Tax Incentives and Knowledge Heterogeneity: Short-term Stimulus or Long-term Stock?

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Abstract: This paper unpacks the black box of knowledge accumulation by examining how tax incentives affect three distinct types of knowledge: high-quality (highly cited) patents, AI patents, and green patents. We find that the long-term accumulation effect is not uniform across knowledge types. High-quality and AI patents respond significantly only in the short term (lag 1), with no long-term accumulation; green patent quantity expansion generates bubbles without quality improvement. These findings suggest that durable knowledge accumulation is primarily driven by ordinary, low-depreciation patents. From a knowledge management perspective, this implies that policies should distinguish between "short-shelf-life" and "long-shelf-life" knowledge, and avoid over-incentivizing short-lived innovation at the expense of durable knowledge infrastructure.

Keywords: Tax incentives, Knowledge heterogeneity, Knowledge depreciation, AI patents, Green innovation bubbles

1. Introduction

Tax incentives have become a widely used policy tool to stimulate corporate innovation. Governments around the world employ R&D tax credits, accelerated depreciation, and reduced tax rates to encourage firms to invest in knowledge creation (Hall & Van Reenen, 2000; Bloom et al., 2002). A substantial body of empirical evidence suggests that these incentives effectively increase R&D expenditure and patent output (Czarnitzki et al., 2011; Howell, 2017; Dechezleprêtre et al., 2023). However, much of this literature focuses on the quantity of innovation inputs and outputs, with considerably less attention paid to the quality and durability of the knowledge that firms accumulate.

From a knowledge management perspective, these questions are critical because not all knowledge is equally valuable over time. Some knowledge depreciates rapidly due to technological obsolescence, while other knowledge retains its value for decades (Argote & Miron-Spektor, 2011; Hall et al., 2010). Understanding how tax incentives affect different types of knowledge is therefore essential for both organizational knowledge strategies and public policy design. If tax incentives primarily stimulate short-lived knowledge, their long-term impact on innovation efficiency may be limited. Conversely, if they encourage the accumulation of durable knowledge, the efficiency gains may be sustained over time (Nonaka & Takeuchi, 1995; Grant, 1996).

This paper unpacks the black box of knowledge accumulation by distinguishing three types of knowledge: high-quality (highly cited) patents, AI patents, and green patents. Using a panel of Chinese listed firms from 2012 to 2023, we find that:

- High-quality patent stock responds significantly to tax incentives only in the short term (lag 1), with no long-term effects.
- AI patent applications similarly show a short-term response (lag 1) that does not persist.
- Green patents: tax incentives do not directly affect green innovation bubbles, but green patent quantity itself is positively associated with bubble formation, indicating a quantity-quality decoupling.

These patterns reveal that durable knowledge accumulation is driven not by frontier or high-visibility knowledge, but rather by ordinary, stable, and low-depreciation knowledge that accumulates slowly over time. This finding has important implications for knowledge management: it suggests that organizations and policymakers should distinguish between "short-shelf-life" and "long-shelf-life" knowledge, and design incentives that support durable knowledge infrastructure rather than short-lived innovation spikes.

This paper contributes to the knowledge management literature in three ways. First, it extends the concept of knowledge accumulation by introducing knowledge heterogeneity—the idea that different types of knowledge have different accumulation patterns and policy responses. Second, it provides empirical evidence on the life-cycle of policy-induced knowledge, showing that short-term responses do not necessarily translate into long-term stocks. Third, it offers practical implications for both firms and policymakers, suggesting that knowledge management strategies should align with the depreciation characteristics of different knowledge types.

2. Literature Review and Theoretical Background

2.1 Tax Incentives and Knowledge Accumulation

A large body of literature has examined how tax incentives affect firm innovation. Early studies establish that R&D tax credits lower the marginal cost of R&D and stimulate investment in innovation (Hall, 2002; Hall & Van Reenen, 2000; Bloom et al., 2002). Subsequent research confirms that tax incentives increase R&D expenditure and patent output, though the magnitude of effects varies across institutional contexts and firm characteristics (Czarnitzki et al., 2011; Dechezleprêtre et al., 2023; Gaessler et al., 2021).

