effectively capturing firms' independent innovation capabilities (Feldman and Kogler, 2010; Long and Wang, 2015).

2.2 Debate over Innovation Quantity and Quality: Criticism of the Patent Bubble

As patent counts have become a key metric for assessing technological innovation, many countries rely on this easily quantifiable measure to guide policy decisions. In response, various incentive programs have been introduced to stimulate further innovation. While these programs have boosted the volume of patents, they have also led to a significant issue: the "Patent Bubble". For example, in 2017, China topped the world with 3.17 million patent applications - more than five times the number filed by the United States, which ranked second. However, China's technological innovation, as reflected by the sheer quantity of patents, is often overstated and does not accurately capture its true technological strength. This discrepancy has sparked ongoing debate about whether patent numbers are a valid measure of innovation, particularly in light of concerns over the so-called "patent explosion" and the trade-off between quantity and quality (Dong and He, 2015). Numerous studies have shown that transitional developing countries tend to produce large volumes of patents, but these are often of low quality (Cai et al., 2017). In many cases, the focus is placed on quantity rather than the value or impact of technological innovation (Harhoff et al., 2003). This trend can be attributed to policies that prioritize quantity over quality: as resources are finite and specialized, an emphasis on increasing quantity often comes at the expense of quality (Mudambi and Swift, 2014). In the patent context, this creates incentives for firms to engage in what is known as "subsidy-seeking innovation" or "strategic patenting" (Shen et al., 2018) - a strategy aimed at increasing patent numbers to secure government subsidies, rather than fostering meaningful technological advances. The strategic focus on "quantity over quality" in government innovation policies (Li, 2012; Chen et al., 2022; Shen et al., 2018) is a fundamental institutional driver of this "strategic innovation", contributing to the misallocation of innovation resources.

2.3 Quantity Bias in Mainstream Patent Quality Measurement

As the importance of innovation quality has become more widely recognized, numerous studies have sought to develop methods for measuring patent quality, typically focusing on three key dimensions: technological innovativeness, legal stability, and application prospects (Dong and He, 2015).First, technological innovativeness refers to a patent's contribution to creativity and novelty beyond the existing state of the art. This dimension is often measured using indicators such as patent citation counts and cumulative citations (Peter, 2006; Gambardella et al., 2008; Jaffe and de Rassenfosse, 2017; Reitzig, 2004; Hsu et al., 2014; Zhao et al., 2018), technological scope (Lerner, 1994; Marco et al., 2019; Jiang et al., 2019), foreign citation rate (Boeing and Mueller, 2016, 2019), number of inventors (Belderbos et al., 2014; Briggs and Wade, 2014; Briggs, 2015), knowledge breadth, and the scope of protection (Lerner, 1994; Aghion et al., 2015; Akcigit et al., 2016; Zhang and Zheng, 2018), among others. Second, legal stability refers to a patent's ability to withstand post-grant challenges, such as invalidation. Key indicators of legal stability include maintenance status during patent re-examination (Schettino and Sterlacchini, 2009; Ye et al., 2012), patent withdrawal and renewal rates (Long and Wang, 2015), patent litigation rates (Harhoff et al., 2003), clarity of language in patent applications (Rai, 2013; Dargaye, 2013), and the granted patent maintenance rate (Schettino and Sterlacchini, 2009; Ye et al., 2012). Third, application prospects reflect the potential economic value a patent can create for related products. This dimension is indirectly measured by factors such as the duration of patent maintenance (Zhu et al., 2009), annual patent lapse rates, number of active patents, N-year patent survival rate, and patent transfer, licensing, and pledging activities (Lanjouw and Schankerman, 2004). Additionally, other indicators such as the percentage of invention patents and the patent approval rate have also been used to assess patent quality (Zhang et al., 2011). These dimensions together provide a comprehensive framework for evaluating the quality and potential impact of patents.

Recent literature on measuring technological innovation has moved beyond the previous focus on quantity, recognizing both the importance and variation in the quality of invention patents. Studies now assess patent quality across technical, legal, and economic dimensions, marking a significant step forward. However, this paper acknowledges that many of these indicators are still influenced by a quantitative perspective. In the technical dimension, patent citations are commonly used to measure firm patent quality (Hsu et al., 2014). This approach, however, has notable limitations: (1) Citation counts do not distinguish between truly original patents and popular "strategic" patents, which may be filed in trending areas and thus receive more citations (Dang and Motohashi, 2015); (2) Citation counts often overlook high-quality "sleeping beauty" patents with interdisciplinary potential and technological value (Du and Wu, 2018); (3) Citation patterns can be distorted by chaotic or excessive citations during "patent bubbles". As such, it is crucial to identify more refined indicators that genuinely capture the quality of technological innovation, grounded in the true nature of innovation itself.

2.4 Measuring the True Value of Innovation: A Methodological Reassessment

Schumpeter's concept of "creative destruction" underscores the essence of innovation as the fundamental engine of economic growth. However, when attempting to measure technological innovation in China, particularly through patent citation data, several challenges arise. One key issue is that China's patent citation practices do not always align with international standards. First, the China National Intellectual Property Administration (CNIPA) initially lacked clear regulations regarding patent citation data. Second, a significant portion of citation data has been added retroactively by patent examiners, introducing potential biases and complicating the reliability of this information. As a result, accurate and dependable patent citation data for businesses remains difficult to obtain. This challenge, however, presents an opportunity to rethink how we measure the quality of technological innovation in China. To address this, this paper proposes using semantic citation analysis as a more effective alternative to traditional citation methods. Unlike physical citations, semantic citation analysis allows for a deeper understanding of the technical content of patents, offering more precise insights into patent quality and a clearer view of the technological development trajectory (Du and Wu, 2018; Guo, 2019). This approach opens new avenues for evaluating the quality of technological innovation. Specifically, this paper employs text analysis techniques and applies a gene-coding analogy to extract "innovation genes" from patents, thereby identifying the original knowledge embedded within them. By utilizing the semantic relationships between patents, it constructs a measurement system that more accurately reflects the true essence of technological innovation quality. In the final section, the paper evaluates the effectiveness of this system in the context of China's technological innovation landscape.

3. Stylized Facts of High-Quality Technological Innovation in China

3.1 Originality as a Strategic Priority in China's Innovation Policy

China's system for incentivizing technological innovation has consistently prioritized the quality of innovation, a focus that has become even more evident in the context of the current wave of disruptive, transformative, and frontier technologies. In this paper, we have collected over 1,000 policy documents related to science and technology innovation published over the past two decades. These documents include laws, administrative regulations, departmental rules, normative policies, development plans, and strategic outlines issued by China's national legislative bodies, the central government, key administrative departments, and representative local governments. The data primarily comes from the State Council, the Ministry of Science and Technology (MOST), and the Ministry of Finance (MOF).

Using a combined approach of text analysis and manual search, we extracted keywords associated with technological innovation from these documents. Textual analysis of over 1,000 policy documents reveals the following key insights: (1) Terms like "originality", "high quality", and "quality" are central to the overarching design of China's technological innovation strategy. (2) In practice, indicators such as patents, invention patents, and R&D are frequently employed to measure the success of technological innovation efforts in the country. At all levels of government, a "patent catch-up strategy" has been the dominant approach to innovation development. Patent application targets are cascaded from national to local governments through top-down policy directives. The implicit pressure to meet patent quantity targets has led local governments to adopt patent development plans with clear, quantifiable objectives, accompanied by a series of innovation incentives aimed at increasing patent numbers. However, this focus on quantity has led to unintended consequences, including the phenomenon of "innovation for the sake of quantity" and the compromise of quality in pursuit of these targets - a practice referred to as "strategic innovation".

3.2 Quantity-Driven Growth in High-Tech Enterprise Applications

High-tech enterprises are the primary applicants for invention patents in China. Since 2007, China has actively fostered innovation in these enterprises through its High-Tech Enterprise program, which offers innovation subsidies to eligible companies. A key criterion for obtaining this designation is the number of patents a company holds[2]. However, once a company is granted High-Tech Enterprise status, no additional patent quantity requirements are imposed. As a result, companies, eager to secure the benefits of this designation, are often incentivized to rapidly expand their patent portfolios, sometimes inflating them, leading to a competitive rush for certification. This phenomenon has resulted in what is often referred to as a "scramble for high-tech status".

