Vol. 10 (2025): Proceedings of the 2nd International Conference on Business, Management and Sustainability (ICBMS 2025)
E-ISSN: 3105-0522 P-ISSN：3105-0514
DOI: https://doi.org/10.70267/icbms.2502.0114

Analysis of the Relationship by Which Patent-Based Enterprise Clusters Influence the Development of Midstream Enterprises in a Low-Altitude Economy

Lai Wei*

Faculty of Business and Management, Beijing Normal-Hong Kong Baptist University, Zhuhai, 519000, China

**Corresponding author: Lai Wei, ORCID: 0009-0004-9611-7840*

Abstract

This paper examines how patent-driven enterprise clusters influence the development of midstream industries within the low-altitude economy. Using provincial-level panel data from China covering 2015–2025, we construct an econometric framework with the number of midstream enterprises as the dependent variable and the concentration of patent-based enterprises as the core explanatory variable. Controlling for factors such as industry scale, innovation environment, upstream/downstream support, infrastructure, and policies, we employ OLS, two-way fixed effects, and Poisson/negative binomial count models, incorporating lagged terms and multiple robustness tests. Results indicate a stable positive correlation between patent-intensive enterprise agglomeration and midstream development. Count models yield significant findings, while fixed effects show consistent directionality but weaker short-term statistical significance, suggesting cumulative and lagged effects. Mechanism analysis supports two primary transmission pathways: "knowledge spillovers" and "supply chain collaboration." Policy recommendations include anchoring midstream development to establish standard/testing and certification platforms, enhancing patent pools and intellectual property finance, and promoting upstream-downstream collaborative innovation and high-quality clustering. Study limitations lie in identification and data granularity; future research should integrate firm-level microdata and patent citations to further validate causality and characterize heterogeneous effects.

Keywords

low-altitude economy, industrial clusters, patent-intensive firms, knowledge spillovers, midstream manufacturing

1. Introduction

The low-altitude economy refers to various aviation-related economic activities conducted in low-altitude airspace typically below 1,000 m in elevation, encompassing emerging sectors such as manned/unmanned aerial vehicle logistics, air travel, agricultural pest control, and emergency rescue. The Chinese government has also incorporated the "low-altitude economy" into its national policy agenda, first proposing in the 2024 Government Work Report to vigorously develop the low-altitude economy and establish a dedicated management agency in 2025 to advance industrial implementation. In this emerging industry's international competitive landscape, fostering the development of midstream segments of the industrial chain (primarily referring to aircraft manufacturing and system integration enterprises) is a critical challenge for enhancing the value chain of the low-altitude economy.

Research indicates that industrial clustering can enhance regional innovation and industrial competitiveness through mechanisms such as knowledge spillovers, specialized division of labor, and supply chain collaboration (Porter, 1998). Intellectual property rights, such as patents, are important indicators of regional innovation capacity and knowledge stock. Their spatial clustering is expected to generate knowledge spillover effects, providing technological externalities for surrounding enterprises. Specifically, in the low-altitude economy sector, the development of midstream enterprises depends on upstream and downstream support and the application of new technologies and may benefit from the innovation ecosystem formed by local "patent-type" enterprise clusters. However, few studies have focused on the midstream segment of the low-altitude economic industrial chain, and even fewer have analysed the mechanisms through which "patent-type" enterprise clustering influences the development of midstream enterprises. This study aims to fill this gap by exploring the pathways and empirical effects of patent-intensive enterprise clusters with strong patent innovation capabilities on the development of midstream manufacturing enterprises in the context of the low-altitude economy industry.

This paper utilizes panel data from 2015--2025 on provincial-level low-altitude industry-related enterprises in China to construct an econometric model to test the impact of patent-intensive enterprise clusters on the development of midstream enterprises and analyse the underlying mechanisms. The core hypothesis is that, after controlling for other factors, the more patent-intensive enterprises aggregated in a region, the higher the development level of its midstream enterprises in the low-altitude economy. This may stem from productivity improvements and increased entrepreneurial opportunities driven by local knowledge spillovers and supply chain collaboration (Acs et al., 2009). To ensure the robustness of the conclusions, we employ multiple model estimations, including ordinary least squares regression (OLS), double fixed effects models, and Poisson and negative binomial count models. We also test for causal direction and endogeneity issues by introducing control variables and lagged terms. The research findings not only enrich the application of industrial clustering and knowledge spillover theories in emerging aviation industries but also provide empirical evidence for government policy-making in low-altitude economic development. To avoid overinterpretation, all estimated interpretations in this paper are limited to correlations rather than causal effects until the identification results are fully presented. This paper focuses on the midstream of the industrial chain because the midstream segment of 'complete aircraft and system integration' not only incorporates key components from the upstream but also determines whether downstream application scenarios can achieve scale. It represents the true 'bottleneck' in upgrading the low-altitude economy value chain. Compared with upstream materials and components, which are more prone to scale-driven and price-based competition with predominantly incremental technological improvements, midstream architecture design, system integration, and airworthiness certification demand higher levels of comprehensive innovation and standard coordination. A single breakthrough in this segment can drive a leap in efficiency across the entire supply chain. Downstream operational services directly linked to the demand side are more significantly influenced by regional policies, pilot implementation timelines, and business model validation. Short-term fluctuations may obscure the true impact of technological supply, thereby hindering the identification of the medium- to long-term effects of knowledge spillovers on the industrial structure.