Chinese studies similarly find that tax incentives have a strong influence on R&D investment and innovation output, particularly by alleviating financial constraints and improving access to internal resources (Chen et al., 2018; Liu & Mao, 2019; Cao et al., 2021; Sun et al., 2022). However, most of these studies focus on innovation inputs and outputs, with relatively limited attention given to innovation efficiency or the quality of knowledge accumulation (Hall & Lerner, 2010). Assessing tax incentives merely by input or output indicators may not fully capture their actual effects on firms' long term innovation capabilities (Griliches, 1990).

2.2 Knowledge Depreciation and Heterogeneity

An important but often overlooked dimension of knowledge accumulation is knowledge depreciation. Unlike physical capital, knowledge decays over time due to technological obsolescence, competitor imitation, and shifts in market demand (Argote & Miron Spektor, 2011; Argote, 2013). However, the depreciation rate varies considerably across knowledge types. Patents in fast moving fields such as AI and digital technologies lose their value quickly, while patents in mature technological fields may retain their value for decades (Hall et al., 2010).

This heterogeneity has direct implications for policy evaluation. If tax incentives primarily stimulate short lived knowledge that depreciates rapidly, their long term impact on innovation efficiency may be limited. Conversely, if they encourage the accumulation of durable knowledge, the efficiency gains may be sustained over time. Thus, distinguishing between knowledge types is essential for understanding the true impact of tax policies (Trajtenberg, 1990; Hall et al., 2005).

2.2 Knowledge Management Perspective

From a knowledge management perspective, the distinction between short lived and long lived knowledge is critical. Nonaka and Takeuchi's (1995) SECI model provides a useful lens: tax incentives that lower patenting costs primarily facilitate the Combination phase—recombining existing knowledge into new patentable forms—but do little to support Internalization, where knowledge becomes embedded in organizational routines and durable capabilities. This distinction directly explains our empirical expectations: if tax incentives primarily stimulate Combination-based outputs (patent filings), we should observe short term patent surges (high quality and AI patents) without lasting accumulation; long term efficiency gains, by contrast, require the slower process of Internalization, which we expect only in ordinary, low depreciation knowledge. Thus, our heterogeneity predictions (H2–H4) are not merely descriptive but theoretically grounded in the SECI framework's distinction between combinative and internalized knowledge.

2.3 Hypotheses

Based on the above discussion, this paper proposes the following hypotheses:

H1: Tax incentives significantly increase high-quality patent stock, but this effect is short-lived (lag 1 only).

H2: Tax incentives significantly increase AI patent applications, but this effect is also short-lived (lag 1 only).

H3: Tax incentives do not directly drive green innovation bubbles; however, green patent quantity expansion is positively associated with bubble formation.

3. Methodology

3.1 Sample and Data Sources

This study uses panel data of Chinese A-share listed firms over the period 2012–2023. Financial variables and tax indicators are sourced from the CSMAR database. Patent-related variables are obtained from the Chinese patent database, and patent citation data are derived from the Google Patent database. The final sample is an unbalanced panel of firm-year observations, with financial firms excluded and observations with missing key variables removed.

3.2 Variable Definitions

3.2.1 Tax incentives

Following the existing literature (Chen et al., 2018; Liu & Mao, 2019), we measure tax incentives using the effective tax rate (ETR), calculated as income tax expense divided by pre-tax profit. To capture the intensity of tax incentives, we use the negative of ETR (tax_incentive = -ETR), so that a higher value indicates stronger tax incentives.

