Data-Factor Marketization and the Efficiency of Urban Innovation Conversion

A Quasi-natural Experiment Based on the Establishment of Data Trading Platforms

Manfei Zhu*

Nankai University, Tianjin, China

*its.manfei@gmail.com

Abstract. Using panel data for Chinese prefecture-level and above cities from 2010 to 2022, this paper treats the establishment of data trading platforms as a quasi-natural experiment and estimates a staggered difference-in-differences model. The reform does not significantly expand patent applications or alter patent-type structure, but it raises lagged invention-patent grant-conversion ratios. The result survives additional controls, endogeneity checks, parallel-trend and placebo tests, alternative definitions, wild-cluster bootstrap inference, and leave-one-province-out tests. Effects are stronger in cities with severe pre-policy conversion bottlenecks and are consistent with an information-matching channel proxied by digital finance. Data-factor marketization therefore appears to improve the conversion of higher-threshold applications into granted innovation outputs rather than simply increasing filing volume.

Keywords: data-factor marketization; data trading platforms; innovation conversion efficiency; invention patents; staggered difference-in-differences

1 Introduction

As the digital economy deepens, data have become an allocable and tradable production factor. In China, data trading platforms combine registration, metadata cataloging, access authentication, compliance review, matching, and secure circulation. The central question is whether this institutional infrastructure expands visible innovation activity or improves the conversion of applications into recognized technological output.

Patent counts remain common measures of regional innovation, but they may reflect filing incentives rather than realized quality or value, and patents differ markedly in technological and economic significance (Griliches, 1990)[7]; (Schankerman & Pakes, 1986)[16]; (A. T. Xu et al., 2022)[18]; (Y. Xu et al., 2022)[22]. If data-market reform mainly improves information flows and resource matching, its effect should be more visible in application-to-grant conversion than in filing volume.

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Unlike subsidies, tax incentives, or R&D grants, data-factor marketization is a digitally enabled institutional reform. By clarifying rights, circulation rules, pricing, governance, and secure exchange, it can reduce information frictions through standardized interfaces, traceable transactions, and platform-based matching without immediately increasing patent filings.

This distinction is especially relevant for invention patents, which face higher technical thresholds and stricter examination than utility models. Because current grants typically originate from earlier applications, lagged grant-conversion ratios provide a cleaner measure of conversion efficiency than same-year ratios.

Existing studies link data-factor marketization to digital transformation, financing constraints, innovation quality, specialized SMEs, urban resilience, green growth, and high-tech innovation. Less is known about which stage of the innovation process is affected or how data platforms reshape matching among innovators, financial institutions, IP service providers, and technology markets.

The analysis uses a 2010-2022 city panel and defines treatment at the provincial level. Although platforms are physically located in specific cities, rules for data rights, public-data opening, transaction standards, and security governance often operate province-wide; treatment therefore captures a regional data-market environment rather than a narrow construction effect.

The estimates show no significant increase in patent applications or systematic change in patent-type structure. The principal effect is a higher lagged invention-patent grant-conversion ratio, including after controlling for lagged application scale, with larger gains where pre-policy conversion bottlenecks were more severe.

2 Literature Review and Research Hypotheses

2.1 Literature Review

This study relates to three literatures. The first examines the economic properties of data and the institutions needed to realize its value. Data are non-rival, reusable, and scalable (Jones & Tonetti, 2020)[10], but these features generate economic value only when secure circulation, credible exchange, pricing, and governance are available (Xu & Zhao, 2020)[20]; prior work also links data to R&D personnel, ICT capital, market integration, and productivity (Fan et al., 2026)[5]; (Xu et al., 2023)[21]; (Lin et al., 2026)[12]; (Zhang et al., 2026)[25]. Related work examines big data, firm dynamics, firm performance, and precise innovation (Farboodi et al., 2019)[6]; (Muller et al., 2018)[13]; (Yin et al., 2025)[24].

The second literature treats data trading platforms as quasi-natural experiments and documents effects on digital transformation (Xu & Wang, 2024)[23], financing constraints (Ouyang & Hu, 2024)[14], innovation quality (Xu et al., 2025)[19], specialized SMEs (Cui & Da, 2025)[2], urban resilience (Zheng & Chen, 2023)[26], and green growth (Dong et al., 2025)[4]. Related research examines key core technology innovation (Deng et al., 2025)[3]. These studies establish platform formation as an identifiable policy shock but rarely examine city-level conversion from applications to granted invention patents.