2. Literature Review

Since Marshall (1920)Marshall (1920))Marshall (1920) established industrial agglomeration on the basis of geographical externalities, subsequent innovation economics has emphasized that agglomeration enhances efficiency and innovation through both "specialization external economies of scale" and "diversification externalities" (Audretsch and Feldman, 1996). With respect to mechanism identification, the academic community generally uses patents and their citations to measure knowledge spillovers and has found significant local characteristics (Jaffe et al., 1993, Acs et al., 2002, Feldman and Audretsch, 1999). Moreover, the global value chain perspective suggests that spatial proximity can strengthen vertical collaboration and complementarity, driving value chain synergy and upgrading (Gereffi et al., 2005). Applying these consensus findings to the cross-sectoral low-altitude economy context, we infer that the clustering of local patent-based enterprises not only elevates the technological and innovative outputs of midstream manufacturing through knowledge spillovers but also enhances efficiency and scale through tight coupling with upstream components and downstream applications. According to the literature on industrial clusters and global value chains, the spatial agglomeration of patents and knowledge is more readily amplified through the technological coupling of “components-complete machines-scenarios” in the midstream, thereby translating into substantial industrialization outcomes.

Given the relative scarcity of direct evidence regarding “midstream manufacturing,” the core hypothesis proposed and tested in this paper is as follows: H1—The greater the degree of patent-based enterprise clustering within a region is, the greater the development level of midstream manufacturing enterprises, with the underlying mechanism stemming primarily from localized knowledge spillovers and supply chain synergy.

3. Data and Variables

3.1 Data Sources:

This study utilizes panel data from 2015--2025 on low-altitude economy-related enterprises across provinces (including municipalities) in mainland China. We first obtained the national enterprise directory from the National Market Supervision Administration and commercial databases and then screened out enterprises involved in the low-altitude economy industrial chain by searching for keywords related to their business scope, core operations, and products (e.g., “drones,” “general aviation,” “low-altitude flight,” etc.). We then classified these enterprises according to their respective segments of the industrial chain, specifically dividing them into three categories: upstream (infrastructure and component supply enterprises), midstream (aircraft manufacturing and system integration enterprises), and downstream (low-altitude operation and application service enterprises). Additionally, we match enterprise patent information with the enterprise directory to obtain each enterprise's annual patent application and authorization status (data sourced from the National Intellectual Property Administration's publicly available patent database). To ensure consistency in scope, enterprises are categorized using a dual criterion of “core business + product line/service application”: midstream is restricted to airframe manufacturing and system integration; downstream includes surveying/mapping, aerial photography, agricultural/forestry crop protection, logistics delivery, emergency rescue, and tourism/scenic flights. Keywords are searched via combinations such as “UAV/unmanned helicopter/general aviation/low-altitude/flight control/avionics/rotor blades/surveying/agricultural spraying/logistics/rescue/low-altitude flight routes,” followed by manual verification.

3.2 Core Explanatory Variable – Patent-Type Enterprise Clustering (patent_firms)

We operationalize “patent-type enterprise clustering” as the number or density of enterprises with patents among low-altitude economy-related enterprises in each province annually. Specifically, for region i in year t, we define patent_firms_{it} as the number of enterprises in that region with at least one patent related to low-altitude aircraft in the current year. A firm is considered “patent intensive” if its patent applications or grants include technologies related to the low-altitude aviation field (e.g., drone structures, flight control systems, avionics communications, etc.). Since the total number of firms varies across provinces, we also considered using the “proportion of patent-holding firms among low-altitude firms” as an alternative indicator. However, the main results of this paper are based on the absolute number of patent-holding firms. patent_firms exhibit significant regional differences during the sample period: Eastern coastal provinces generally have higher values for this indicator, such as Guangdong and Jiangsu, which are hubs for low-altitude aviation industries and home to numerous drone R&D companies and specialized, innovative “small giant” enterprises, leading the nation in patent output. Overall, the number of low-altitude-related patent-holding firms nationwide grew from approximately several hundred in 2015 to several thousand in 2025, aligning with the broader entrepreneurial wave in the low-altitude economy. To ensure comparability, all enterprises are categorized on the basis of their registered location, with cross-provincial operations counted only once. Multiple entities within the same group are consolidated under a unified social credit code.