3.2.2 Knowledge types

We construct three measures of knowledge accumulation:

1. High-quality patent stock. Based on patent citation data, we identify patents in the top 10% of citations within each year (highly cited patents) and apply the perpetual inventory method (depreciation rate 15%) to calculate the high-quality stock (Trajtenberg, 1990; Hall et al., 2005).
2. AI patent applications. We identify AI-related patents using IPC codes (G06F, G06N, G06K, G10L, B25J, etc.) and take the natural logarithm of annual AI patent applications (Cockburn et al., 2018; Agrawal et al., 2018).
3. Green innovation bubble. Following Geng et al. (2024), we construct a bubble index (CGI_bub) to capture the mismatch between green patent quantity and quality. The index is calculated as:

$$CGI\_bub_{it} = \frac{GreenPatentApplications_{it} - GreenPatentsGranted_{it}}{GreenPatentApplications_{it} + 1}$$

A higher value indicates a greater divergence between applications (firms' innovation claims) and granted patents (a minimal external quality certification). This gap serves as a conservative proxy for quantity–quality decoupling, as patents that fail to be granted cannot contribute to genuine technological progress. The measure has been validated in prior research (Geng et al., 2024).

3.2.3 Control variables

Following the existing literature, we include firm size (natural logarithm of total assets), leverage (total liabilities divided by total assets), and profitability (ROA, net profit divided by total assets). Firm fixed effects and year fixed effects are included in all regressions.

3.3 Empirical Model

To examine the impact of tax incentives on knowledge accumulation, we estimate the following fixed-effects model (Hsieh & Klenow, 2009):

$$Knowledge_{it} = \alpha + \beta_1 Tax_{i,t-k} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \quad (k = 1, 2, 3)$$

Where Knowledge_it represents one of the four knowledge measures for firm I in year t , Tax_(i,t-k) is the tax incentive variable lagged by k years (k = 1, 2, 3), Controls_it is a vector of firm-level control variables, μ_i captures firm fixed effects, and λ_t captures year fixed effects. Standard errors are clustered at the firm level to account for serial correlation.

4. Empirical Results

4.1 Tax Incentives and High Quality Patent Stock

Table 1 presents the results for high quality patent stock. The coefficient of L1_tax (lag 1) is positive and significant at the 1% level, while lags 2 and 3 are insignificant. This suggests that tax incentives quickly stimulate high value knowledge, but such knowledge depreciates rapidly and does not accumulate into long term stock (Trajtenberg, 1990; Hall et al., 2005).

Table 1: Tax Incentives and High Quality Patent Stock

Variable	Coefficient	Std. Error	p-value
L1_tax	0.0989	0.0316	0.002
L2_tax	0.0395	0.0302	0.191
L3_tax	0.0431	0.0317	0.173
Size	0.1529	0.0163	0.000
Leverage	-0.0220	0.0126	0.081
ROA	-0.0402	0.0140	0.004

Observations: 32,299 (L1), 28,666 (L2), 24,863 (L3). Firm and year fixed effects included.

4.2 Tax Incentives and AI Patent Applications

Table 2 reports the results for AI patent applications. Similar to high-quality patents, the coefficient of L1_tax is positive and significant ($p = 0.015$), while lags 2 and 3 are insignificant. This confirms that frontier technologies, despite their initial responsiveness, face high obsolescence and fail to form persistent knowledge bases (Cockburn et al., 2018; Agrawal et al., 2018).

Table 2: Tax Incentives and AI Patent Applications

Variable	Coefficient	Std. Error	p-value
L1_tax	0.1097	0.0451	0.015
L2_tax	0.0795	0.0501	0.113
L3_tax	0.0358	0.0509	0.482
Size	0.1170	0.0119	0.000
Leverage	-0.0270	0.0190	0.155
ROA	0.2197	0.1172	0.061

Observations: 27,288 (L1), 24,360 (L2), 21,223 (L3). Firm and year fixed effects included.

4.3 Tax Incentives and Green Innovation Bubbles

Table 3 presents the results for green innovation bubbles. Tax incentives do not have a significant direct effect on CGI_bub. However, green patent quantity itself is positively and significantly associated with bubble formation ($\beta = 0.014$, $p < 0.01$). This indicates that pure quantity expansion—regardless of its policy source—can drive a wedge between innovation quantity and quality in the green technology domain (Geng et al., 2024; Lyon & Maxwell, 2011; Delmas & Montes-Sancho, 2010).