The third literature concerns innovation measurement and patent-grant lags. Patent counts are convenient but imperfect because patent quality and value vary widely (Griliches, 1990)[7]; (Schankerman & Pakes, 1986)[16]; (Hall et al., 2005)[8], while grant lags reflect technical complexity, review capacity, and institutional procedures (Harhoff & Wagner, 2009)[9]; (Popp et al., 2004)[15]; (Wen, 2012)[17]. Distinguishing scale, structure, and conversion therefore permits a more precise assessment of data-market reform.

2.2 Theoretical Mechanisms and Research Hypotheses

Data-factor marketization may reduce information frictions, transaction costs, and resource mismatches among innovators, data providers, financial institutions, service agencies, and governments. Searchable catalogs, standardized products, digital identity verification, compliance records, and transaction traces can improve the environment in which earlier invention applications become granted patents.

Hypothesis 1: Data-factor marketization increases the lagged grant-conversion ratio of urban invention patents.

The effect should be stronger where pre-policy conversion bottlenecks are more severe. Low-conversion cities are more likely to have incomplete innovation services, weak technology-information matching, and limited financial support, giving improved data circulation and allocation greater marginal value.

Hypothesis 2: The positive effect of data-factor marketization on the lagged grant-conversion ratio of urban invention patents is stronger in cities with more severe pre-policy innovation-conversion bottlenecks.

Digital finance provides a plausible information-matching channel. Better data availability and usability can help financial institutions assess firms' operations, R&D capacity, and credit risk; because patent examination requires sustained expenditure and professional services, improved financing and matching may support conversion.

Hypothesis 3: Data-factor marketization increases the lagged grant-conversion ratio of urban invention patents partly by promoting digital finance and improving the information-matching environment.

3 Research Design

3.1 Institutional Background and Identification Strategy

Data trading platforms provide registration, compliance review, matching, product display, pricing, and transaction governance, turning dispersed data resources into assets circulated under formal digital procedures. Their operation relies on data-management systems, metadata standards, secure access control, traceability, and interoperability.

The empirical strategy estimates a staggered difference-in-differences model. Treatment is defined at the provincial level because platform effects may diffuse through provincial rules, public-data governance, transaction norms, security standards, and intercity linkages; the platform is thus treated as regional institutional infrastructure.

3.2 Model Specification

To test the effect of data-factor marketization on urban innovation conversion efficiency, the baseline regression model is specified as follows:

$$Y_{ipt} = \alpha + \beta\, DidProv_{pt} + \gamma\, X_{it} + \mu_i + \lambda_t + \varepsilon_{ipt} \quad (1)$$

Here, i, p, and t denote city, province, and year. The dependent variable captures innovation scale, patent structure, or conversion. The treatment indicator equals one after a city's province establishes a data trading platform. City-level controls are included, city and year fixed effects absorb time-invariant heterogeneity and common shocks, and standard errors are clustered by province.

3.3 Variable Definitions

Dependent variables. Innovation is measured by scale (log total and invention-patent applications), structure (patent-type shares), and conversion (lagged invention-patent grant-conversion ratios).

Because invention patents involve examination lags, current grants are divided by lagged applications rather than current applications:

$$GrantRateInvLk_{it} = \frac{GrantInv_{it}}{ApplyInv_{i,t-k}}, \quad k = 1,2,3 \quad (2)$$

Current invention-patent grants are divided by applications lagged one, two, or three years, capturing how earlier filings translate into later grants. Because the measure uses city-year aggregates rather than patent-level links, baseline ratios are winsorized at the 1st and 99th percentiles.

Core explanatory variable. The treatment indicator equals one for cities in a province after a data trading platform is established and zero otherwise.

Control variables include log per capita GDP, R&D intensity, log population, and the tertiary-sector share. To reduce confounding from related policies, the regressions also control for smart-city pilots, Broadband China pilots, and innovative industrial-cluster policies where relevant. Related studies examine the innovation effects of national policies and regional innovation environments (Chen et al., 2022)[1]; (Li & Wang, 2024)[11].