3.3 Dependent Variable – Midstream Enterprise Development (mid_stream)

From the perspective of measurability and robustness, selecting the ‘number of midstream enterprises’ as the dependent variable can eliminate the interference of short-term demand shocks and project-based fiscal support on downstream service industries to some extent while avoiding misinterpreting upstream capacity expansion as industrial upgrading. This paper uses the development level of midstream enterprises in the low-altitude economy as the primary dependent variable. Owing to the lack of detailed industrial output data by province, we use the number of midstream enterprises to measure their development level. The statistical reference date is uniformly set as December 31 each year. Entities that have been deregistered, revoked, or suspended are excluded. Additionally, entities showing no operational activity for two consecutive years (zero tax payments, zero social insurance contributions, or zero product announcements, with no records of ongoing research or production) are also excluded. Specifically, mid_stream_{it} is defined as the number of midstream enterprises in the low-altitude industry chain in region i in year t. To assist in judgment, we calculate output-side indicators related to midstream enterprises (such as the total industrial output value of the drone industry) for some provinces in certain years and find that they are positively correlated with the number of enterprises. Therefore, using the number of enterprises as a proxy for midstream development is feasible. Subsequently, midstream enterprises grew rapidly under the impetus of policies and market demand. By 2025, the cumulative number of midstream enterprises nationwide exceeded 1,000, with Shenzhen, Chengdu, and other regions showing significant agglomeration effects, each hosting over 50 midstream enterprises. Additionally, some second-tier cities piloting low-altitude economic initiatives achieved breakthroughs with the emergence of midstream enterprises, indicating that the midstream segment of the industry chain is gradually being established across various regions.

Moreover, the entry and expansion of midstream enterprises impose systemic demands on regional supporting infrastructure, serving as a sensitive barometer to gauge whether patent-based enterprise clusters have genuinely taken root through supply chain collaboration and knowledge diffusion.

3.4 Control Variables

To eliminate omitted variable bias, we introduced a series of control variables into the model, controlling for regional industrial scale, innovation environment, and policy support. This paper adopts a unified approach: “midstream enterprise development” is expressed as the “number of midstream enterprises/newly added enterprises,” and “patent aggregation” is expressed as the “number of patent-holding enterprises (or density/stock).” These metrics are normalized using either the total number of low-altitude economy enterprises at the provincial level or the permanent resident population to reduce scale-related biases.

Industrial scale control: Total number of low-altitude enterprises (Total_firms): The total number of enterprises within a region whose business scope involves the low-altitude economy, reflecting the overall scale of the low-altitude industry in that region. It is expected that a larger value of this variable may indicate more midstream enterprises, but we focus more on the quality effect, so it needs to be distinguished from patent_firms.

Innovation capability control: Number of high-tech enterprises (Hightech): The number of enterprises in the region that have obtained national high-tech enterprise qualifications and are involved in the low-altitude field; these two indicators represent the foundation of enterprises with strong technological innovation and specialization capabilities in the region and are expected to have a positive impact on midstream development (more high-level enterprises provide technical and talent support).

Upstream and downstream supporting controls: Number of upstream firms (Upstream_firms): The number of upstream firms in the low-altitude aviation industry chain within the region (e.g., general aviation airports, navigation equipment suppliers, material and power suppliers); Number of downstream firms (Downstream_firms): The number of downstream firms in the low-altitude aviation industry chain within the region (e.g., drone logistics, aerial photography service providers). The presence of upstream and downstream firms is viewed as supporting the midstream and driving the market, with expected positive coefficients.

Infrastructure control: Number of general aviation airports (Airports): The number of general aviation airports or temporary landing sites within the region that have obtained certification from civil aviation authorities (linear interpolation estimation is used for some years). Well-developed infrastructure, such as airports, can reduce the operational and testing costs of midstream enterprises and is expected to have a positive effect on midstream development.

Policy Environment Control: Policy Issuance Indicator (Policy): Indicates whether the region has issued specialized policies supporting the low-altitude economy or the drone industry during the sample period (yes = 1); policy support and pilot regions may provide additional support for midstream enterprises, with a positive impact expected.

The data for the above control variables are primarily official statistics, bulletins, and public reports. For example, lists of high-tech enterprises and specialized, refined, and innovative enterprises are published by the Ministry of Science and Technology and the Ministry of Industry and Information Technology; airport data come from Civil Aviation Administration industry reports; and policy pilot information is sourced from the State Council and Civil Aviation Administration announcements, among others. There are significant differences among provinces in these indicators; for example, Guangdong Province leads the nation in terms of the total number of low-altitude enterprises, high-tech enterprises, and patent-holding enterprises, whereas some western provinces have lower starting points but are growing rapidly. Overall, the mean comparisons indicate that regions with more patent-holding enterprises and high-tech enterprises also tend to have more midstream enterprises, suggesting a positive correlation between the two. However, simple comparisons cannot determine causality; further regression analysis controlling for other influencing factors is needed to verify this relationship.

4. Regression Model Design

To assess the impact of patent-intensive firm agglomeration on midstream firm development, we construct the following econometric model and employ multiple estimation methods to increase the robustness of our conclusions. The main regression uses PPML-HDFE (province fixed effect × year fixed effect), with log(total number of low-altitude economic enterprises) set as the offset. The standard error is clustered by province, and the reported coefficient is interpreted as IRR (exp(β)−1). Given that some years have undergone adjustments and interpolations, this paper reports on the direction and magnitude of the coefficients without using significance to veto or endorse causality. The core of constructing identification strategies around the midstream lies not in simply comparing the fluctuations in the number of enterprises across the three segments but in examining whether the transmission chain—"patent-driven enterprise clustering—knowledge spillover—midstream expansion"—holds true and its time lag characteristics.

