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Policy Implications of Data Element Marketization for Urban Green Development: A Concise Evidence-Based Report from China

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Abstract: *This paper investigates the impact of data element marketization on urban green development in China, using the staggered establishment of Big Data Trading Platforms in 269 prefecture-level cities as a quasi-natural experiment. Employing a staggered difference-in-differences (DID) approach, the results show that data element marketization significantly promotes urban green development, particularly by enhancing green technological innovation and FinTech development. The effect is stronger in cities with greater fiscal decentralization, lower fiscal pressure, more advanced market systems, and higher public environmental awareness. Moreover, the influence of local governments' economic and environmental targets is found to be critical in shaping the green outcomes. This study contributes to the understanding of digital factors in sustainable urban governance and offers practical insights for future policy design in the digital economy era.*

Keywords: *Data Element Marketization; Urban Green Development; Green Technological Innovation; Fintech*

1. Introduction

In recent years, with mounting environmental pressures, Chinese cities face an urgent need to strike a new balance between economic growth and green transformation. Against the backdrop of the digital economy, the marketization of data elements has emerged as a key driver of urban green development (Zheng et al., 2024; Kong et al., 2021) [1][2]. As a new type of production factor, the efficient circulation of data not only optimizes resource allocation but also offers new tools for green technological innovation and environmental governance. Existing research has highlighted that green technological innovation plays a central role in promoting urban green development by enabling energy conservation, emissions reduction, and industrial upgrading (Li & Li, 2021; Xiao et al., 2022) [3][4]. Meanwhile, the development of digital finance helps alleviate financing constraints and improves the efficiency of green investments, thereby enhancing cities' financial capacity to support sustainable transformation (Guo et al., 2020; Fang & Yang, 2021) [5][6]. However, the effectiveness of data element marketization varies across cities, depending on fiscal structure, market development level, and public environmental participation. Moreover, local governments' policy preferences—as reflected in their economic growth and environmental targets—may significantly influence the green effects of data element marketization (Yu et al., 2019; Li et al., 2020) [7][8]. In regions with overly ambitious growth targets, environmental concerns may be sidelined, whereas in areas with stronger environmental constraints or more flexible target-setting, data elements are more likely to fulfill their green potential. This study uses a quasi-natural experiment based on the phased establishment of big data trading platforms in 269 prefecture-level cities in China since 2014, applying a staggered difference-in-differences (DID) approach (Goodman-Bacon, 2021) [9]to evaluate the impact of data element marketization on urban green development. It further investigates the mediating roles of green technological innovation and FinTech development (Jiang, 2022) [10]. By doing so, this paper contributes to the theoretical framework linking the digital economy with green development and provides empirical support and policy insights for achieving high-quality, sustainable urban development under China's "dual carbon" goals.

2. Data and methods

2.1 Model Construction

This study focuses on prefecture-level and above cities in China, using panel data from official sources. Cities with significant data gaps were excluded from the analysis. As data element marketization was introduced at different times across cities, this allowed for a staggered evaluation of its impact. A difference-in-differences (DID) approach was employed to compare outcomes between cities that adopted the reforms at different times, isolating the specific impact of the marketization changes. Missing values were addressed to ensure the reliability and completeness of the data. By emphasizing practical applications in urban sustainability and green governance, this approach provides valuable insights for policy evaluation and urban planning. The model specification is as follows:

$$UGD_{it}=\alpha+\beta Mde_{it}+\delta control_{it}+\mu_i+\gamma_i+\varepsilon_{it} \quad (1)$$

In equation (1), i is the i—th city, and t represents the year, UGD_{it}denotes urban green development for city i in year t, $Mde_{it}$is the proxy variable for data element marketization, $control_{it}$represents the set of control variables, μ_i and γ_i denote city fixed effects and time fixed effects and respectively, ε_{it} (1) is the random disturbance term.

The key explanatory variable in this study is "data element marketization" (Mde_{it}), and the significance and direction of its coefficient (β) are crucial for hypothesis testing. A statistically significant positive β suggests that data element marketization positively contributes to urban green development, supporting Hypothesis 1. Conversely, an insignificant or negative β implies no effect or an inhibitory impact, leading to rejection of the hypothesis. The absolute magnitude of β indicates the strength of the effect, with a larger absolute value signifying a greater impact of marketization on green development.