3.4 Data Sources and Sample Construction

The sample covers Chinese prefecture-level and above cities from 2010 to 2022. Patent data are compiled from public intellectual-property sources and aggregated to city-years; platform dates are manually collected from public information; socioeconomic controls mainly come from statistical yearbooks and official releases.

City names and administrative divisions are standardized, severely incomplete observations are removed, and patent, socioeconomic, platform, and policy variables are matched at the city-year level. Untrimmed conversion measures are used in robustness tests.

3.5 Descriptive Statistics

Descriptive statistics are reported in Table 1. About 34.8 percent of city-year observations are exposed to data-factor marketization. The mean log values of total and invention-patent applications are 7.578 and 6.254, while the mean lag-1, lag-2, and lag-3 invention-patent grant-conversion ratios are 0.309, 0.365, and 0.436.

Table 1. Descriptive statistics

Variable	N	Mean	SD	Min	Max
Data-market policy	4517	0.348	0.476	0.000	1.000
ln total apps	3900	7.578	1.898	0.000	12.679
ln invention apps	3900	6.254	1.952	0.000	12.063
Inv conversion L1	3570	0.309	0.148	0.000	0.758
Inv conversion L2	3272	0.365	0.174	0.022	0.875
Inv conversion L3	2974	0.436	0.227	0.023	1.209
ln invention grants	3900	4.831	2.001	0.000	11.387
ln GDP pc	3861	10.695	0.577	8.672	12.591
R&D intensity	3861	0.015	0.030	0.000	0.936
Population size (log)	3874	14.991	0.903	5.991	17.285
Share of tertiary industry	4325	0.427	0.103	0.098	0.839

Note: Conversion ratios are winsorized at the 1st and 99th percentiles. Log variables use ln(x+1).

4 Baseline Regression Results

The baseline analysis separates innovation scale, patent structure, and application-to-grant conversion. The evidence rejects a quantity-expansion interpretation and instead points to improved conversion of invention patents.

4.1 Data-Factor Marketization and Innovation Scale

Table 2 shows no significant effect on total or invention-patent applications: the treatment coefficients are -0.1029 and -0.0826. This is consistent with a reform that improves information and matching rather than directly subsidizing R&D or filing.

Table 2. Data-factor marketization and innovation outcomes

Variable	Total apps	Inv apps	Overall eff.	Inv eff.	Utility share	Inv share
Data-market policy	-0.1029	-0.0826	0.0384*	0.0304*	0.0092	-0.0093
	(0.0688)	(0.0879)	(0.0217)	(0.0160)	(0.0201)	(0.0234)
Observations	3822	3822	3818	3813	3818	3818
Adj. R-squared	0.9658	0.9499	0.2806	0.3451	0.6374	0.5712

Note: Province-clustered SEs in parentheses. *, **, *** denote 10%, 5%, and 1% significance. City/year fixed effects and city controls included.

4.2 Data-Factor Marketization and Innovation Structure

Columns (5) and (6) of Table 2 show no systematic shift in patent-type shares: the utility-model and invention-patent share coefficients are 0.0092 and -0.0093. Same-year grant/application measures are only preliminary because current grants do not strictly correspond to current applications.

4.3 Data-Factor Marketization and Lagged Invention-Patent Grant-Conversion Ratios

Table 3 sharpens the interpretation. All-patent estimates are unstable and insignificant, whereas invention-patent coefficients for lag-1, lag-2, and lag-3 conversion are 0.0469, 0.0514, and 0.0576, significant at the 1, 1, and 5 percent levels. Relative to sample means, these correspond to increases of about 15.2, 14.1, and 13.2 percent.

The reform therefore appears to improve the conversion of higher-threshold invention patents, whose grants depend more heavily on technology maturity, resource allocation, and professional services.

Table 3. Lagged grant-conversion ratios

Variable	Overall L1	Overall L2	Overall L3	Inv L1	Inv L2	Inv L3
Data-market policy	0.0435	0.0246	-0.0010	0.0469***	0.0514***	0.0576**
	(0.0287)	(0.0575)	(0.0939)	(0.0155)	(0.0183)	(0.0224)
Observations	3525	3232	2939	3520	3227	2934
Adj. R-squared	0.4288	0.3012	0.2933	0.4169	0.5009	0.4441

Note: Province-clustered SEs in parentheses. *, **, *** denote 10%, 5%, and 1% significance. City/year fixed effects, city controls, and policy controls included.