3.2.1 Model specification

Using a multi-source matched database from 2007 to 2016 and a multi-period difference-in-differences (DID) method, this paper empirically investigates the change in invention patent quantity before and after companies achieve High-Tech Enterprise certification, indirectly assessing whether a "patent surge" or "patent bubble" exists during the application for this designation. The econometric model is specified as follows:

$$Patent_{it}=\alpha+\beta Gxqy_{it}+\gamma X+\delta_i+\mu_t+\varepsilon_{it} \tag{1}$$

In the above equation, $patent_{it}$ denotes the number of granted patent inventions for firm i in year t. The regression analysis employed transformations of the dependent variable, including log(patent+1),

[2] While the program sets a minimum patent threshold for certification, in practice, most companies exceed this baseline by a significant margin.

the inverse hyperbolic sine (IHS), and PPML. $Gxqy_{it}$ is the dummy variable for High-Tech Enterprise status: A dummy variable is used to indicate High-Tech Enterprise status, taking a value of 1 if the firm is certified and 0 otherwise. X are control variables potentially affecting firms' technological innovation. To address the potential impact of High-Tech Enterprise status on these control variables, we control for the pre-event time trends by interacting the 2007 baseline values of these variables with year dummies. δ and μ_t represent firm and time-fixed effect, respectively, controlling for unobserved time-invariant firm-level heterogeneity and macro-level time trends. ε_{it} denotes the error term. For Model (1), data on the dependent variable $Patent_{it}$ come from the SIPO, while data on the independent variable $Gxqy_{it}$ are sourced from the Department of High and New Technology Development and Industrialization of the Ministry of Science and Technology (MOST). The main control variables are: (1) Firm size (log of operating profit and year-end total assets); (2) Tax payment (log of current-year tax payment); (3) Fixed assets (calculated using the perpetual inventory method); (4) Government subsidies (log of subsidies received from government agencies).

To capture the dynamic effects of High-Tech Enterprise certification on firms' innovation output, we decompose the average treatment effect ($Gxqy_{it}$) into dynamic treatment effects. To capture the effects in the first three years after certification, three dummy variables, $Gxqy_{1it}$, $Gxqy_{2it}$ and $Gxqy_{3it}$[3] are created. Our sample includes only firms that were recognized as High-Tech Enterprises between 2007 and 2016. This selection criterion ensures sample comparability and is based on the use of dummy variables. The econometric model is specified as follows:

$$Patent_{it}=\alpha+\beta\sum_{j=1}^{3}Gxqy_{jit}+\gamma X+\delta_i+\mu_t+\varepsilon_{it} \tag{2}$$

In equation (2), $Gxqy_{jit}$ equals 1 if year t is the j^{th} year after the firm's High-Tech Enterprise recognition, and 0 otherwise.

3.2.2 Preliminary evidence of a quantitative leap

Table 1, columns (1)-(4) show the average treatment effect of High-Tech Enterprise recognition on firms' granted invention patents. Columns (1) and (2) report estimates for the full sample, while columns (3) and (4) report estimates for the High-Tech Enterprise subsample. Overall, High-Tech Enterprise recognition significantly increases the number of firms' invention patents by nearly 0.2. However, the full sample estimates are clearly subject to sample selection bias: Compared with other enterprises, High-Tech Enterprises exhibit a distinct pattern of innovation output, with a surge before recognition and a decline immediately after[4]. Because high-tech enterprises are more comparable, the results in columns (3) and (4) provide a clearer reflection of the policy effect of high-tech enterprise recognition. On the whole, high-tech enterprise designation did not lead to an increase in firms' invention patent output.

Table 1: Preliminary Evidence of a "Quantitative Leap": Two-way Fixed-Effects Model

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(patent+1)	arcsinh	ln(patent+1)	arcsinh	ln(patent+1)	arcsinh	ln(patent+1)	arcsinh
Gxqy	0.1530*** (0.0042)	0.1964*** (0.0057)	-0.0176 (0.0121)	-0.0232 (0.0147)				

[3] We define the treatment period as spanning from the year of High-Tech Enterprise recognition (t=0) to three years post-recognition (t=3), and our analysis includes only treated firms within this period.

[4] We also conducted a parallel trend test. Column (1) did not pass the parallel trend test, but column (2) did. Due to space constraints, these results are not reported here.

Table 1 Continued

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(patent+1)	arcsinh	ln(patent+1)	arcsinh	ln(patent+1)	arcsinh	ln(patent+1)	arcsinh
$Gxqy_1$					-0.0073 (0.0069)	-0.0071 (0.0078)	-0.0203** (0.0102)	-0.0260** (0.0133)
$Gxqy_2$					0.0237*** (0.0073)	0.0335*** (0.0088)	-0.0089 (0.0089)	-0.0122 (0.0116)
$Gxqy_3$					0.0684*** (0.0072)	0.0908*** (0.0092)	0.0736*** (0.0090)	0.0920*** (0.0117)
Sample size	3204585	3204585	61750	61750	2986395	2986395	61750	61750
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: (1) Figures in parentheses are standard errors; (2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; (3) The same applies below.

The High-Tech Enterprise designation is valid for three years. High-Tech enterprises that have exceeded their validity period need to undergo a review to determine if they still meet the certification criteria. This also suggests the potential for R&D manipulation incentives among High-Tech Enterprises: Namely, the reallocation of R&D activities across different time periods. In light of this, we performed dynamic effect tests of the High-Tech Enterprise designation in columns (5) through (8), with (5) and (6) representing the full sample regressions and (7) and (8) showing the results for the High-Tech Enterprise sample. The results presented in columns (5) and (6) indicate that High-Tech Enterprise designation does not yield an increase in technological innovation output during the first year post-designation; the within-group comparison results in columns (7) and (8) further demonstrate that the number of invention patents for High-Tech Enterprises actually declines in the first year following designation, with no evidence of a policy-driven effect observed in the second year. For the lagged High-Tech Enterprise certification dummy $Gxqy_3$, the estimated coefficients in columns (5)-(8) are all significantly positive, indicating a significant increase in the innovation output of High-Tech Enterprises in the year prior to the review. These results suggest that there is significant time manipulation of corporate R&D activities during the High-Tech Enterprise certification process. That is, it is not that the policy effect of High-Tech Enterprise certification is insignificant, but rather that time manipulation leads to a clear "quantity jump" before certification and review.

3.2.3 Heterogeneous treatment effect (HTE)

The use of a two-way fixed effects model to estimate a staggered DID design is vulnerable to bias due to the presence of heterogeneous treatment effects, which can lead to biased estimated coefficients. While the Bacon decomposition indicates severe bias from "forbidden comparisons" in two-way fixed effects estimates, the dynamic nature of High-Tech Enterprise certification - where firms can both gain and lose status - necessitates the use of robust DID estimators. As a result, we employed a series of heterogeneous robust DID estimators, drawing on methods from Gardner (2021), Borusyak et al. (2022), De Chaisemartin and D'Haultfoeuille (2020), Callaway and Sant'Anna (2021), Sun and Abraham (2021), and Cengiz et al. (2019). The average treatment effect results from the heterogeneity-robust estimators, and the results are consistent with those in Table 1. Furthermore, we present the dynamic treatment effects of the heterogeneous robust DID estimators in Table 2.

Table 2: Preliminary Evidence of "Quantity Leap": Heterogeneous Robust DID Estimators

Variable	(1)	(2)	(3)	(4)	(5)
	Borusyak et al. (2022)	De Chaisemartin and D'Haultfoeuille (2020)	Callaway and Sant'Anna (2021)	Sun and Abraham (2021)	Cengiz et al. (2019)
$Gxqy_1$	-0.0251*** (0.0053)	0.0046 (0.0065)	-0.0112* (0.0066)	-0.0074 (0.0071)	-0.0072 (0.0064)
$Gxqy_2$	0.0571*** (0.0083)	0.0530*** (0.0083)	0.0238*** (0.0071)	0.0440*** (0.0079)	0.0243*** (0.0068)
$Gxqy_3$	0.1147*** (0.0074)	0.1775*** (0.0111)	0.0786*** (0.0073)	0.1315*** (0.0098)	0.0692*** (0.0072)
Sample size	3857950	2658271	2894186	3030861	38006133
Controls	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y

Note: (1) In Table 2, the dependent variable is specified as the natural logarithm of one plus the number of patents (ln(*patent*+1)). (2) The results obtained using the inverse hyperbolic sine (IHS) transformation are qualitatively similar and are omitted due to space limitations.

3.3 Rushing for Growth: "Quality Decline" in the "Patent Catch-up Plan"

The drive for policy gains is not confined to the micro level of high-tech enterprises, but extends to the macro level, where regions compete for growth. A case in point is that, in the context of innovation-driven development, local governments have assigned paramount importance to innovation, leading to the direct implementation of "patent catch-up plans" designed to increase patent output. These plans are manifested in documents such as government annual work reports, "Five-Year Plans", and annual patent application quotas[5]. This creates a significant constraint on the evaluation of government performance, as the inclusion of tasks with specific quantitative targets in work reports and plans may incentivize a decline in patent quality.