This study also addresses endogeneity and heterogeneity bias. Endogeneity may arise because data element marketization is not entirely exogenous—its implementation may be influenced by pre-existing conditions, such as digital infrastructure development, leading to potential sample selection bias. To mitigate this, we use the instrumental variable (IV) method, with an interaction term between the 1988 "Eight Vertical and Eight Horizontal" national fiber optic network node policy and the annual mean number of data element marketization projects across prefecture-level cities as the instrument, strengthening the robustness of our estimates. Heterogeneity bias is another concern, as data element marketization was implemented gradually, with earlier adopters potentially distorting estimates for later adopters. To address this, we apply Goodman-Bacon (2021)'s decomposition method, breaking down the estimated regression coefficients into multiple 2×2 DID subgroups, which further validates the staggered DID approach and ensures the accuracy and reliability of our results.

2.2 Variable Selection

2.2.1 Dependent Variable: Urban Green Development

Urban green development is commonly measured using index systems or efficiency measurement methods (Wang et al., 2023; Wei & Hou, 2022). Efficiency methods, such as Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), are widely used. Compared to SFA, DEA evaluates multiple inputs and outputs simultaneously. However, traditional DEA models are limited by radial and angular constraints, failing to account for slack improvements. To address this, this study adopts the Super-SBM (Slack-Based Measure) model, an enhancement of the non-radial, non-angular SBM model by Tone (2002). Following Wei & Hou (2022), a newly designed indicator system for urban green development is used, as outlined in Table 1.

(1) Input Indicators: The study incorporates three dimensions—labor, capital, and resource inputs. Capital input is measured by fixed asset capital stock, estimated at the city level using the perpetual inventory method (Zhang et al., 2004), adjusted for the 2000 baseline and city-specific investment indices. Labor input is based on the number of employed persons each year. Resource input includes urban construction land area, total water supply, and electricity consumption.

(2) Expected Outputs: Economic growth is measured by real GDP (adjusted to 2000 constant prices), social equity by urban residents' average wages (adjusted for CPI based on the 2000 benchmark), and environmental greening by urban park green space area, reflecting ecological sustainability.

(3) Undesirable Outputs: Undesirable outputs focus on pollutant emissions to capture the environmental burden of urban industrial activities. Indicators include industrial wastewater discharge, sulfur dioxide (SO_2) emissions, and industrial smoke (dust) emissions, providing a comprehensive evaluation of the negative environmental impacts of urban development. The specific measurement indicators are presented in Table 1.

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Table 1: Measurement System for Urban Green Development in China

Primary Indicators	Secondary indicators	Tertiary indicators
Input Indicators	capital input	Capital stock of fixed assets
	Labor input	Number of employed persons at year-end
	Resource input	Urban construction land area
		Total water supply
		Total electricity consumption
Expect output indicators	Economic development	Regional GDP
	Social Equity	Average wage of urban residents
	Environmental greening	Park green area
Undesired output indicators	Pollutant emissions	Industrial wastewater discharge volume
		Industrial sulfur dioxide emissions
		Industrial smoke and dust emissions

Source: National Bureau of Statistics of China, Urban Social Survey Division. China Urban Statistical Yearbook. China Statistics Press, 2007–2020.

2.2.2 Core Explanatory Variable: Data Element Marketization (Mde_{it})

Existing studies often use the establishment of Big Data Trading Platforms as an exogenous shock to measure data element marketization (Zhao et al., 2024; Zheng et al., 2024) [1]. Following this approach, this study constructs a measurement framework using an interaction term between the Big Data Trading Platform establishment year dummy variable and the policy dummy variable. Specifically, the establishment year dummy variable is defined with 2015 as the reference point, where cities are assigned 0 before establishment and 1 after establishment, while the policy dummy variable distinguishes between cities with and without a platform, assigning 0 to cities without a platform and 1 to those with a platform. The final measure is the interaction of these two dummy variables, allowing for a robust identification of the effects of data element marketization.

2.2.3 Control Variables

Urban green development is influenced by various factors, and failure to control for these may cause endogeneity due to omitted variable bias. To ensure robustness, this study includes several control variables. Degree of openness to trade (Open) is measured by the ratio of imports and exports to regional GDP, adjusted by exchange rates. Human capital stock (Human) is represented by the number of enrolled students in higher education, with a logarithmic transformation. Industrial structure rationalization (Structure) is assessed using the Theil index, following Gan et al. (2011). Government intervention (Gov) is captured by the ratio of government fiscal expenditure to GDP. Economic development level (Gdp) is measured by real GDP, also log-transformed. Urbanization level (Urban) is evaluated by the ratio of the urban permanent population to the total permanent population. Financial development (Finance) is quantified as the ratio of total bank loans and deposits to GDP, log-transformed. Population size (Population) is measured by the total year-end population, with a logarithmic transformation for consistency. A detailed description of these variables is provided in Table 2.

