The Digital Yuan Pilot and Its Role in Promoting Green Finance Development: A Quasi-Natural Experiment Using Panel Data from Prefecture-Level Cities

Jiayi Chen

School of Finance, Renmin University of China, Beijing 100086, China

chenmarf460@gmail.com

Abstract. This study, based on panel data from 293 prefecture-level cities in China between 2020 and 2021, uses propensity score matching with difference-in-differences (PSM-DID) to systematically examine the impact of the digital yuan pilot program on the development of green finance. The results show that the digital yuan pilot significantly promotes the development of green finance, evidenced by a notable increase in the green total factor productivity (GTFP) in the pilot regions. Further heterogeneity analysis reveals that the pilot's effect is more pronounced in non-resource-based cities, cities with lower fiscal pressure, and cities with relatively underdeveloped internet infrastructure. Moreover, mechanism analysis suggests that the digital yuan pilot indirectly fosters the development of green finance by enhancing market liquidity and boosting consumption levels. This study not only fills the gap in the research on the relationship between the digital yuan and green finance but also provides valuable insights for policymakers.

Keywords: Digital Yuan; Green Finance; Prefecture-level City Panel Data; PSM-DID; Green Total Factor Productivity (GTFP).

1. Introduction

In recent years, the pilot scope of the digital yuan has continuously expanded, achieving significant results in its application within domestic retail payments (Buckley et al., 2022). Meanwhile, green finance, as a key tool for addressing climate change and promoting sustainable economic development, has gradually become a focal point for both academia and practice (Akomea-Frimpong et al., 2022). However, research on whether and how the digital yuan pilot drives the development of green finance remains somewhat limited.

Our preliminary empirical results show that the digital yuan pilot significantly promotes the development of green finance. This finding suggests that the rollout of the digital yuan provides a more efficient and transparent financial operating environment, thereby enhancing the appeal and impact of green finance.

2. Literature Review

2.1 Digital Currency Pilot

With the rapid development of digital technologies, the digital yuan, as a new form of currency, is gradually coming into the public eye. In recent years, central bank digital currencies (CBDCs) have garnered widespread attention globally. CBDCs can enhance payment efficiency, stability, and security, support the internationalization of currencies, promote financial inclusion, and potentially reduce the costs of the monetary system, positioning them as a potential pillar of future international payment systems (Iulia Monica et al., 2023).

As a result, central bank digital currencies have become a key research focus in the field of financial technology, with central banks around the world launching digital currency pilot programs due to the many advantages offered by digital currencies (Lavinia Adelina Mitrache et al., 2023).

In China, the digital yuan (DC/EP), a typical representative of CBDCs, stands out due to its development and pilot implementation (Chaowei Xu et al., 2022). In fact, the digital yuan has demonstrated broad applications and potential advantages in the retail payments sector, such as efficiency, convenience, and security (Pangyue Cheng, 2022).

The issuance of the digital yuan has indeed had a positive impact on the financial sector, with studies analyzing the various positive effects of the digital yuan pilot on financial stability (Meng Y et al., 2024). However, research on the impact of digital currencies on green finance has largely been qualitative. Based on relevant studies, this paper proposes the following hypothesis:

H1: The digital currency pilot has a significant impact on the development of green finance.

2.2 Green Finance

In recent years, with the rapid development of the digital economy, digital currencies, as an important component of financial innovation, have gradually shown their potential in the field of green finance.

Acquah et al. (2023) explore the intrinsic link between green practices and financial instruments, providing indirect evidence for understanding how the digital yuan promotes green finance.

Huang and Chen (2024) directly link data-driven industries with green total factor productivity (GTFP). Using panel data from 277 cities in China from 2008 to 2020, they analyze the impact and mechanisms of data-driven industries on GTFP. Their study finds that data-driven industries significantly enhance GTFP by improving resource allocation efficiency and promoting AI innovation and entrepreneurial activities. This research provides direct support for understanding the role of digital currencies as key financial tools in the data economy era, particularly in driving the development of a green economy.

Other studies further examine the impact of digital technologies on GTFP. They find that digital technologies have a significant positive impact on GTFP, emphasizing the role of digital technologies in improving resource use efficiency, facilitating information sharing, and reducing costs, thus contributing to the development of a green economy. This insight is particularly relevant for exploring the impact of the digital yuan pilot on green finance (Li et al.,2024).

2.3 How Digital Currency Pilot Projects Affect Green Finance

Some experiments suggest that green finance enhances GTFP primarily through multiple channels, including improving resource allocation efficiency, promoting green technological innovation, and driving industrial upgrading. Although this research does not directly address the digital yuan, it provides an important perspective for understanding the effectiveness of green finance policies, implying the potential of multiple factors in facilitating the transition to a green economy (Lin et al., 2023).

Digital finance does indeed play a role in promoting sustainable development. One study analyzes the current state, challenges, and future directions of green digital finance development in Asia and Europe through several case studies (Wang & Zhao, 2024). By combining digital technologies with green financial instruments, green digital finance can benefit financial markets in various ways, such as reducing financing costs, enhancing financial inclusion, and promoting environmentally-friendly projects (Taghizadeh-Hesary et al., 2022). Another study highlights that CBDCs not only reduce the costs of currency issuance and circulation and mitigate environmental impacts but also foster the development of green finance by enhancing financial inclusion and improving transaction transparency (Náñez et al., 2023).