3.3.1 Assessing invention patent quality using a duplicate checking method

This paper focuses on assessing the quality of technological innovation. The aim of this section is to use stylized facts to highlight a "quantitative surge" coupled with a corresponding "qualitative deterioration" in innovation activities. In the absence of a novel metric for measuring technological innovation quality, we apply a duplicate-checking method to perform a basic assessment of invention patent quality. The core assumption is that if the abstract of an invention patent closely resembles the text of existing patents in a comprehensive patent database, it may indicate a lack of novelty, raising concerns about the patent's inventiveness. Statistical analysis reveals that patents with greater overlap with prior knowledge are often simple reformulations of existing ideas, suggesting a decline in originality. To evaluate the degree of textual overlap, this paper employs the following methodology for Chinese granted invention patents from 2000 to 2016: We implemented a Python-based algorithm to detect textual similarity among scientific and technological projects. The algorithm was then applied to assess the textual overlap of each granted invention patent against a dynamically updated database of all patents issued prior to the patent's grant date. Using Gensim for textual similarity analysis, we considered any continuous sequence of eight or more identical characters as a match. We calculated a textual overlap score for each patent's abstract to determine its repetition rate. Finally, by applying a weighted average based on patent citation counts, we computed the annual average textual overlap score

[5] For example, Anhui Province issued "Ensuring the Completion of the Annual Patent Application Volume Task" in 2007, while Zhejiang Province clarified the patent doubling target in the "Twelfth Five-Year Plan".

for granted invention patents across provinces. A high average repetition rate at the provincial level suggests potentially lower technological innovation quality.

3.3.2 Model specification

Using a multi-period DID approach with provincial-level invention patent data from 2000 to 2016, this paper empirically examines the effect of “local patent catching-up policies” on invention patent quality. The econometric model is specified as follows:

$$Quality_{it}=\alpha+\beta zgjh_{it}+\eta X+\lambda_i+\delta_t+\varepsilon_{it} \quad (3)$$

In equation (3): $zgjh_{it}$ is an indicator variable equal to one if province i implemented a patent catching-up policy in year t, and zero otherwise[6]; $Quality_{it}$ represents the average repetition rate (expressed as a percentage) of invention patents applied for by province i in year t; X denotes the interaction term between pre-treatment control variables for province and year dummies, where pre-treatment control variables include three-year averages (1997-1999) of variables such as provincial GDP; α is the constant term; β and η are parameters to be estimated; λ_i, δ_t, and ε_{it} represent province fixed effects, year fixed effects, and the error term, respectively.

3.3.3 Preliminary evidence of “quality decline”

We present the empirical findings on the “quality slide” within the context of the “patent catching-up plan” in Table 3.

Table 3: Preliminary Evidence of “Quality Decline”[7]

Variable	(1) TWFE	(2) TWFE	(3) TWFE	(4) Borusyak et al. (2022)	(5) Callaway and Sant’Anna (2021)	(6) Cengiz et al. (2019)
zgjh	9.8872*** (1.7716)	7.5457*** (1.8252)	7.1162*** (1.9507)	12.8669*** (2.7631)	10.1498*** (2.1437)	10.9223*** (2.7124)
Sample size	510	510	510	510	510	975
Controls	N	Y	Y	Y	Y	Y
Time FE	N	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y

Note: For heterogeneous robust DID estimations, we employed the group-time average treatment effect, stacked regression, and an imputation method. The results are presented in (4)-(6), respectively.

The results presented in Table 3 indicate that the estimated coefficient of *zgjh* is statistically significant and positive at the 1% level. For instance, in column (2), the estimated coefficient of *zgjh* is 7.546, indicating that provinces implementing the patent catching-up plan experienced a 7.546 percentage point increase in the text repetition rate of patent abstracts. Here, a threshold of 12 repeated characters was applied, with the results presented in column (3). To further strengthen the robustness of our findings on heterogeneous treatment effects, we utilized several alternative estimators. All models consistently indicated a significant “quality slide”. In other words, the focus on meeting patent quantity targets and fulfilling task requirements has resulted in a deterioration of patent quality.

[6] Data on these policies were primarily drawn from the compilation of provincial patent incentive policies by Long and Wang (2015). This was further supplemented by keyword searches in the PKULAW and PKU Legal databases, as well as through general web searches, using search terms such as “province name + patent application + subsidy/funding/grant”.

[7] In fact, we also selected the standards of 6 and 10 character repetitions to measure patent quality, and the results are still robust.

4. Theoretical Foundations of a Technological Innovation Quality Measurement System

Compared to other patent types, invention patents - commonly used as a benchmark for assessing technological innovation - exhibit considerable variability in quality and substantial internal heterogeneity. These patents differ significantly in terms of originality, impact, and longevity. This variation underscores the necessity for a more nuanced analysis of invention patents, identifying the "innovation genes" that truly capture the quality of innovation.

4.1 "Innovation Genes" and Gene Coding: An Analogical Narrative for Innovation Quality Assessment

Knowledge is the wellspring and driving force behind technological innovation, which encodes new insights, with outputs like patents serving as tangible expressions. Innovation activities can be compared to gene coding in three ways: (1) Coding activities: Gene coding governs biological traits through transcription and translation, much like knowledge recombination drives innovative outputs embodied in patents. (2) Mutation process: Genetic mutations, which alter DNA sequences, fuel biological diversity, while original innovation involves the disruptive creation and recombination of existing knowledge. (3) Spatial carriers: Just as gene coding is restricted to coding regions, technological innovation thrives within specific spatial carriers, such as cities.

The concept of "innovation genes" presents significant advantages - both theoretically and practically - over traditional indicators used to assess the quality of technological innovation. (1) A microcosm of the macrocosm: Just as gene mutations reveal inherent individual variations, offering insights into an individual's condition, "innovation genes" serve as the foundational elements of technological progress. They provide a micro-level perspective that helps us understand the core principles and quality of technological advancements. (2) High predictability: Just as genetic mutations and recombination influence an individual's future development, the encoding of "innovation genes" directly shapes the future trajectory of innovation. These genes act as both a "barometer" and a "weathervane", offering a high degree of predictability for shifts in technological innovation quality over time. (3) A basis for policy evaluation: Just as environmental factors influence genetic recombination and mutation, the broader innovation ecosystem shapes the activity of technological "innovation genes". The resulting patterns provide direct, micro-level evidence that can guide the development and refinement of technological innovation policies.

4.2 Technological Innovation Quality: Indicators and Comparative Analysis

In this paper's empirical measurement, "innovation genes" are used to measure innovation quality.

4.2.1 Innovation originality (IO)

Innovation originality measures whether "innovation genes" within a patent are original or were the first to be identified. If a city is a source of innovation, it should generate more original genes and drive the innovative development of other cities through flow, spillover, and combination. This paper identifies earlier-identified "innovation genes" as original, reflecting their understanding of future technologies and trends and their forward-looking nature. Specifically, this paper identifies "innovation genes" that emerge earlier chronologically as original "innovation genes" x_{ijklt}.

$$x_{ijklt}=\begin{cases} 1,\ \mathit{if}\ n_{ijklt}\leq N_{jk}\times 5\%\cap N_{jk}\in[50,+\infty)\ \mathit{or}\ n_{ijklt}\leq\cap N_{jk}\in[20,50) \\ 0,\ \mathit{else} \end{cases} \tag{4}$$

In equation (4), N_{jk} denotes the total count of "innovation gene" j occurrences in industry k; n_{ijklt} indicates the temporal rank of "innovation gene" j within patent l of firm i in industry k during year t; and x_{ijklt} signifies the originality of "innovation genes" within patent l of firm i in industry during year t.

An “innovation gene” is considered original if its temporal rank falls within the top 5%, assigning it a value of 1; otherwise, the value is set to 0[8]. Furthermore, a small number of total occurrences for certain “innovation genes” could suggest their relative uncommonness. Therefore, this paper introduces two thresholds: if an “innovation gene” occurs less than 20 times, it is excluded from the analysis; if it occurs between 20 and 50 times, the first instance is identified as the original innovation gene.

Once “innovation genes” are identified, the originality-based technological innovation quality IO_{it} of firm i at year t can be calculated using the following formula:

$$IO_{it}=\sum_{k}^{K}\sum_{l}^{L}\sum_{j}^{J}x_{ijklt} \tag{5}$$

In equation (5), K is defined as the total number of industries covered by all authorized patents of firm i during year t; J is defined as the number of “innovation genes” present in the l^{th} patent of firm i within industry k during year t; and L is defined as the total count of authorized invention patents held by firm i within the industry k during year t.