Table 2: Definitions of Key Variables

Variable Category	Variable Name	Variable Code	Definition & Measurement
Dependent variable	Urban green development	UGD	Defined using a newly designed indicator system in this study
Independent variable	Data Element Marketization	Mde	"Big Data Trading Platform" policy dummy variable, where cities without a platform are assigned 0, and cities with a platform are assigned 1
Control variables	Degree of Openness to Trade	Open	Ratio of total imports and exports (converted using exchange rates) to regional GDP (%)
	Human Capital Stock	Human	Number of enrolled students in higher education institutions, logarithmic transformation applied
	Industrial Structure Rationalization	Structure	Measured using the Theil index to assess the rationalization of industrial structure (%)
	Government intervention	Gov	Ratio of general government fiscal expenditure to regional GDP (%)
	Economic development level	Gdp	Measured by real GDP (billion yuan) at the city level
	Urbanization level	Urban	Ratio of urban permanent population to total permanent population (%)
	Financial development degree	Finance	Ratio of total bank loans and deposits to regional GDP (%)
	Population size	Population	Total population at end of year (100 million)

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2.3 Data Sources

This study utilizes panel data from 269 prefecture-level cities in China spanning the period 2007–2023 as the research sample. Data related to data element marketization were manually collected by the authors from provincial and municipal government websites as well as other relevant sources. The measurement data for urban green development were obtained from the National Bureau of Statistics of China, Urban Social Survey Division, including the China Urban Statistical Yearbook and other official publications. Data for control variables were sourced from the China Urban Statistical Yearbook, China Regional Economic Statistical Yearbook, provincial and municipal statistical yearbooks, and the EPS Database. Missing values were supplemented using linear interpolation, and winsorization was applied to certain indicators to mitigate the influence of outliers.

3. Results Analysis

3.1 Descriptive Statistics

This study performs a descriptive statistical analysis of key variables to summarize the basic characteristics of the sample. Table 3 presents the sample size, mean, standard deviation, minimum, and maximum values for each variable. The results show significant regional disparities in urban green development levels. Data element marketization is relatively low across the sample, though some cities have adopted these reforms. Trade openness exhibits broad variation, while human capital stock is concentrated but with a substantial gap between the highest and lowest values. Industrial structure rationalization varies across cities, reflecting diverse industrial development patterns. Government intervention levels are relatively concentrated, while economic development levels are stable. Urbanization levels show moderate variation, and financial development is widely distributed. Population size is relatively concentrated within the sample. A detailed summary of the descriptive statistics is provided in Table 3.

Table 3: Descriptive statistics of the key variables

variable	Sample size	Mean	Standard deviation	Minimum	Maximum
UGD	4570	0.3 46	0.1 44	0.103	1.1 95
Mde	4570	0.02 3	0.1 52	0	1
Open	4570	0.1 91	0. 311	0.002	1. 91 3
Human	4570	1 1 . 23	1. 661	4.522	1 4 . 8 2
Structure	4570	0.2 9 6	0. 240	-0.029	1. 812
Gov	4570	0.1 98	0. 112	0.043	1. 582
Gdp	4570	2.3 4 2	0. 085	1.525	2. 653
Urban	456 6	0.5 6 1	0. 182	0.115	1 .025
Finance	4570	0.7 8 7	0. 433	-0.531	3. 508
Population	4570	1. 9 67	0.1 44	1.064	2. 216

3.2 Benchmark regression

To examine the impact of data element marketization on urban green development, this study employs a staggered difference-in-differences (DID) model with year- and city-fixed effects, with regression results presented in Table 4. In Column (1), without control variables and fixed effects, the coefficient of data element marketization is significantly positive, indicating a positive impact on urban green development. Columns (2) to (4) progressively incorporate control variables, time-fixed effects, and city-fixed effects, while clustering standard errors at the city level. In all models, the coefficients for data element marketization remain positive and statistically significant at the 1% level, confirming its significant role in enhancing urban green development. These results support Hypothesis 1, demonstrating that data element marketization effectively promotes urban green development.

Table 4. Benchmark regression results

Variable	(1) UGD	(2) UGD	(3) UGD	(4) UGD
Mde	0.0 98***	0.0 44***	0.0 92***	0.0 92***
	(0.01 6)	(0.01 4)	(0.01 1)	(0.02 1)
Controlled variable	No	Yes	Yes	Yes
Year fixed effect	No	No	Yes	Yes
City fixed effect	No	No	Yes	Yes
Observations	4570	456 6	456 6	456 6
Adjusted R2	0.01 6	0.2 44	0. 201	0.2 15

Note: *, * * and * * * denote significance levels at 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses.