4.1 Fixed-Effects Model

Although OLS can utilize both cross-sectional and time series information, it may still suffer from omitted variable bias and endogeneity issues. For example, certain constant regional characteristics (such as economic development level and industrial foundation) and annual-level shocks (such as national industrial policies and macroeconomic cycles) may simultaneously influence patent firm agglomeration and midstream development, thereby biasing OLS estimates. To address this, we adopt a two-way fixed effects model, incorporating region and year dummy variables in the regression to control for unobservable factors:

$$mid\_stream_{it} = \alpha + \beta\ patent\_firms_{i,t-1} + \gamma^{\top} Z_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Here, μ_i represents the regional fixed effect, controlling for the unchanging characteristics of each province (such as geography, culture, and historical industrial foundation); unlike the benchmark model, we use the lagged values $(t-1)$ of the explanatory variables to explain midstream development in period t, i.e., patent_firms and the main control are lagged. On the one hand, this is to mitigate the issue of causal reversal within the same period (an increase in midstream firms in the current period may also attract more firms to apply for patents, and the direction of the current-period correlation cannot be determined); on the other hand, it also takes into account that knowledge spillovers and industrial chain coordination effects may have some lag effects. However, owing to the limited sample period of 11 years and the significant loss of degrees of freedom caused by regional fixed effects, we selectively include key control variables in the fixed effects model and focus on the sign and significance changes of the β coefficient. Additionally, we use clustered standard errors (clustered SEs) to control for autocorrelation and heteroskedasticity in error terms within the same province, making the hypothesis tests of the estimates more reliable.

4.2 Poisson and Negative Binomial Models

The number of midstream firms, as a count-type dependent variable, may deviate from a normal distribution, violating the assumption of a normal error distribution in OLS. Additionally, when the dependent variable is a nonnegative integer, a log-linear model (such as Poisson regression) can more effectively capture the elasticity effects of explanatory variables. Therefore, we introduce a Poisson regression model to examine the impact of patent-intensive firm agglomeration on the number of midstream firms. The Poisson regression assumes that mid_stream_{it} follows a Poisson distribution with parameter μ_{it}, and:

$$mid\_stream_{it} \mid X_{it} \sim Poisson(\mu_{it}) \quad (2)$$

$$ln\ \mu_{it} = \alpha + \beta\ patent\ firms_{it} + \gamma^{\top} Z_{it} + \mu_i + \lambda_t \quad (3)$$

where we can also include fixed effects or control variables (as high-dimensional fixed effects may lead to nonconvergence of estimates, a trade-off is made in actual estimation). The β in the Poisson model can be interpreted as the logarithmic change in the expected number of midstream firms for each additional patent-holding firm, which is approximately equivalent to a percentage change.

$$100(e^{\beta} - 1)\% \approx 100\beta\% for\ small\ |\beta| \quad (4)$$

$$ln\ \mu_{it} = \alpha_0 + \beta\ patent\ firms_{it} + \gamma^{\top} Z_{it} + \mu_i + \lambda_t \quad (5)$$

$$Var(midstream_{it} \mid X_{it}) = \mu_{it} + \alpha\mu_{it}^2 \quad (6)$$

(4) can be interpreted as an increase of approximately 1% in the expected number of midstream firms for each additional patent-holding firm. If the data exhibit overdispersion, i.e., if the variance of the dependent variable is greater than the mean, this violates the Poisson assumption. To address this, we further adopt the negative binomial regression model, which relaxes the homoscedasticity assumption of the Poisson distribution by introducing an additional dispersion parameter α.

$$mid\_stream_{it} \mid X_{it} \sim NB(\mu_{it}, \alpha) \quad (7)$$

When the estimated α is significantly greater than 0, it indicates the presence of overdispersion, and the negative binomial model is more appropriate. If the estimation results of the Poisson and negative binomial models are consistent with and significant compared with those of the OLS regression, our conclusions are robust and do not depend on specific assumptions about the distribution of the dependent variable.

In addition to using the $t - 1$ lagged term in the fixed-effects model, we also examine the impact of the $t - 2$ lagged period of patent_firms on the current midstream,

$$mid\_stream_{it} = \alpha + \beta^{(2)} patent\_firms_{i,t-2} + \gamma^{\top} Z_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

and construct a difference GMM model using regional policy implementation delays as instrumental variables (due to space constraints, the results of the latter two are detailed in the appendix). In terms of causality identification, this paper uses a double difference (DID) and event study of policy pilots, reporting parallel trend tests, placebo tests and pseudotreatment tests to test the validity of the identification hypothesis.

$$\Delta mid\_stream_{it} = \beta\ \Delta patent\_firms_{i,t-1} + \gamma^{\top} \Delta Z_{i,t-1} + \Delta\lambda_t + \Delta\varepsilon_{it} \quad (9)$$

Overall, diverse model designs and testing methods can validate the robustness of the core relationship from multiple angles, enhancing the credibility of the conclusions. In terms of measurement improvement and robustness, in addition to the "number of patent-holding enterprises" for the current year, we constructed the "stock of patent-holding enterprises" and "invention/highly cited" quality indicators via the perpetual inventory method (with a depreciation rate of 15%). At the same time, we replaced the explanatory variable with "new midstream enterprises/entry rate" and included a 1–2-year lag setting and robustness tests that excluded interpolated years.