4.2.2 Impact assessment (IA)

The quality of a firm’s technological innovation should also be reflected in the extent to which its invention patents influence subsequent invention patents. As analyzed above, the physical citation count of patents is often used to measure the degree of influence of patents on subsequent research activities. Different from existing research, this paper will use semantic citation counts to measure the quality of technological innovation in the influence dimension. When defining semantic citation relationships, if “innovation gene” i appears later than “innovation gene” j, it is a semantic citation of j by i. This paper defines innovation impact IA_{it} as the semantic citation count of a patent. The technological innovation quality of firm i in year t within the sample period can be expressed as:

$$IA_{it}=\sum_{1}^{m}\sum_{k}^{K}\sum_{l}^{L}\sum_{j}^{J}S_{ijkl,t+m}, t\leq m \tag{6}$$

In equation (6), $S_{ijkl,t+m}$ is defined as the total number of semantic citations received by the “innovation gene” j embedded in the l^{th} patent of firm i operating within industry k during year t throughout the sample period; m is defined as the temporal length of the sample period.

4.2.3 Innovation vitality (IV)

Beyond originality and influence, we also assess innovation quality based on the duration of “innovation genes”, reflecting their longevity. The innovation duration of firm i at year t within the sample period is defined as IV_{it}, which can be expressed as:

$$IV_{it}=\frac{\sum_{k}^{K}\sum_{l}^{L}\sum_{j}^{J}(y_{ijklt}-t)}{\sum_{k}^{K}\sum_{l}^{L}p_{iklt}} \tag{7}$$

In equation (7), y_{ijklt} denotes the final year of occurrence within the sample period for the “innovation gene” j of firm i’s l^{th} patent in industry k during year t, and p_{iklt} indicates the count of “innovation genes” within that patent.

Our three indicators for assessing the quality of technological innovation are designed to capture key aspects of China’s innovation contextual narrative, addressing critical challenges in the respective dimension: (1) Innovation originality: Evaluates the uniqueness, pioneering nature, and foundational role of technical methods, emphasizing their novel and de novo creation. (2) Innovation influence: Measures the impact of technological methods on subsequent innovations, particularly their ability to inspire and shape follow-on activities. (3) Innovation duration: Assesses the longevity of a method’s influence, focusing on its sustained relevance over time.

[8] In fact, we also selected criteria of 1%, 2%, and 10%, which basically does not change the ranking results of Figures 3 to 5.

5. Semantic Measures of Technological Innovation Quality: A Validity Analysis

5.1 Textual Analysis of Technological Innovation Quality

5.1.1 Data description

This study utilizes granted Chinese invention patent data from 1986-2016[9], sourced from the State Intellectual Property Office (SIPO). Covering 279 Chinese prefecture-level cities and their subordinate administrative divisions (counties, townships, villages, towns, and street units), the dataset includes information on granted patents from these jurisdictions between 1986 and 2016, such as "patent title", "application date", "application address", "patent classification number", and "patent applicant", comprising 2.9 million records.

The utilized invention patent data serves several key purposes: (1) extracting "innovation genes" from patent titles via word segmentation; (2) converting patent application addresses to administrative division codes; (3) mapping patent classification codes to corresponding national economic sectors; and (4) calculating "innovation gene" lifespans based on patent application dates.

5.1.2 Data cleansing

This study uses data on invention patents granted to Chinese enterprises from 1986 to 2016. The data, obtained from the State Intellectual Property Office of the People's Republic of China (SIPO), is encoded in Unicode format. The raw data contained instances of misalignment and missing values, which we addressed using the following procedures:

Data misalignment correction: We found that a significant number of patent classification numbers were incorrectly placed within the patent applicant field. Because patent classification numbers consistently begin with a capital letter, we implemented a simple rule: if the first character of the data in the applicant field was uppercase, we moved that data to the patent classification number field. This corrected the misalignment.

Missing value imputation and handling: The raw data had missing values for key variables, including patent name, patent application date, and patent application address. To solve this problem, we used cross-referencing with other patent databases, including the Wanfang Patent database, to impute the missing information. After this imputation process, approximately 1.23% of the sample still had missing data for these key variables. We removed these incomplete records from the analysis. Given the small proportion of missing data and the assumption that the missingness was random (Missing Completely At Random, MCAR), we believe this removal will have a negligible impact on our findings.

5.1.3 Lexicon construction

This study constructs a comprehensive, industry-wide lexicon based on the default dictionary provided by the Jieba segmentation tool. To enhance coverage of industry-specific terminology, we integrated industry-specific lexicons from over 30 sectors, guided by the 2017 National Economic Industry Classification of China. This resulting lexicon encompasses both common vocabulary and specialized terms from various industries.

In subsequent text analysis and word segmentation, this custom-built lexicon serves as the foundation for identifying and segmenting the titles of granted patents. This approach aims to maximize the reliability and effectiveness of the segmentation results. By developing this comprehensive lexicon of innovation-related terms across industries, we address the limitations of Jieba's default dictionary,

[9] Innovation impact is measured using semantic citation counts, with a three-year citation window. Given potential shifts in knowledge diffusion and innovation dynamics post-2020 due to the COVID-19 pandemic, the analysis's time frame concludes in 2016.

which contains a relatively limited vocabulary. This allows us to more effectively identify relevant segments of innovation knowledge within patent information and, consequently, more accurately capture the "innovation genes" present in each granted invention patent.

5.1.4 Illustration of Jieba segmentation

Based on the industry-wide lexicon and stop word list developed in the preceding stage, we perform word segmentation on each patent to extract its embedded "innovation genes". Figure 1 illustrates this process:

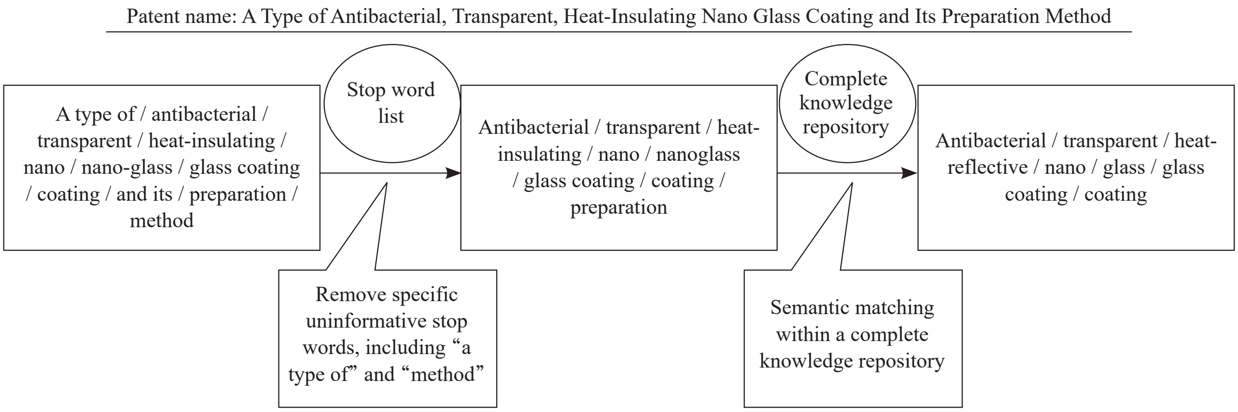

Figure 1: Illustration of "Innovation Gene" Extraction Using Text Segmentation

We obtained approximately 370,000 "innovation genes" from 2,905,721 granted invention patents spanning 1986-2016 through data cleaning and Jieba word segmentation. These genes constitute our "innovation gene" database (see Table 4).

Table 4: Sectoral Distribution of Chinese Technological "Innovation Genes" (1986-2016)

All sectors	Agriculture	Mining	Manufacturing	Electric heating	Building	Information	Services
371,517	19,714	5,942	245,822	15,867	23,218	36,448	24,506

5.2 Measuring Technological Innovation Quality: A Comprehensive Comparison of Existing Indicators[10]

Drawing on existing literature, this paper highlights the advantages of leveraging semantic citation analysis to evaluate the quality of technological innovation. Through text analysis, we have extracted key "innovation genes" for further assessment. Notably, our semantic citation analysis provides a more accurate measure of technological innovation quality compared to traditional methods. However, a significant challenge in establishing the scientific rigor of our approach lies in identifying an appropriate benchmark for comparison, as existing indicators are often marred by measurement biases. The subsequent sections of this paper will address this challenge in detail.

[10] Existing innovation measurement indicator systems also include some macro-level indicator systems, such as the China National Innovation Index released by the Chinese Academy of Science and Technology for Development (CASTED), and the China Innovation Index (CII) developed by the research group of the Department of Social, Science and Technology of the National Bureau of Statistics (NBS) in its "China Innovation Index Research". These types of indicators focus on the macro scale, which is different from the focus of this paper, and therefore will not be discussed.