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3.3 Parallel Trend Test

A key requirement for accurately estimating the staggered difference-in-differences (DID) model is to verify whether the treatment group (cities that implemented data element marketization) and the control group (cities without implementation) followed a parallel trend in urban green development levels before the intervention. The parallel trend assumption ensures that any observed post-intervention differences can be attributed to data element marketization, rather than pre-existing variations in development trends. If, before the implementation of data element marketization, the treatment and control groups exhibit inconsistent trends in urban green development, it suggests the presence of a pre-treatment time trend, indicating that changes in green development levels may not be solely caused by data element marketization.To verify the validity of the staggered DID approach, this study uses the period immediately before policy implementation as the baseline period and constructs the test model shown in Equation (2) to examine the effects of data element marketization before and after implementation.

$$Y_{it}=\alpha+\beta_k\sum_{k=-3}^{k=6}D_{i.k}+\delta control_{it}+u_i+\gamma_t+\varepsilon_{it} \tag{2}$$

In the model, $D_{i.k}$represents a series of dummy variables, where D1—D3indicate the three periods before the implementation of data element marketization,D0represents the period of implementation, and D1—D6 denote the six post-implementation periods. This study sets the first pre-policy period D1 as the baseline period, meaning it is excluded from the regression model to serve as the reference point。The coefficient β_k captures the effect of data element marketization on urban green development. If β_k is statistically insignificant for k<0 (i.e., the pre-policy periods), it indicates that the parallel trend assumption holds, meaning that there were no pre-existing differences between the treatment and control groups before the policy was implemented. Conversely, if β_k is significant in pre-policy periods, it suggests that the treatment group exhibited a prior time trend, violating the parallel trend assumption. From the parallel trend test results reported in Figure1, the estimated coefficients for D2-3 are statistically insignificant, indicating that before the implementation of data element marketization, there was no significant difference in urban green development trends between the treatment and control groups. This confirms that the treatment group did not exhibit a pre-existing time trend, thereby satisfying the parallel trend assumption necessary for the validity of the staggered DID approach.

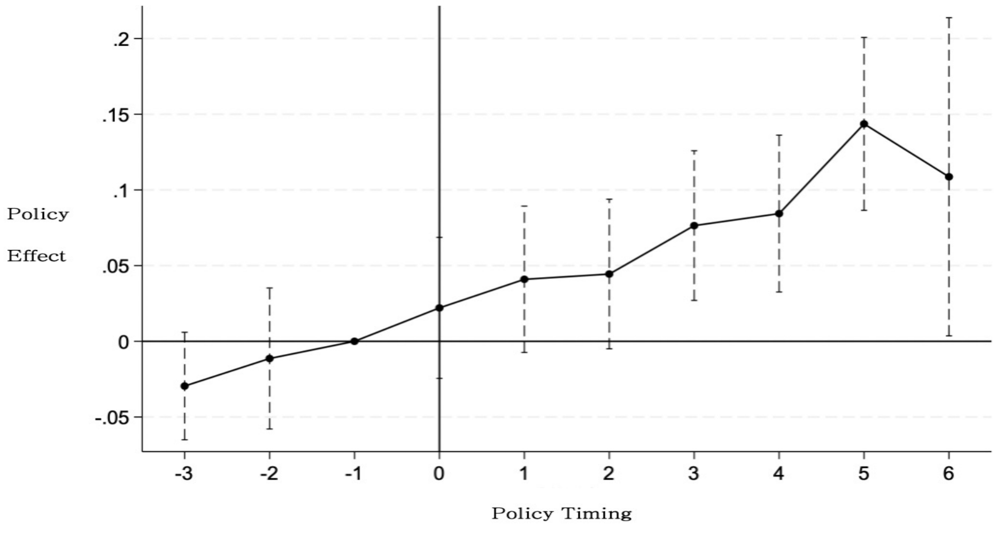

Figure 1: Parallel Trend Test Plot

4. Conclusion and suggestion

This study provides empirical evidence that the marketization of data elements significantly facilitates urban green development in China. Through green technology innovation and FinTech advancement, data flows improve environmental governance and enhance resource efficiency. These effects are more pronounced in regions with favorable governance conditions, such as fiscal autonomy and strong public

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environmental engagement. Additionally, the alignment of local government targets—balancing economic growth and environmental priorities—plays a crucial mediating role. The findings highlight the importance of integrating digital infrastructure with green policy strategies. To fully leverage data as a production factor, policymakers should improve data trading mechanisms, encourage innovation, and tailor governance strategies to local institutional conditions. Future research may expand to cross-regional comparisons and explore synergies between data governance and broader sustainability goals.

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