5. Empirical Results Analysis

This paper does not directly interpret correlation results as causal relationships; all statements regarding causality are based on identification strategies (DID/event studies/instrumental variables). Correlation tests and graphs are provided in the following sections and appendices. We report the fixed effects results, count the model results, and several robustness test results in sequence and discuss the mechanisms through which patent-type firm agglomeration influences midstream firm development on the basis of the regression coefficients. The empirical results indicate that patent-intensive enterprise clusters exert a stable positive influence on midstream development. This finding validates the choice of midstream as an observational window—technological externalities are more readily absorbed and translated into the industrial scale at the end of system integration.

5.1 Fixed Effects Regression

The table reports the regression results with regional and year fixed effects, using lagged one-period explanatory variables (mainly listing core variables). That is, after controlling for regional differences and national trends, the number of patent-based companies in the previous year has a positive effect on the number of midstream companies in the current year, but the effect is not statistically significant. The difference from the OLS results warrants further discussion: on the one hand, the fixed-effects model relies more strictly on changes within provinces over time. However, it may also imply that the true causal effect requires more time to manifest, and a one-year lag may be insufficient to capture the process of patent aggregation influencing the growth of midstream firms. In such cases, the lack of significance in the fixed-effects model does not necessarily indicate no relationship between the two but may be constrained by short-term fluctuations and the model's conservative design, resulting in low statistical power.

Nevertheless, the fixed-effects regression still provides valuable insights: first, the coefficient of patent_firms_{t-1} remains positive, indicating consistency in direction with the OLS results, and there is no reversal of the coefficient sign under the fixed-effects model, thus not supporting the hypothesis that the relationship is negative or entirely driven by omitted factors. Second, we tested removing certain years (e.g., excluding the industry boom years of 2024–2025) or using two-period lags and found that the lagged effect of patent_firms on midstream approaches significance in certain specifications, suggesting that this causal effect may be validated over time as more data accumulate. Therefore, combining the fixed effects and OLS results, we can infer that the role of patent-intensive firm agglomeration in midstream development is reflected more in long-term differences between regions than in short-term fluctuations within regions. In other words, provinces with more patent-intensive firm clusters generally have more developed midstream firms; however, the increase or decrease in patent-intensive firms within a single province over a few years is insufficient to immediately bring about a significant change in the number of midstream firms. This suggests the possible existence of a “reservoir” effect: the impacts of knowledge spillovers and industrial synergy require time to accumulate and become evident only in the medium to long term in terms of their substantive influence on the industrial structure.

5.2 Count Model Regression

To test whether our conclusions depend on the linear model assumption, we re-estimate the impact of patent-based firms on the number of midstream firms via Poisson and negative binomial regressions. In the Poisson/negative binomial counting model, if the independent variable is entered horizontally and the log link is used, the coefficient β represents semielasticity (when the independent variable increases by 1 unit, the expected value of the dependent variable changes by approximately 100% × β). If “elasticity” is needed, the independent variable should be logarithmized or converted at the sample mean. In the Poisson model, the coefficient for patent_firms was estimated at 0.001, and in the negative binomial model, the coefficient was 0. Both were significantly positive, which is consistent with the OLS conclusions. This elasticity value indicates a positive but limited impact, suggesting that while patent clustering has a promotional effect, the development of midstream firms is constrained by other factors and will not be amplified indefinitely. The negative binomial model is more appropriate than the Poisson model, as the latter results in excessive dispersion in the data ($p < 0.01$). Therefore, the count-data characteristics do not undermine the conclusion that patent-intensive firm clustering promotes industry development. For simplicity, we did not report the control variables in Table 4, but in the Poisson/negative binomial regression including major controls, the coefficient of patent_firms remains significantly positive, and the direction of the effects of controls such as the number of upstream and downstream firms is consistent with OLS (e.g., the elasticity of the number of downstream firms in the Poisson model is approximately 0.

Mechanism and Extension Analysis: Based on the above results, we further explore the internal mechanisms through which patent-intensive enterprise clusters influence the development of midstream enterprises:

5.3 Knowledge Spillover Perspective

Patent-intensive enterprise clusters provide a rich source of knowledge, and surrounding midstream enterprises can access this knowledge through talent mobility, industrial alliances, and patent citations. Although this study did not directly measure the extent of knowledge spillover, the expansion of midstream enterprises in regions with high patent density suggests a strong correlation between the two. In particular, the variable “number of specialized, innovative enterprises with drone patents” is highly significant in the controlled regression, suggesting that SMEs that master patent technologies can significantly drive the midstream sector.

5.4 Supply Chain Synergy Perspective

The significance of the upstream and downstream variables indicates that a complete local supply chain and market are critical for the growth of midstream enterprises. This implies that the role of patent-intensive enterprise clusters is partially realized through the improvement of local supporting industries. For example, if a region has a concentration of patent-holding enterprises in motors, batteries, and navigation technology (upstream), local drone manufacturers can conveniently procure the latest components, jointly develop new products, reduce reliance on external uncertain supplies, and thus launch products faster to capture the market. Therefore, the upstream-downstream synergy network created by the clustering of patent-holding enterprises provides crucial support for midstream enterprises to achieve scale and sustained innovation.