5.2.1 A series of indicators measuring the level of technological innovation

Measuring innovation quality typically involves evaluating the level of technological innovation embedded in patents or products, a widely adopted practice in both academia and industry. This evaluation generally focuses on three key categories of indicators: (1) Citation indicators, such as the frequency with which a patent is cited; (2) Technological intersection factors, including the number of inventors, the diversity of knowledge areas involved, and the breadth of patent protection; and (3) International engagement, which looks at the proportion of global patent filings and the rate of foreign citations. These indicators primarily assess the extent of patent innovation from the standpoint of technical attributes and academic value, highlighting the scientific and technological importance of the innovation.

Table 5: Indicators for Measuring Technological Innovation Quality

Category	Physical Citation	Scope of Technology Coverage			International Engagement	
	Number of citations	Number of inventors	Knowledge breadth	Scope of rights protection	Proportion of international applications	Rate of foreign citations
Indicator	Number of times a patent is cited	Number of inventors	Number of CPC categories	Text, descriptions, and illustrations	International patents / total number of patents	International citations / total citations
Meaning	More citations suggest greater influence of the patent	Collaborative patents offer higher quality	Cross-disciplinary patents offer higher quality	Broader coverage means better quality	International patents are of better quality	Patents with international influence have better quality
Data scale	Patent level	Patent level	Patent level	Patent level	Corporate level	Patent level
Advantages	Reasonable measurement	Simple and straightforward	Simple and straightforward	Highly professional	Simple and straightforward	Reasonable measurement
Disadvantages	Tend to cite the latest and currently popular literature, lacking coverage of all relevant literature	Doubtful logic	Doubtful logic	Hard to quantify	Doubtful logic, numerous zero values	High data requirements, numerous zero values
Application scenarios	Numerous and extensive	Cooperation between innovation entities	Cross-disciplinary and domains of innovation collaboration	Few	Multinational companies or global expansion	International comparable technologies or products

Citation count, determined by the number of cited patents, remains the most widely used metric in research due to its robust data availability, sound theoretical foundation, and broad applicability. However, alternative indicators such as inventor count and knowledge breadth - which measure the scope of patent technologies - provide distinct advantages for analyzing inter-organizational and interdisciplinary collaborations. Additionally, indicators that emphasize transnational dimensions, such as the involvement of foreign inventors or international patent filings, are particularly valuable for assessing cross-border technological activities.

5.2.2 Legal text content indicators

Unlike indicators that primarily evaluate the degree of technological innovation, legal text content analysis emphasizes assessing the quality of innovation. This approach examines elements within patent application text and legal status, incorporating indicators such as the number and scope of claims, legal status, and the characteristics of textual content.

Table 6: Technological Innovation Quality: Legal Text-Based Indicators

Category	Rights claim	Legal status			Text content	
	Priority	Maintenance of granted patents	Ratio of invalid patents	Effective duration	Language clarity	Repetition
Specific measurement	Number of priority rights	Valid patents / total number of patents	Invalid patents / total number of patents	Patent grant date to expiration date	NLP method	Gensim algorithm, etc.
Meaning	Level of importance attached by a firm to an international patent filing	Maintenance rate reflects corporate patent valuation	Low-value patents have a high invalidity ratio	Effective duration reflects corporate patent valuation	Level of innovation is positively correlated with text quality	High-repetition patents rely more on existing patents.
Data scale	Patent level	Corporate level	Corporate level	Patent level	Patent level	Patent level
Advantages	Introduce firm behavior	Simple and straightforward			Simple and straightforward	Simple and straightforward
Disadvantages	Lack comparability	Subjectivity and strategic behavior			Logically doubtful	Poor comparability at small scale
Application scenarios	Corporate technology cluster and international patent layout	Corporate strategic and tactical behaviors			Few	Simple verification at the large scale

This series of indicators is based on strong underlying assumptions:

Patent value and quality: Indicators such as claims and legal status presume that innovative entities have a precise understanding and evaluation of their patents' value and that this value accurately reflects the patents' quality.

Textual content analysis: Indicators based on textual content assume that the clarity and repetition rate of language in patent applications are directly correlated with the quality of innovation.

These foundational assumptions invite scrutiny regarding the indicators' logic and comparability. As a result, their application may be more appropriate in specific contexts or for straightforward validation purposes rather than broader or generalized analyses.

5.2.3 Indicators of potential applications

Indicators of application potential often assess the quality of technological innovation indirectly by examining patent costs and value, relying on indicators such as patent status and market transactions. Patent status and legal status are essentially similar: while the latter infers quality from patent value, the latter focuses on measurement by legal clauses.

Table 7: Technological Innovation Quality: Application Prospect Indicators

Category	Patent Status			Market Transactions		
	Patent expiration	Patent maintenance	Patent survival	Patent transfer	Patent licensing	Patent pledge
Specific indicators	Annual expiration rate	Number of valid patents	Patent survival rate	Number of transfers	Number of licenses	Number of pledges
Meaning	Patent maintenance costs, and the resulting patent status reflects a company's valuation and, indirectly, the patent's quality.			Patent quality can be inferred from its commercialization success, market recognition, and associated market valuation.		
Data scale	Corporate level			Patent level		
Advantages	Introduces self-valuation behavior			Introduces market valuation of patents		
Disadvantages	Subjectivity and strategic behavior			Underestimates the value and quality of basic research		
Application scenarios	Corporate strategies and behaviors			Applied patent evaluation		

5.3 Assessing Technological Innovation Quality: An Effectiveness Analysis in Narrative Contexts

The preceding sections used qualitative comparisons to evaluate the strengths and limitations of various indicators and their application contexts. They also justified the scientific rigor of our measurement approach. However, a quantitative analysis has yet to be conducted. Since no single indicator is universally applicable, and this study focuses on assessing the quality of technological innovation represented by invention patents within the Chinese context and institutional narrative, the subsequent analysis will center on the citation index (physical citations), a widely recognized and utilized benchmark.

5.3.1 Year-end patent application rush and its impact on effectiveness analysis: systematic bias

Businesses, universities, and research institutions are the primary drivers of R&D and innovation, and they are often subject to top-down incentives and performance evaluations. To meet annual targets for R&D expenditure and patent filings, these entities frequently engage in end-of-year pushes, accelerating spending and filing activities as the assessment period draws to a close. This is particularly evident in the context of patent applications. Figure 2, which displays the monthly percentage distribution of patent applications and grants based on filing and grant dates, highlights the year-end rush. The left and right panels show the filing and granting patterns of invention patents, respectively. Notably, the year-end surge in patent applications is striking: in November and December, patent filings account for 10.73% and 14.03% of the annual total, significantly exceeding the average monthly proportion of 8.33%. In contrast, filings in January and February drop sharply to 5.75% and 4.55%, reinforcing the conclusion that this end-of-year phenomenon is a consistent feature of invention patent applications.

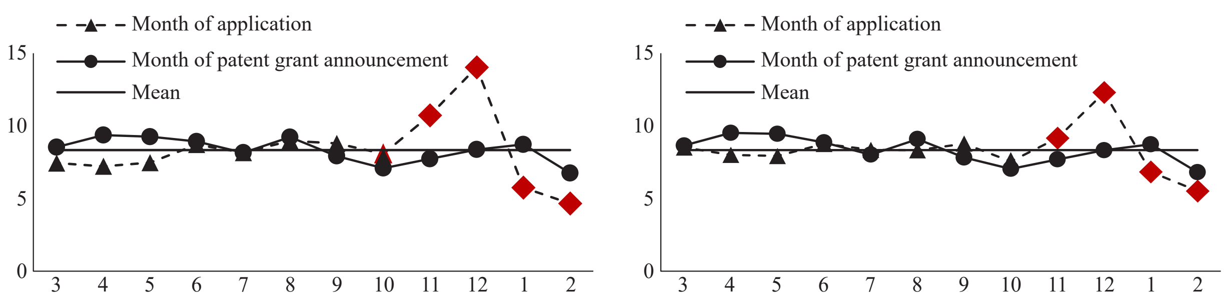

Figure 2: Monthly Filings and Grants for Chinese Invention Patents (1985-2016)

Note: (Left) Invention patent filings; (Right) Granted invention patents. The red square line indicates the "patent surge" phenomenon for patent applications from November to February.