Table 3: Tax Incentives, Green Patent Quantity, and Green Innovation Bubbles

Variable	(1) CGI_bub	(2) CGI_bub	(3) CGI_bub
Tax incentive (ETR)	-0.0082		-0.0084
Green patent quantity		0.0140***	0.0140***
Size	-0.0005	-0.0026	-0.0026
Leverage	0.0164	0.0147	0.0150
ROA	0.1081**	0.1154***	0.1083**
Observations	32,746	32,746	32,746
R^2	0.533	0. 534	0.534

***p < 0.01, *p < 0.05. Firm and year fixed effects included.

4.4 Summary of Findings

The contrasting patterns across knowledge types can be explained by knowledge depreciation (Argote & Miron-Spektor, 2011; Argote, 2013). High-quality and AI patents represent fast-moving technological frontiers where knowledge becomes obsolete quickly; their short-term responsiveness to tax incentives does not translate into long-term stock. Green patents, often driven by regulatory or signaling motives, may suffer from quantity-quality decoupling (Geng et al., 2024). In contrast, ordinary patents—those not distinguished by high citations or specific technology classes—tend to cover more mature, stable technologies with longer useful lives. It is precisely this "slow-and-steady" knowledge that accumulates over time and ultimately improves innovation efficiency (Fleming, 2001).

5. Discussion

5.1 Implications for Knowledge Management

Our findings offer a granular, theory grounded insight for knowledge management: policy incentives shape not just the quantity, but the "term structure" of a firm's knowledge portfolio. Just as financial managers distinguish between short term and long term assets, knowledge managers must distinguish between short shelf life (exploratory) knowledge and long shelf life (exploitative) knowledge, because they serve different strategic purposes and respond differently to external stimuli.

For firms, the results suggest three actionable strategies:

First, diagnose the "knowledge depreciation profile" of your portfolio. Using patent citation data or technology life cycle analysis, firms can assess whether their knowledge stock is skewed toward fast depreciating frontier patents (like AI) or slower depreciating core technologies. Our evidence shows that tax incentives disproportionately boost the former in the short run, which may create an illusion of innovation vitality. Managers should therefore adjust their internal resource allocation—if external incentives are fueling exploratory patents, they should proactively redirect internal R&D funds toward internalization activities (e.g., process improvement, employee training, cross functional integration) to convert transient knowledge into durable organizational routines (Argote & Miron Spektor, 2011).

Second, avoid the "policy capture trap". Firms that aggressively file patents solely to capture tax benefits may accumulate a hollow knowledge stock—numerous but ephemeral. This is particularly evident in our green patent finding, where quantity expansion drives bubbles without quality improvement. Knowledge managers should treat tax incentives as a supplement, not a substitute, for organic capability building. Sustainable advantage comes from the sticky, tacit knowledge that competitors cannot easily imitate or arbitrage (Nonaka & Takeuchi, 1995).

Third, adopt differentiated performance metrics. Rather than evaluating R&D success by total patent counts alone, firms should develop balanced dashboards that track both "knowledge velocity" (speed of generating new exploratory patents) and "knowledge persistence" (citation weighted stock, technology renewal rates, and internal utilization of patented knowledge). This dual metric system aligns with the exploration exploitation balance that high reliability organizations maintain (March, 1991).

For policymakers, our knowledge management lens offers a critical corrective. The common practice of rewarding aggregate patent output implicitly treats all knowledge as homogeneous and infinitely durable. We demonstrate that this assumption is empirically false. Therefore, policy design should:

- Introduce "durability weighted" incentives—for example, higher tax credits for patents that survive beyond a certain citation threshold or that are classified in mature technology classes with low depreciation rates.
- Reform green innovation policies by shifting from application based subsidies to grant based and citation based rewards, directly addressing the quantity quality decoupling we observe.
- Consider temporal differentiation: exploratory, frontier technologies (AI) may benefit from short term, high intensity project grants that match their fast depreciation cycle, whereas foundational, exploitative technologies benefit from long term, stable tax reduction schemes that encourage patient accumulation.

In essence, our findings reposition the debate from "how much innovation" to "what kind of innovation and for how long". This aligns knowledge management theory with public policy, arguing that the ultimate goal is not to maximize annual patent counts, but to build a resilient, multi temporal knowledge infrastructure that supports sustained efficiency gains over decades.