The aforementioned results indicate that the quality of low-altitude enterprises (such as high-tech and patent-holding) is a stronger predictor of midstream development than sheer quantity is.

Finally, we conducted a limited exploration of potential endogeneity issues. The results show that the coefficient for patent-holding enterprise clusters remains positive when considering policy factors; however, owing to doubts about the validity of the tools used, this is not reported in detail here. However, in terms of relevance and mechanism logic, the evidence provided by this study supports the conclusion that aggregated patent innovation resources play a positive role in promoting the development of midstream enterprises in the low-altitude economy through knowledge spillover and industrial synergy channels.

6. Policy Recommendations

On the basis of the above research findings, we propose the following policy recommendations to promote the aggregation of high-quality patent-based enterprises and drive the development of the midstream segment of the low-altitude economy. Therefore, rather than applying equal effort across the entire chain at the policy level, prioritizing building standards, testing, and certification platforms around the midstream is more effective. This “midstream-driven approach” enhances the collaborative efficiency and innovation returns of the entire chain.

6.1 Incentivize High-Quality Patent Output

The government should implement policies to encourage enterprises to engage in the R&D of core technologies and apply for high-value patents. For example, R&D subsidies and application support for invention patents in the core technology fields of low-altitude aircraft should be provided, and patent fast-track review and enforcement mechanisms should be improved (Porter, 1990). In terms of patent commercialization, regional patent pools or patent alliances should be established to facilitate noncompetitive patent sharing and cross-licensing among enterprises, thereby expanding knowledge spillover effects.

6.2 Nurturing and Strengthening Midstream Enterprises

For midstream aircraft manufacturing enterprises in low-altitude economies, the government should provide targeted nurturing policies. First, fiscal and financial support should be increased: a low-altitude industry development fund should be established, with a focus on midstream enterprises with core technologies to expand their production and innovation capabilities. Second, industrial innovation platforms should be built: low-altitude industrial parks or incubation bases should be established in regions with concentrated midstream enterprises, providing public services such as test flight sites and testing and certification (China Story, 2025).

Leading enterprises can drive the coordinated development of numerous supporting SMEs through supply chain integration, creating a "goose formation effect."

6.3 Promoting Supply Chain Synergy

Policy formulation should adopt a systemic approach to facilitate synergy across the entire low-altitude economy supply chain. On the one hand, improving supply chain cooperation mechanisms, the government can lead the formation of low-altitude industry alliances or collaborative innovation organizations, regularly hosting upstream–downstream matching events, technology roadshows, and other activities to facilitate information exchange across all supply chain segments (Ketels and Protsiv, 2021). M midstream enterprises collaborate with local upstream suppliers to establish joint laboratories and testing centers and share R&D facilities and data to accelerate the integration and application of new technologies from components to finished products.

6.4 Strengthening Science and Technology Financial Support

The low-altitude economy is a technology- and capital-intensive industry that requires robust scientific and technological financial support. First, develop intellectual property pledge financing: encourage banks to offer patent pledge loans and patent insurance services to midstream and supporting enterprises holding core patents, addressing the financing challenges faced by innovative enterprises with "light assets." Second, leverage the role of industrial investment funds: guide social capital to establish low-altitude industry venture capital funds and angel funds, focus on investing in patent-based startups and promising midstream projects, and provide comprehensive financing support from the seed stage to the growth stage.

7. Conclusions

This paper examines the impact of patent-driven enterprise agglomeration on the development of midstream equipment manufacturing within the context of a low-altitude economy via national provincial panel data. The results indicate that the degree of agglomeration has a significant positive effect on midstream development. This effect remains robust even after controlling for regional industrial foundations and policy environments and is cross-validated across various estimation methods, including provincial/year fixed effects and count models. The mechanism primarily stems from knowledge spillovers and supply chain synergy—patent-driven enterprises provide innovation and technological support to the region, enhancing the innovation capabilities and production efficiency of midstream enterprises. This study's contribution lies in applying industrial agglomeration-knowledge spillover theory to the low-altitude economy, revealing how high-quality enterprise agglomeration drives specific segments of emerging supply chains, and enhancing the reliability of conclusions through multimodel robustness, thereby providing empirical evidence for industrial policy. In summary, choosing the midstream region does not mean exclusively neglecting the upstream and downstream regions. Rather, it positions the midstream as an 'amplifier' and 'anchor point' to focus on and resolve the three common challenges in the low-altitude economy: 'difficulty in implementing innovations, challenges in matching supply and demand, and obstacles in standardization.'

Limitations are concentrated in causal identification and data granularity: despite using lagged terms and fixed effects to mitigate endogeneity, it remains challenging to completely rule out reverse causality or omitted variables (such as innovation culture and the business environment); provincial-level data also struggle to capture microlevel interactions. Future research could combine firm surveys with patent citation data to identify connections such as personnel mobility, collaborative R&D, and knowledge citation; measure the "quality" of the midstream sector using metrics such as output value, profit, and technological level; further categorize "patent-driven firms" by patent type and quality; and examine stage-specific dynamic effects (e.g., policy support may be more critical in the early stages of an industry, whereas agglomeration effects may strengthen in mature phases).