Given the continuity of corporate R&D activities and the inherent dynamics of innovation, the year-end surge in patent applications likely reflects a trade-off between "quantity" and "quality", where a spike in the number of filings may result in a corresponding decline in quality. To investigate this phenomenon, we empirically examine the impact of year-end surges on patent quality, using various indicators of technological innovation quality. Logically, under fixed resource constraints, it is not possible to simultaneously maximize both the quantity and quality of innovation outputs. Drawing on the framework established by Alfaro-Ureña et al. (2022), we apply an event study methodology to assess how year-end surges affect the quality of technological innovation at the prefecture-level city. The corresponding econometric model, designed to evaluate the validity of indicators based on the timing of patent application surges, is outlined as follows:

$$Patent_{itm}=X_{it}^{\mathrm{T}}\beta+\sum\nolimits_{m=\underline{T}}^{\overline{T}}\theta D_{itm}+\alpha_i+\mu_{pt}+\xi_{itm} \qquad (8)$$

In equation (8), $Patent_{itm}$ denotes the technological innovation quality in prefecture-level city i during year t and month m, which is log-transformed before being included in the model. The vector X_{it} represents control variables at the prefecture-level city-year level, capturing factors such as economic development, infrastructure, and the overall climate of the city. The monthly dummy variables are denoted by D_{itm}, $D_{itm}:=\mathbb{I}[m\in\underline{T},\overline{T}]$, where $\mathbb{I}[.]$ is an indicator function for each month. The model also includes prefecture-level city fixed effects α_i and province-year fixed effects μ_{pt}. Additionally, θ represents the effect of specific months, which is the key coefficient of interest. The vector β contains the coefficients for the control variables, and ξ_{itm} is the random error term. Based on the pattern observed in Figure 4, we set $\underline{T}$=11 for November and $\overline{T}$=12 for December, aligning with the year-end surge period.

Table 8: Policy Effects of Year-End Surges in Patent Applications: Validity Test of Indicators

	(1)	(2)	(3)	(4)	(5)
	Originality	Citation count	Influence	Original impact	Vitality
D_{itm}	-12.1556*** (2.5420)	0.2455* (0.1284)	0.1161* (0.0673)	-10.1168** (4.6727)	-6.9203*** (2.5586)
Sample size	343572	343572	343572	343572	343572
Control variable	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y
Prefecture-level city FE	Y	Y	Y	Y	Y

Notes: (1) Vitality is calculated using patent data up to the end of 2022. To account for the potential bias introduced by shorter observation windows for newer patents, we conduct robustness checks by considering the vitality of granted patents within n calendar years of their filing date. The table above reports results for n = 6; (2) All results are clustered at the prefecture-level city level.

As shown in the Table 8, the year-end surge in patent applications leads to a notable distortion in average patent quality during November and December, compared to other months. Specifically, our originality indicator reveals that the average originality of patents filed at year-end is 12.156% lower, whereas the commonly used citation count shows a slight increase of 0.246%. Logically, patents filed during the year-end surge should not exhibit superior quality compared to those filed throughout the year; in fact, they are more likely to be of lower quality. Therefore, the results in columns (1) and (2) suggest that our originality indicator is significantly more effective in capturing patent quality than citation count. For robustness, we also tested our constructed impact indicator, which closely resembles the citation count. As demonstrated in columns (2) and (3), this indicator supports the findings, confirming the similarity between the two measures. Furthermore, to highlight the advantages of originality in evaluating patent quality during the year-end surge, we used an alternative measure based on the subsequent citations of original patents - what we refer to as the "original impact indicator. The results, shown in column (4), indicate that the semantic citation count for patents filed during the year-end surge is significantly lower by 6.920%. Finally, we employed the vitality indicator for further testing, and again observed a decline in patent quality during the year-end surge, as reflected in the vitality scores. Overall, due to the systematic bias introduced by the year-end surge in patent applications, the originality, vitality, and original impact indicators developed in this paper provide a more accurate measure of patent quality compared to the traditional patent citation count.

5.3.2 Evaluating the effectiveness of patent prior art citations: The role of individual bias

The Chinese patent examination system requires applicants to provide technologies in the prior art section that are useful for understanding, searching, and examining the patent. Applicants are also allowed to cite reference documents that reflect this prior art. To increase their chances of obtaining a patent, applicants often have an incentive to signal innovation by omitting certain reference documents, thereby manipulating the appearance of their patents as more pioneering than they actually are. This practice allows non-pioneering patents to be portrayed as pioneering through selective citation.

In a study based on U.S. patent application data, Dimos and Regan (2022) found that 22% of U.S. patent applications included citation information added by patent examiners, rather than the applicants themselves. This highlights the potential for citation manipulation in patent filings. The study suggests that relying on citation counts as an indicator of originality may lead to an overestimation of a patent's true innovative contribution.

To assess the validity of our technological innovation quality indicators, we employed the following identification strategy: First, we analyzed the correlation between original patents and patent applications that claim pioneering status. Second, we investigated the relationship between pioneering status and originality with citation count, using citation count as a widely recognized measure of patent quality. Third, we applied a stacking effect identification strategy to compare the effectiveness of pioneering status and originality from the perspective of citation count. The results of these estimations are presented in Table 9.

Table 9: Validity Tests of Indicators Based on Patent Citation Information

	(1)	(2)	(3)	(4)	(5)	(6)
	Originality	Adjectivally qualified originality	Citation count	Citation count	Citation count	Citation count
Pioneering	0.5576^{***} (0.1169)	0.6103^{***} (0.1399)	1.2418^{***} (0.3241)			
Originality				2.0736^{***} (0.4765)		
Pioneering but not original					0.2103^{**} (0.1048)	
Pioneering and original					1.4588^{***} (0.4057)	1.5556^{***} (0.4445)
Original but not pioneering						0.7011^{*} (0.3719)
Sample size	9176	9176	9176	9176	9176	9176
Control variables	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Prefecture-level city FE	Y	Y	Y	Y	Y	Y

Notes: (1) Pioneering status indicates whether citation information is missing in the prior art section of the patent application; it takes a value of 1 if missing, and 0 otherwise; (2) All results are clustered at the prefecture-city level; (3) Citation counts are the average number of citations per patent at the prefecture-city level.

Column (1) of the table above explores the correlation between the pioneering status reported in patent citation information and actual originality. While the two are significantly positively correlated, the correlation coefficient between the applicant's declared pioneering status and true originality is smaller than anticipated. This may be because the originality claimed by applicants does not necessarily reflect disruptive innovation, but rather incremental improvements based on existing technologies. To address this, we adopt the methodology of Chen et al. (2022), introducing adjectives to more precisely capture the degree of originality. Using this refined approach, we re-examine the correlation, and the results are presented in Column (2). Here, we observe that the correlation coefficient between the applicant's declared pioneering status and true originality remains modest. In Columns (3) and (4), we further investigate the relationship between declared pioneering status (self-reported innovativeness) and originality with citation counts. The results reveal that the correlation between originality, as measured in this study, and citation count is significantly stronger than the correlation between pioneering status and citation count[11].

5.3.3 Validity analysis of granular instrumental variables: Correction for systematic and individual biases

The above analysis highlights the presence of both systematic and individual biases in patent applications, suggesting that innovation quality cannot be accurately gauged through direct indicators such as citation counts of patent applications or grants alone. To address this issue, one potential strategy is to leverage granular instrumental variables (GIVs) to account for these biases and provide a more accurate measurement of technological innovation quality. A significant body of literature has shown that many key decisions are influenced by a small number of large entities, such as major firms, industries, or countries. The actions and shocks of these large players can have a disproportionate impact on their respective industries or economies, with their idiosyncratic shocks contributing to broader economic fluctuations (Gabaix, 2011; Carvalho and Gabaix, 2013; Acemoglu et al., 2017; Banarjee and Li, 2022). In a similar vein, Gabaix and Koijen (2020) describe these entities as "big granules". By assigning greater weight to these large players, they propose using the individual shocks of these granules as instrumental variables, which can help isolate the effects of technological innovation from the interference of common trends or heterogeneous shocks that affect individual entities. This method is known as using granular instrumental variables (GIVs). In economies with a significant number of large granules, leveraging the individual shocks of these entities can effectively eliminate the confounding influence of common trends and individual heterogeneity. In the subsequent sections, this paper will apply the concept of GIVs to construct appropriate instruments and test the key indicators of technological innovation quality, as discussed earlier.

n_{ikt} is defined as the technological innovation quality observed for firm i in prefecture-level city k during month t. It consists of three components: (1) true innovation quality u_{ikt}, which is not directly observable; (2) systematic bias u_{kt}, representing prefecture-level city k-specific disturbances faced by firm i at time t; and (3) individual bias, expressed as the product of a common shock η_t faced by firm i at time t and the intensity of the firm's exposure to this shock λ_i, represented as:

$$n_{ikt}=\lambda_i\eta_t+u_{kt}+u_{ikt} \tag{9}$$

Considering a simplified scenario: λ_i=1, i.e., uniform loadings, and aggregating equation (9) by summing across firms within prefecture-level city k based on their size, we obtain the size-weighted innovation quality of prefecture-level city k, represented as:

$$n_{kt}^S=\eta_t+u_{kt}+\sum\nolimits_{i\in k}S_i^k u_{ikt} \tag{10}$$

Similarly, the average weighted innovation quality of prefecture-level city k is defined as n_{kt}^E:

$$n_{kt}^E=\eta_t+u_{kt}+\sum\nolimits_{i\in k}E_i^k u_{ikt} \tag{11}$$

In the above equation, $E_i^k=\frac{1}{N}$. Subtracting equation (10) from equation (11) yields the first granular instrumental variable z_{kt}^1:

$$z_{kt}^1=n_{kt}^S-n_{kt}^E=\sum\nolimits_{i\in k}S_i^k u_{ikt}-\sum\nolimits_{i\in k}E_i^k u_{ikt} \tag{12}$$