Table 4 controls for lagged application scale in regressions for log grants. All-patent specifications remain insignificant, while invention-patent coefficients are 0.1328, 0.1222, and 0.0829. Lagged applications are strongly positive, but the policy retains an independent association with invention-patent grants.

These coefficients imply approximate grant increases of 14.2, 13.0, and 8.6 percent, reducing concern that the conversion results are driven by denominator changes.

Table 4. Grant outcomes with lagged applications controlled

Variable	Overall L1	Inv L1	Overall L2	Inv L2	Overall L3	Inv L3
Data-market policy	0.0552	0.1328***	0.0028	0.1222***	-0.0175	0.0829*
	(0.0403)	(0.0463)	(0.0504)	(0.0438)	(0.0519)	(0.0482)
Lagged apps	0.7667***	0.4312***	0.4741***	0.4579***	0.2404***	0.3160***
	(0.0465)	(0.0367)	(0.0385)	(0.0334)	(0.0320)	(0.0306)
Observations	3529	3529	3236	3236	2943	2943
Adj. R-squared	0.9889	0.9709	0.9785	0.9742	0.9758	0.9719

Note: Province-clustered SEs in parentheses. *, **, *** denote 10%, 5%, and 1% significance. Dependent variables are log grants.

5 Robustness Tests

5.1 Parallel-Trend Test

The event-study specification tests whether treated and control cities followed similar pre-policy trends. The year before platform establishment is the reference period; insignificant lead coefficients support identification, while post-policy coefficients describe the reform's dynamic effect.

The year before platform establishment is the reference period. The event-study model is:

$$Y_{ipt} = \alpha + \sum_{k\neq -1} \delta_k D_{pt}^{k} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{ipt} \quad (3)$$

Pre-policy coefficients test whether treated and control cities diverged beforehand, while post-policy estimates trace reform dynamics; insignificant pre-policy effects support the identifying parallel-trends assumption.

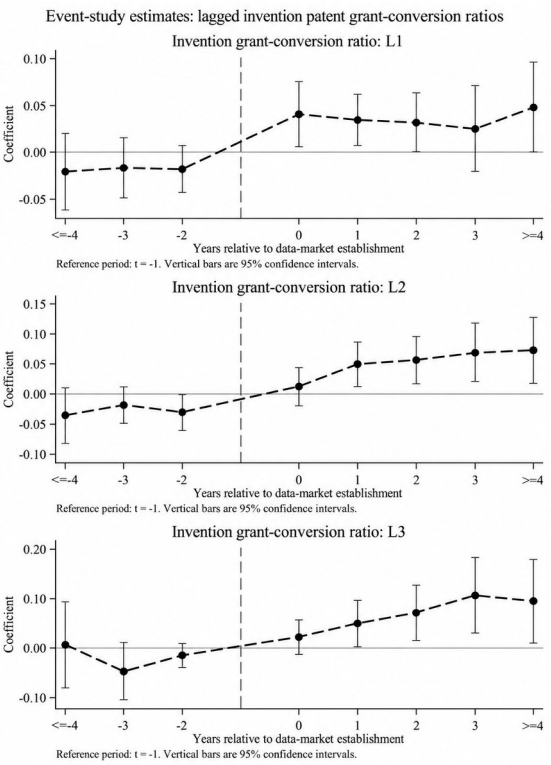


Fig. 1. Parallel-trend test: lagged invention-patent grant-conversion ratios

Figure 1 and Table 5 show no systematic pre-policy divergence. The post-policy estimates turn positive, consistent with a gradual reform effect.

The placebo test randomly assigns pseudo treatment groups and policy years over 500 replications. Estimates cluster near zero rather than the actual coefficients, indicating that the baseline results are unlikely to reflect random fluctuations or mechanical correlation.

Table 5. Joint tests of pre-policy trends

Dependent variable	F statistic	p-value	Observations	Adj. R-squared
Inv conversion L1	0.688	0.567	3520	0.417
Inv conversion L2	1.747	0.179	3227	0.505
Inv conversion L3	1.171	0.337	2934	0.452

Note: Joint tests for pre-policy indicators. City/year fixed effects, city controls, and policy controls included.