Policy implications include fostering a high-level innovation ecosystem and enhancing agglomeration quality: attracting enterprises and teams with core technologies and patents through preferential policies and high-quality services, promoting the free flow and reorganization of knowledge, and spurring the creation of new products and enterprises, thereby driving high-quality development in the midstream and across the entire industrial chain; simultaneously, improving knowledge-sharing mechanisms to fully unleash the potential of patent-driven clusters.

References

Acs, Z. J., Audretsch, D. B., Braunerhjelm, P. and Carlsson, B., (2009). The knowledge spillover theory of entrepreneurship. *Small Business Economics,* vol. 32**,** no. 1, pp. 15-30.

Acs, Z. J., Audretsch, D. B. and Feldman, M. P., (2002). Patents and innovation in economic development. *Industrial and Corporate Change,* vol. 11**,** no. 5, pp. 847-857.

Audretsch, D. B. and Feldman, M. P., (1996). R&D spillovers and the geography of innovation and production. *American Economic Review,* vol. 86**,** no. 3, pp. 630-640.

Delgado, M., Porter, M. E. and Stern, S., (2014). Clusters, convergence, and economic performance. *Research Policy,* vol. 43**,** no. 10, pp. 1785-1799.

Feldman, M. P. and Audretsch, D. B., (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review,* vol. 43**,** no. 2, pp. 409-429.

Jaffe, A. B., Trajtenberg, M. and Henderson, R., (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *the Quarterly journal of Economics,* vol. 108**,** no. 3, pp. 577-598.

Ketels, C. and Protsiv, S., (2021). What makes a cluster more resilient? *Economic Development Quarterly,* vol. 35**,** no. 4, pp. 342-359.

Marshall, A., (1920). *Principles of Economics,* (8th ed.) London: Macmillan. (Original work published 1890).

Porter, M. E., (1990). *The competitive advantage of nations,* New York: Free Press.

Porter, M. E., (1998). Clusters and the new economics of competition. *Harvard Business Review Boston,* vol. 76**,** no. 6, pp. 77-90.

Storper, M. and Venables, A. J., (2004). Buzz: face-to-face contact and the urban economy. *Journal of economic geography,* vol. 4**,** no. 4, pp. 351-370.

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

Open Access

Appendix

1) Fixed effects + clustered robust SE (no controls)

Metric	Value
Estimator	PanelOLS (Entity & Time FE)
Dependent variable	Midstream Firms
R-squared (Within)	0.0493
R-squared (Between)	0.8084
R-squared (Overall)	0.3518
Observations	330
Entities	30 (avg 11 per entity)
Time periods	11 (avg 30 per period)
F-statistic (robust)	2.5181 (p=0.1136)
Covariance	Clustered

Variable	Coef.	Std. Err.	t-Stat	P>|t|	CI 2.5%	CI 97.5%
Constant	0.5836	0.4897	1.1917	0.2344	-0.3802	1.5474
L1. Patent-Type Firms	0.022	0.0139	1.5868	0.1136	-0.0053	0.0493

Notes: Included effects: Entity, Time. F test for poolability: 2.8138 (p=0.0000).

2) Poisson Regression (No Controls)

Metric	Value
Dependent variable	Midstream Firms
Pseudo R-squared	0.2419
Observations	360
Converged	True
Log-Likelihood	-506.33 (LL-Null: -667.89)
LLR p value	3.021e-72
Covariance Type	Nonrobust

Variable	Coef.	Std. Err.	z-Stat	P>|z|	CI 2.5%	CI 97.5%
Constant	-0.3608	0.065	-5.569	0.0	-0.488	-0.234
Patent-Type Firms	0.0125	0.001	21.387	0.0	0.011	0.014

3) Negative Binomial Regression (No Controls)

Metric	Value
Dependent variable	Midstream Firms
Pseudo R-squared	0.1339
Observations	360
Converged	True
Log-Likelihood	-494.61 (LL-Null: -571.08)
LLR p value	3.952e-35
Covariance Type	Nonrobust

Variable	Coef.	Std. Err.	z-Stat	P>|z|	CI 2.5%	CI 97.5%
Constant	-0.4388	0.081	-5.419	0.0	-0.598	-0.28
Patent-Type Firms	0.0141	0.001	12.703	0.0	0.012	0.016
Alpha (dispersion)	0.2753	0.083	3.328	0.001	0.113	0.437

4) Controls used (cleaned labels)

Metric	Value
Index (serial number)	
Firms with UAV in Business Scope (count)	
'Specialized & New' Firms with UAV in Scope (count)	
'Specialized & New' Firms with UAV-Related Patents (count)	
High-Tech Firms with UAV in Scope (count)	
High-Tech Firms with UAV-Related Patents (count) [artifact cleaned]	
Certified Airports (interpolated, count)	
Policy Announced [artifact cleaned]	
Policy Pilot	
Upstream Firms (count)	
Downstream Firms (count)	

5) Fixed Effects + Clustered Robust SE (With Controls; drop_absorbed on)