Since u_{ikt} represents a firm-level specific shock, it only affects specific firms. It is straightforward to derive that the exogeneity assumption holds for all i, k, and t, i.e., it is easy to obtain $E[z_{kt}\varepsilon_{kt}]=0$ based on $E[u_{ikt}\varepsilon_{kt}]=0$. Where, ε_{kt} represents the aggregated value of the error term in equation (9) at the prefecture-level city level. Based on equation (12), it can also be derived that z_{kt}^1 satisfies the relevance assumption, i.e., $E[z_{kt}n_{kt}^S]\neq0$. In equation (9), we considered the case of uniform loadings. In fact, the common shocks

[11] This conclusion is based on the Chow test results.

in the observed variation of innovation quality may include not only the single factor η_t, and the degree to which each sample i is affected by the factors also varies. To capture the effects of multiple factors and heterogeneous shocks, we further rewrite equation (9) as:

$$n_{ikt}=\lambda_i\eta_t+u_{kt}+u_{ikt},\ \lambda_i\eta_t=\sum_{f=1}^{r}\lambda_i^f\eta_t^f \tag{13}$$

In equation (13), λ_i^f represents the factor loading, measuring the impact of the f^{th} common factor η_t^f on the firm i's observable innovation quality; u_{kt} represents the common shock at the prefecture-level city level; u_{ikt} represents the firm-level specific shock; and r is the number of factors. For equation (13), the key is to extract the specific shocks to construct the GIV. Aggregating equation (13) at the prefecture-city level by firm innovation output size yields the change in observable innovation quality of prefecture-level city k:

$$n_{kt}^S\equiv\sum_{i\in k}S_i^k n_{ikt}=\sum_{i\in k}\sum_{f=1}^{r}S_i^k\lambda_i^f\eta_t^f+u_{kt}+\sum_{i\in k}\sum_{f=1}^{r}S_i^k u_{ikt} \tag{14}$$

In equation (14), $\sum_{i\in k}S_i^k=1$. Equation (14) can be further expressed in vector form as:

$$n_t=\Lambda\eta_t+u_t \tag{15}$$

In equation (15), n_t, η_t and u_t are all $NK\times1$ column vectors; K is the number of industries; Λ is an $NK\times r$ matrix and satisfies $E[\eta_t\varepsilon_t]=0$. We construct a set of weights $\Gamma\in R^{NK}$ orthogonal to Λ, satisfying $\Gamma'\Lambda=0$. At this point, the second GIV can be constructed:

$$z_{kt}^2=\Gamma' n_t=\sum_{i\in k}\Gamma_i n_{ikt} \tag{16}$$

Next, we construct two granular instrumental variables (GIVs) for citation counts, z_{kt}^1 and z_{kt}^2, and further test the correlation between the instrumental variables and the originality and originality impact constructed in this paper, and compare the results with the estimated coefficients of citation counts. The estimation results at this point are shown in Table 10.

Table 10: Validity Analysis of Granular Instrumental Variables (Correlation Comparison)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Originality			Originality impact		
Citation count	0.4816*** (0.1002)			0.2258*** (0.0694)		
z_{kt}^1		0.8556*** (0.1745)			0.4144*** (0.1163)	
z_{kt}^2			0.8860*** (0.1728)			0.4957*** (0.1329)
Sample size	343572	343572	343572	343572	343572	343572
Controls	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y

As can be seen, after introducing granular instrumental variables to eliminate systematic and individual biases in patent citation counts, the correlation between the granular instruments and the originality constructed in this paper significantly increased: compared with the coefficient of citation counts (0.482), the coefficients of the two granular instrumental variables become significantly larger, which further supports the conclusion that the originality and originality impact constructed in this paper are more effective than citation counts.

6. Application Analysis: Indicator Extension and Family Tree

6.1 Indicator Extension

The above analysis measures the quality of corporate technological innovation across three dimensions - innovation originality, innovation impact, and innovation vitality - and finds, within the specific context of China, that these indicators are more effective than traditional indicators like patent citation counts. However, each indicator has its own emphasis and potential “measurement biases” in certain situations (Figure 3): (1) Innovation Originality focuses on novel, first-of-its-kind patents, emphasizing “from zero to one”, but may encourage obscure or niche innovations that prioritize novelty over practical value. (2) Innovation Impact measures the influence on subsequent R&D, which can lead to a bias toward “hot topics” or “popular fields” rather than more foundational breakthroughs. (3) Innovation Vitality emphasizes the longevity of impact but may overlook the role of newer innovations and is influenced by random factors, affecting its reliability in certain contexts.

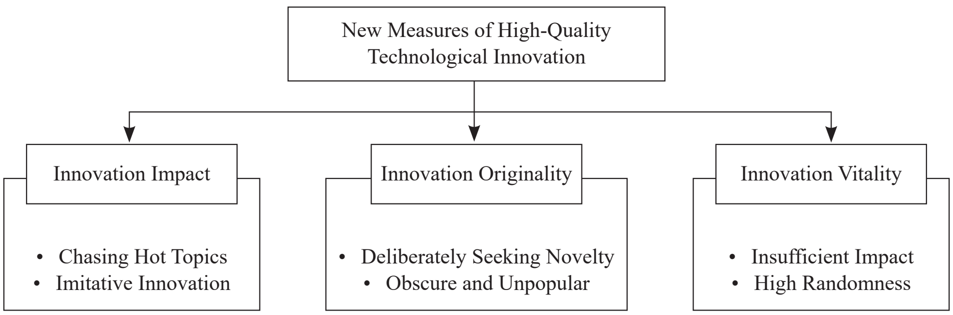

Figure 3: New Measures of Technological Innovation Quality (Potential Problems and Metric Expansion)

In light of the limitations and strengths of these three categories of indicators when individually assessing technological innovation quality, we further consolidate them into two composite indicators:

(1) Innovation originality affect (*IOA*). To account for both patent originality and impact, this paper introduces the IOA index, which is measured by the total semantic citation count of original patents within the sample period.

$$IOA_{it}=\sum_{0}^{M}\sum_{k}^{K}\sum_{l}^{L}\sum_{j}^{J} s_{ijkl,t+m}x_{ijklt}, m\in[0,M] \tag{17}$$

In equation (17), $s_{ijkl,t+m}$ denotes the number of semantic citations received in year $t+m$ by the “innovation gene” j of the l^{th} patent belonging to firm i in industry k. M represents the time lag between the end of the sample period and year t. x_{ijklt} denotes whether the “innovation gene” j present in the firm i’s patent l in sector k during year t is original.

(2) Innovation originality-vitality (*IOV*). Drawing on the strengths of both innovation originality and innovation vitality, we introduce the *IOV* index to assess the longevity of original innovative genes.

$$IOV_{it}=\frac{\sum_{k}^{K}\sum_{l}^{L}\sum_{j}^{J}(y_{ijklt}-t)x_{ijklt}}{\sum_{k}^{K}\sum_{l}^{L}p_{iklt}} \tag{18}$$

In equation (18), y_{ijklt} denotes the final year within the sample period that features the “innovation gene” of the l^{th} patent held by firm i in industry k during year t, while p_{iklt} denotes the count of “innovation genes” present in the l^{th} patent of firm i in industry k during year t.

(3) Affect originality-vitality (*AOV*). Drawing on the strengths of both innovation impact and

innovation vitality, we introduce the AOV index to assess the longevity of the impact generated by "innovation genes".

$$AOV_{it}=\frac{\sum_{k}^{K}\sum_{l}^{L}\sum_{j}^{J}(y_{ijklt}-t)S_{ijkl,t+m}}{\sum_{k}^{K}\sum_{l}^{L}p_{iklt}} \tag{19}$$

6.2 Family Tree

To summarize, we have synthesized the key existing indicators for evaluating technological innovation quality and developed a comprehensive family tree of measurement systems for high-quality technological innovation (Figure 4). These indicators can be broadly categorized into six distinct scenarios: (1) Disruptive technology and general-purpose applications: relevant across various contexts, primarily utilizing indicators based on originality, impact, and vitality as developed in this study; (2) Interdisciplinary research and collaborative innovation: focused on indicators that assess the technological scope within the broader framework of innovation assessment; (3) Technology deployment and commercialization: centered on market transaction indicators, specifically within the context of technology citations; (4) International technology transfer and global contexts: emphasizing indicators related to the foreign dimensions and global attributes of technological innovation.