5.2 Placebo Test

The placebo test randomly assigns pseudo treatment groups and policy years and repeats the regression 500 times. If the baseline result reflected random fluctuations or mechanical correlation, pseudo policies would often produce estimates close to the actual one. As shown in Table 6, placebo estimates are concentrated near zero.

Table 6. Placebo tests

Dependent variable	Actual estimate	Mean placebo estimate	Empirical p-value
Inv conversion L1	0.0469	0.0003	0.000
Inv conversion L2	0.0514	-0.0001	0.010
Inv conversion L3	0.0576	0.0008	0.086
ln invention grants	0.1222	0.0013	0.014

Note: 500 placebo replications. The grant model controls lag-2 invention applications.

5.3 Alternative Variable Definition

As shown in Table 7, using untrimmed ratios yields lag-1, lag-2, and lag-3 coefficients of 0.0511, 0.0517, and 0.0552, all positive and significant. The result is therefore not driven by winsorization or a particular lag window.

Table 7. Untrimmed lagged invention-patent conversion ratios

Variable	Invention L1	Invention L2	Invention L3
Data-market policy	0.0511***	0.0517**	0.0552**
	(0.0159)	(0.0191)	(0.0245)
Observations	3520	3227	2934
Adj. R-squared	0.358	0.457	0.327

Note: Province-clustered SEs in parentheses. *, **, *** denote 10%, 5%, and 1% significance. L1-L3 indicate denominator lags.

5.4 Control Variables and Endogeneity Checks

Additional specifications address omitted variables, reverse causality, and policy selection. The preferred lag-2 coefficient remains positive without controls, with city controls, with smart-city, Broadband China, and industrial-cluster controls, and with pre-policy innovation foundations interacted with year effects: 0.0480, 0.0514, 0.0514, and 0.0343.

Earlier platform adoption by stronger innovation systems could generate reverse causality. Staggered DID, lagged outcomes, fixed effects, controls, province trends, and pre-policy innovation-base interactions mitigate this concern by focusing on changes around the platform shock rather than permanent technological differences.

Lead placebo tests fail to reject joint insignificance for lag-1, lag-2, and lag-3 outcomes ($p = 0.4918$, 0.1816, and 0.2676), and province-level selection tests show no stable evidence that higher pre-policy conversion predicts earlier adoption.

5.5 Statistical Inference and Sample-Sensitivity Tests

Because treatment varies by province and the number of clusters is limited, Table 8 reports wild-cluster bootstrap inference and leave-one-province-out tests. Bootstrap p-values are 0.006, 0.014, and 0.028 for the three conversion outcomes and 0.014 for log invention grants; all leave-one-province-out estimates remain positive.

Table 8. Inference and sample sensitivity

Dependent variable	Wild bootstrap p-value	Leave-one-province-out coefficient range
Inv conversion L1	0.006	[0.0387, 0.0529]
Inv conversion L2	0.014	[0.0396, 0.0564]
Inv conversion L3	0.028	[0.0442, 0.0680]
ln invention grants	0.014	[0.0944, 0.1361]

Note: Wild bootstrap uses 499 replications; leave-one-province-out ranges report coefficient minima and maxima.

6 Further Analysis: Heterogeneity and Mechanisms

Further analysis examines heterogeneity by pre-policy conversion bottlenecks and an information-matching mechanism proxied by digital finance.

6.1 Heterogeneity under Innovation-Conversion Bottlenecks

If the reform improves information and resource matching, gains should be larger where applications initially converted less efficiently. Such cities likely had weaker innovation services, IP support, financing, and technology-information matching.

High-bottleneck cities are identified by low pre-policy invention-patent conversion. The interaction model is specified as follows:

$$Y_{ipt} = \alpha + \beta_0 DidProv_{pt} + \beta_1(DidProv_{pt} \times HighGap_i) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{ipt} \quad (4)$$

The treatment coefficient captures the effect in low-bottleneck cities; its interaction with the high-bottleneck indicator measures the additional effect, and their sum gives the total high-bottleneck effect.