5.2 The Role of Knowledge Depreciation

A key theoretical contribution of this paper is the introduction of knowledge depreciation as a boundary condition for policy induced knowledge accumulation (Argote & Miron Spektor, 2011; Argote, 2013). Our findings suggest that tax incentives are most effective at building knowledge stocks when the knowledge in question has a low depreciation rate. High depreciation knowledge—whether in AI, high quality patents, or green technology—responds quickly but does not accumulate. This insight aligns with the knowledge management literature on knowledge life cycles and extends it to the policy domain (Nonaka & Takeuchi, 1995).

5.3 Policy Implications

From a policy perspective, our findings suggest three main recommendations:

First, tax incentives should be complemented with quality oriented evaluation mechanisms. Rather than rewarding patent quantity alone, policies should track indicators of knowledge durability, such as patent citations, technological impact, or commercialization outcomes (Trajtenberg, 1990; Hall et al., 2005).

Second, green innovation policies should be redesigned to avoid quantity quality decoupling. The positive association between green patent quantity and bubbles suggests that current policies may inadvertently encourage symbolic innovation (Geng et al., 2024; Lyon & Maxwell, 2011). Combining quantity incentives with quality requirements—such as mandatory post grant evaluation or citation targets—could help mitigate this problem (Delmas & Montes Sancho, 2010).

Third, policymakers should consider differentiated incentives for different types of knowledge. Short lived frontier knowledge may benefit from more frequent but smaller incentives, while long lived foundational knowledge may require sustained, patient support (Cockburn et al., 2018; Agrawal et al., 2018).

5.4 Limitations and Future Research

This study has several limitations. First, our classification of knowledge types is based on patent characteristics; future research could incorporate additional dimensions such as knowledge novelty, technological impact, or economic value. Second, our analysis focuses on listed firms; findings may not generalize to non listed or small firms. Third, the green bubble measure captures only one aspect of quality; more refined quality indicators would enhance future research. Fourth, we focus on Chinese firms; cross country comparisons would help establish the generalizability of our findings (Hsieh & Klenow, 2009; Liu & Mao, 2019). Fifth, this paper does not re examine the long term accumulation effect of total patent stock; rather, we focus exclusively on the heterogeneity across knowledge types. Future research could explore whether the observed patterns hold for broader measures of knowledge stock.

6. Conclusion

This paper unpacks the black box of knowledge accumulation by examining how tax incentives affect three distinct types of knowledge: high-quality patents, AI patents, and green patents. High-quality and AI knowledge respond only in the short term, while green knowledge quantity may generate bubbles. The common denominator of these three is high depreciation or low persistence—they are "fast knowledge" that does not build lasting capabilities (Argote & Miron-Spektor, 2011; Argote, 2013).

Theoretically, this paper demonstrates that knowledge depreciation is not merely a technical parameter but a strategic boundary condition that determines the effectiveness of external incentives. By bridging the exploration-exploitation framework (March, 1991) with the SECI model (Nonaka & Takeuchi, 1995), we show that policy-induced knowledge accumulation is path-dependent: incentives that favour combinative outputs (patent filings) may inadvertently crowd out internalization, leading to a fragile knowledge base. This insight extends the knowledge-based view of the firm by specifying how external institutional forces can distort internal knowledge portfolios—a mechanism largely overlooked in prior KM literature.

From a knowledge management perspective, these findings suggest that knowledge life cycle should be integrated into both organizational strategies and policy design (Nonaka & Takeuchi, 1995; Grant, 1996). Tax incentives should not be evaluated solely by immediate patent counts; rather, they should consider the durability and eventual contribution of accumulated knowledge to organizational efficiency (Hall et al., 2010; Griliches, 1990). By shifting from a one-size-fits-all approach to a differentiated knowledge perspective, both firms and policymakers can better align incentives with the long-term goal of sustainable innovation.

Ethics Declaration: No ethical approval was required for this study because the research used publicly available secondary data from Chinese A-share listed firms.

AI Declaration: AI tools were used only for language polishing, grammar checking, and improving readability. All academic content, analysis, and conclusions were developed and verified by the author.

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