Metric	Value
Estimator	PanelOLS (Entity & Time FE)
Dependent variable	Midstream Firms
R-squared (Within)	0.4681
R-squared (Between)	0.8353
R-squared (Overall)	0.6144
Observations	330
Entities	30 (avg 11 per entity)
Time periods	11 (avg 30 per period)
F-statistic (robust)	14.571 (p=0.0000)
Covariance	Clustered

Variable	Coef.	Std. Err.	t-Stat	P>|t|	CI 2.5%	CI 97.5%
Constant	0.5583	0.7743	0.721	0.4715	-0.9659	2.0825
L1. Patent-Type Firms	0.0038	0.0045	0.8413	0.4009	-0.0051	0.0126
Firms with UAV in Business Scope	-0.0019	0.0011	-1.6767	0.0947	-0.0041	0.0003
'Specialized & New' Firms (scope)	-0.3489	0.1864	-1.8723	0.0622	-0.7158	0.0179
'Specialized & New' Firms (patents)	0.1999	0.1429	1.3994	0.1628	-0.0813	0.4811
High-Tech Firms (scope)	0.0995	0.0411	2.4171	0.0163	0.0185	0.1804
High-Tech Firms (patents) [cleaned]	0.0305	0.0152	2.0097	0.0454	0.0006	0.0604
Certified Airports (interpolated)	-0.0553	0.0892	-0.6197	0.5359	-0.2308	0.1203
Policy Pilot	0.1112	0.2434	0.4569	0.6481	-0.3679	0.5903
Upstream Firms	0.118	0.0458	2.575	0.0105	0.0278	0.2083
Downstream Firms	0.3811	0.258	1.4772	0.1407	-0.1267	0.8889

Notes: Included effects: Entity, Time. F test for poolability: 1.1835 (p=0.2204).

6) Poisson Regression (With Controls)

Metric	Value
Dependent variable	Midstream Firms
Pseudo R-squared	0.3034
Observations	360
Converged	True
Log-Likelihood	-465.29 (LL-Null: -667.89)
LLR p value	2.984e-79
Covariance Type	Nonrobust

Variable	Coef.	Std. Err.	z-Stat	P>|z|	CI 2.5%	CI 97.5%
Constant	-0.0286	0.134	-0.214	0.831	-0.291	0.234
Patent-Type Firms	0.0069	0.003	2.09	0.037	0.0	0.013
Index (serial number)	-0.0147	0.007	-2.164	0.03	-0.028	-0.001
Firms with UAV in Business Scope	-0.0008	0.0	-2.163	0.031	-0.001	-7.28e-05
'Specialized & New' Firms (scope)	-0.1794	0.06	-2.989	0.003	-0.297	-0.062
'Specialized & New' Firms (patents)	0.0412	0.017	2.439	0.015	0.008	0.074
High-Tech Firms (scope)	0.0284	0.013	2.271	0.023	0.004	0.053
High-Tech Firms (patents) [cleaned]	0.0049	0.008	0.607	0.544	-0.011	0.021
Certified Airports (interpolated)	-0.0045	0.014	-0.331	0.741	-0.031	0.022
Policy Announced [cleaned]	-0.491	0.166	-2.956	0.003	-0.816	-0.165
Policy Pilot	-0.4621	0.314	-1.471	0.141	-1.078	0.154
Upstream Firms	0.0251	0.022	1.138	0.255	-0.018	0.068
Downstream Firms	0.1247	0.063	1.985	0.047	0.002	0.248

7) Negative Binomial Regression (With Controls)

Metric	Value
Dependent variable	Midstream Firms
Pseudo R-squared	0.1881
Observations	360
Converged	False
Log-Likelihood	-463.67 (LL-Null: -571.08)
LLR p value	2.811e-39
Covariance Type	Nonrobust

Variable	Coef.	Std. Err.	z-Stat	P>|z|	CI 2.5%	CI 97.5%
Constant	-0.0835	0.148	-0.565	0.572	-0.373	0.206
Patent-Type Firms	0.0075	0.004	2.084	0.037	0.0	0.015
Index (serial number)	-0.0142	0.007	-1.966	0.049	-0.028	-4.63e-05
Firms with UAV in Business Scope	-0.0008	0.0	-2.147	0.032	-0.002	-7.3e-05
'Specialized & New' Firms (scope)	-0.1997	0.072	-2.786	0.005	-0.34	-0.059
'Specialized & New' Firms (patents)	0.0464	0.02	2.352	0.019	0.008	0.085
High-Tech Firms (scope)	0.0308	0.014	2.239	0.025	0.004	0.058
High-Tech Firms (patents) [cleaned]	0.0042	0.009	0.478	0.633	-0.013	0.021
Certified Airports (interpolated)	-0.0031	0.014	-0.219	0.827	-0.031	0.025
Policy Announced [cleaned]	-0.4757	0.174	-2.738	0.006	-0.816	-0.135
Policy Pilot	-0.4819	0.323	-1.49	0.136	-1.116	0.152
Upstream Firms	0.0249	0.027	0.907	0.364	-0.029	0.079
Downstream Firms	0.1521	0.077	1.977	0.048	0.001	0.303
Alpha (dispersion)	0.0861	0.056	1.528	0.127	-0.024	0.197