Table 9. Heterogeneity by conversion bottlenecks

Dependent variable	Low effect	High add-on	High total	N
Inv conversion L1	-0.0003 (0.0162)	0.0860*** (0.0130)	0.0857*** (0.0160)	3520
Inv conversion L2	0.0127 (0.0211)	0.0701*** (0.0169)	0.0829*** (0.0184)	3227
Inv conversion L3	0.0438 (0.0320)	0.0249 (0.0262)	0.0686*** (0.0189)	2934
ln inv grants + lagged apps	0.0384 (0.0485)	0.1521*** (0.0376)	0.1905*** (0.0490)	3236

Note: SEs in parentheses. *, **, *** denote 10%, 5%, and 1% significance. High-bottleneck cities have low pre-policy conversion.

Table 9 shows that effects are concentrated in high-bottleneck cities. For lag-1 and lag-2 conversion, low-bottleneck effects are insignificant, while interaction terms are 0.0860 and 0.0701, both significant at 1 percent. Total high-bottleneck effects are 0.0857 and 0.0829, indicating that the reform primarily repairs conversion bottlenecks.

6.2 Digital Finance and the Information-Matching Mechanism

The digital inclusive finance index proxies for information infrastructure, financial availability, and credit-recognition capacity. By improving data circulation and usability, data markets may reduce information asymmetry among innovators, financial institutions, and service providers through data analytics, online credit records, platform interfaces, and algorithm-assisted risk identification.

$$M_{ipt} = \alpha + \theta\, DidProv_{pt} + \gamma\, X_{it} + \mu_i + \lambda_t + \varepsilon_{ipt} \quad (5)$$

$$Y_{ipt} = \alpha + \beta\, DidProv_{pt} + \rho\, M_{ipt} + \gamma\, X_{it} + \mu_i + \lambda_t + \varepsilon_{ipt} \quad (6)$$

The mechanism test first estimates whether data-factor marketization improves digital finance and then adds the index to the conversion model. It is interpreted as supportive evidence rather than a full causal decomposition.

Data-factor marketization raises the digital inclusive finance index by 2.3813, significant at 5 percent. As shown in Table 10, after the index is included, the policy coefficient remains positive and significant; digital finance is insignificant at shorter lags but positive and significant in the lag-3 conversion and grant specifications.

Table 10. Digital finance mechanism

Dependent variable	Baseline policy	With digital finance	Digital finance	N
Inv conversion L1	0.0469*** (0.0155)	0.0459*** (0.0158)	0.0004 (0.0007)	3505
Inv conversion L2	0.0514*** (0.0183)	0.0500** (0.0188)	0.0008 (0.0009)	3212
Inv conversion L3	0.0576** (0.0224)	0.0542** (0.0228)	0.0025** (0.0012)	2921
ln inv grants + lagged apps	0.1222*** (0.0438)	0.1089** (0.0416)	0.0053** (0.0022)	3221

Note: SEs in parentheses. *, **, *** denote 10%, 5%, and 1% significance. Mechanism variable: digital inclusive finance index.

7 Conclusions and Policy Implications

Treating data trading platform establishment as a quasi-natural experiment, this paper finds no significant expansion of patent applications or change in patent-type structure, but a robust increase in lagged invention-patent grant-conversion ratios, including after controlling for lagged application scale. The evidence is consistent with a digitally mediated institutional reform that improves information processing, data circulation, and innovation-resource matching, especially in cities with severe conversion bottlenecks.

7.1 Policy Implications

Policy should shift from platform establishment to effective operation. Platforms require reliable data-management systems, credible rules for rights and pricing, secure access control, metadata standards, interoperability, public-data opening, and traceable circulation. They should connect with technology markets, IP platforms, science-and-technology finance, and industrial innovation systems through interoperable interfaces and shared evaluation tools.

Cities with weak grant conversion should receive targeted support in public-data openness, IP services, digital finance, and professional innovation services; stronger cities should prioritize high-quality datasets, cross-regional collaboration, privacy protection, and higher-value outcomes.

7.2 Limitations and Future Research

Three limitations remain. Platform establishment does not measure transaction scale, data-product quality, or actual use; aggregate lagged conversion does not capture commercialization through transfer or licensing; and city-level data cannot identify firm- or patent-level mechanisms. Future research could combine platform transactions, firm-patent links, licensing records, technology-market transactions, and longer panels.

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