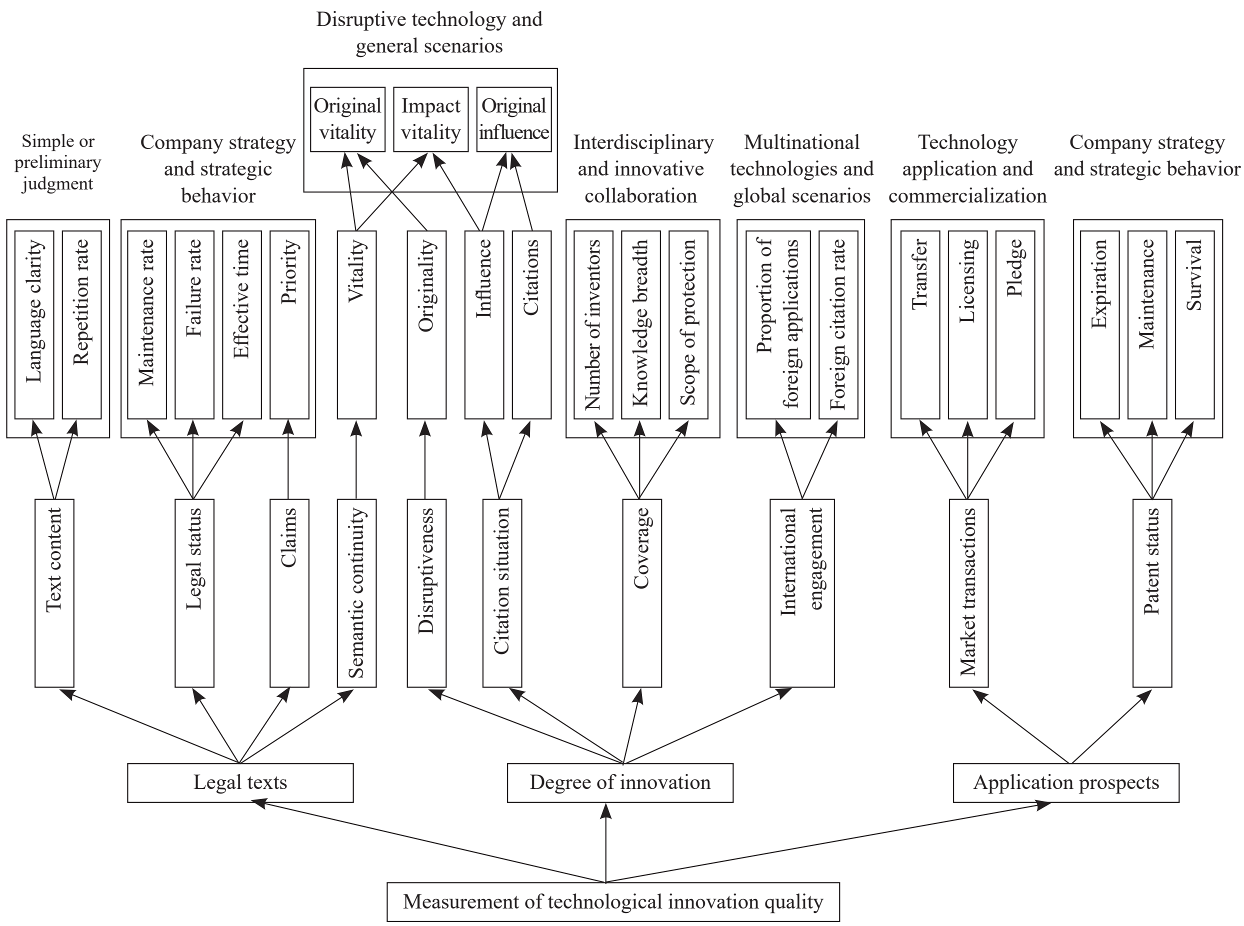

Figure 4: Family Tree of Technological Innovation Quality (Indicators and Scenarios)

7. Conclusion and Policy Recommendations

In the face of rapidly accelerating advancements in disruptive, transformative, and frontier technologies, this paper aims to establish a comprehensive framework for identifying and measuring high-quality technological innovation. Our analysis, drawing on representative innovation scenarios in China, highlights the following key findings:

(1) Innovation policy vs. practical implementation: While China's national innovation policy places a strong emphasis on quality, practical efforts in innovation often suffer from strategic challenges. A primary issue is the tendency to prioritize quantity over quality, resulting in shortcomings in the current quality indicators used to assess technological progress.

(2) Effective indicators for measuring innovation quality: Indicators such as originality, impact, and vitality - derived from advanced methods like textual analysis and semantic citation analysis - are more effective in capturing the true quality of technological innovation compared to conventional measures.

(3) Superior performance of novel indicators: Validity tests, including analysis of patent application rushes, patent citation data, and granular instrumental variables, demonstrate that our proposed indicators outperform traditional indicators like citation counts in evaluating the quality of innovation.

(4) Context-specific applicability of indicators: Different innovation contexts - such as technology application and commercialization, corporate strategy, interdisciplinary research, and collaborative innovation - demand tailored indicators. Our framework, in particular, is well-suited for assessing disruptive innovations and technologies with broad, general-purpose applications.

Based on these findings, we offer several important policy recommendations:

First, selecting appropriate indicators based on specific application scenarios and developmental contexts is critical to avoiding the misuse and misapplication of technological innovation indicators. As shown in the comparative analysis of the technological innovation quality family tree and related indicators presented in this paper, each indicator has distinct strengths and weaknesses, and using them improperly can undermine measurement accuracy. For example, our originality and impact indicators are particularly suited for evaluating disruptive technologies and general-purpose applications, while market transaction indicators excel in assessing technology commercialization and application. Additionally, indicators focused on international engagement attributes are more appropriate for analyzing cross-border technologies and global contexts. In China's innovation landscape, a longstanding challenge has been the relative scarcity of disruptive, frontier, and original technologies, positioning the country more as a follower than a leader in the global innovation network. In the era of high-quality development, fostering and leading original innovation for future industries has become increasingly essential. Therefore, at the national level, it is crucial to proactively identify, evaluate, and forecast emerging technological frontiers and trends, while developing adaptive innovation incentives and mechanisms that encourage risk-taking and tolerate failure.

Second, a technology innovation assessment system focused on quality must be established to address strategic innovation challenges. The primary obstacle to China's innovation-driven development strategy is the insufficient proportion of original, disruptive, and revolutionary innovations, resulting in "bottlenecks" and an "outsider" status in critical high-tech sectors. While China's overarching innovation policy emphasizes quality, practical implementation often prioritizes quantity. A key contributing factor is the difficulty in accurately measuring and analyzing innovation quality. For example, in current high-tech enterprise certification and local government patent initiatives, patent quantity is often the main metric or development target, which incentivizes rent-seeking behavior through patent applications aimed at securing policy benefits. To address this issue, when formulating policies and designing innovation incentives, the government should adopt the innovation quality measurement system proposed in this paper. By using enterprise innovation quality as a key performance indicator, it can replace or reduce the emphasis on quantity-based indicators, thereby improving the effectiveness of innovation incentive policies. Leveraging the series of technological innovation quality indicators and their appropriate application contexts, science and technology authorities and local governments can integrate innovation quality into their evaluation and assessment frameworks. By prioritizing "quality" and relegating "quantity" to a secondary role, a system can be cultivated where "good money drives out bad", fostering more impactful and sustainable technological innovation.

Third, the predictive capabilities of technological innovation quality indicators should be effectively harnessed to identify and analyze emerging technologies and future industry trends. The accelerating pace of disruptive, frontier, and transformative technological advancements is reshaping traditional industries while giving rise to new sectors, business models, and formats - significantly influencing future economic development. The transition from innovation to industrial application is a multi-stage process - from basic research to applied research, and eventually to market deployment - marked by inherent time lags. As such, identifying foundational and applied technologies with the potential to drive future industries is crucial for building dynamic advantages at the national, regional, and sectoral levels. By leveraging the predictive power of relevant technological innovation quality indicators, we can analyze and anticipate emerging technologies and industry dynamics more effectively. This will enable the development of methodologies for seizing emerging industrial opportunities, capturing nascent technological frontiers, and securing critical technology links. Such insights empower enterprises and government agencies to better understand and navigate future technological trajectories, position themselves strategically in high-tech sectors, anticipate future needs, and align with the direction and context of technological development. This proactive approach will help secure a competitive edge in industrial upgrading and global competition. Ultimately, by using predictive innovation quality indicators, China can position itself as a leader in global innovation and provide strong evidence to guide the design, formulation, and refinement of innovation incentive policies.

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