3. Data and Methods

3.1 Data Source and Description

This study uses a panel dataset covering 293 prefecture-level cities in China from the beginning of 2020 to the end of 2021. Based on publicly available information from the People's Bank of China and the Ministry of Commerce, 16 cities that implemented the digital currency pilot at the beginning and end of 2020 are selected as the experimental group to assess the impact of the digital currency pilot on green finance. Simultaneously, cities without reliable data sources are excluded, and the remaining cities that did not implement the pilot program are used as the control group.

Missing data are handled using mean imputation. All data used in this study are sourced from the China Urban Statistical Yearbook.

3.2 Data and Variables

3.2.1 Explained Variables

Green total factor productivity (GTFP) measures productivity growth and environmental improvement from the perspectives of economic growth and environmental pollution (Rusiawan et al., 2015). This study adopts GTFP as an indicator to measure the development of green finance, specifically using the green finance index.

To comprehensively assess the impact of expected and non-expected outputs, this study employs the non-expected SBM model, a derivative model from data envelopment analysis.

Assume there are N cities, each of which is an independent, efficient decision-making unit (DMU). Each DMU has three vectors: input vector $X = [x_1, \ldots, x_N]$, expected output vector $Y^g = [y_1^g, \ldots, y_N^g]$, and non-expected output vector $Y^b = [y_1^b, \ldots, y_N^b]$ (Moradi et al., 2023). The production possibility is determined by the following equation:

$$P = \left\{(x, y^g, y^b) \mid x \geq X\lambda, y^g \geq Y^g, y^b \geq Y^b\lambda, \lambda \geq 0\right\}$$

In this equation, $X > 0$, $Y^g > 0$, $Y^b > 0$, λ are the weight vectors of the cross-sectional data. The non-radial SBM—non-expected component can be described by the following equation:

$$\rho^* = min \frac{1 - \frac{1}{s}\sum_{i=1}^{s} \frac{m_i^-}{x_{io}}}{1 + \frac{1}{m_1 + m_2}\left(\sum_{r=1}^{m_1} \frac{m_r^g}{y_{r0}^g} + \sum_{r=1}^{m_2} \frac{m_t^b}{y_{r0}^b}\right)}$$

$$x_0^b - \sum_{j=1}^{n} \lambda_j x_j - m^- = 0$$

$$\sum_{j=1}^{n} \lambda_j y_j^g - y_0^g - m^g = 0$$

$$y_0^b - \sum_{j=1}^{n} \lambda_j y_0^b - m^b = 0$$

$$\lambda, m^-, m^g, m^b > 0, \sum_{j=1}^{n} \lambda_j = 1$$

In the above equation, s is the input vector $X = [x_1, \ldots, x_N]$, m_1 is the expected output vector, and $Y^g = [y_1^g, \ldots, y_N^g]$ m_2 is the non-expected output vector $Y^b = [y_1^b, \ldots, y_N^b]$. m^g (m^b) represents the expected (non-expected) output slack vector, while m^- denotes the input slack vector (Zhao & Irfan, 2023). The model employs Variable Returns to Scale (VRS) estimation.

3.2.2 Explanatory Variables

The key explanatory variable in this study is *Treat_time*. This variable is used to measure whether a city has become a pilot city for the digital yuan. *Treat_time* is the product of two dummy variables, *Treat* and *Time*. If a city is a digital yuan pilot city, **Treat** takes the value of 1, otherwise, it takes the value of 0. If a city has become a digital yuan pilot city at the specified time, *Time* takes the value of 1, otherwise, it takes the value of 0.

We include various control variables to account for other factors that may influence green finance and isolate the specific impact of the digital yuan pilot cities. The selected control variables are as follows:

Education Investment (EI): The ratio of educational expenditure to regional GDP.

Technology Investment (TI): The ratio of science and technology expenditure to regional GDP.

Consumer Spending (CS): The ratio of total retail sales of consumer goods to regional GDP.

Financial Scale (FS): The ratio of the year-end balance of loans and deposits from financial institutions to regional GDP.

Government Intervention (GI): The ratio of local general public budget expenditure to regional GDP.

All of the above data are logarithmically transformed to mitigate multicollinearity.

3.2.3 Mechanism Variables

Based on the analysis of the industrial transformation brought about by the digital city pilot, this study includes the following mechanism variables:

Tertiary Industry Share of Total GDP (TGRPT): The proportion of the total GDP represented by the tertiary industry in the entire city.

Tertiary Industry Share of GDP in Urban Districts (TGRPD): The proportion of the GDP from the tertiary industry within the urban districts of the city.

Table 1 below provides the descriptive statistics for all the variables used in this study.

Table 1. Descriptive statistics

	The full sample			The treatment group			The control group		
Variable Obs	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.
GTFP	3,102	0.33	0.11	18	0.47	0.09	3,084	0.33	0.10
lnEI	3,146	-3.45	0.45	21	-3.64	0.37	3,125	-3.45	0.45
lnTI	3,146	-6.17	0.81	21	-5.17	0.82	3,125	-6.18	0.80
lnCS	3,145	-1.01	0.36	21	-0.93	0.20	3,124	-1.01	0.36
lnFS	3,146	0.84	0.42	21	1.55	0.23	3,125	0.83	0.42
lnGI	3,146	-1.69	0.45	21	-1.81	0.41	3,125	-1.69	0.45
TGRPT	2,860	43.74	77.29	21	64.18	10.35	2,839	43.59	77.55
TGRPD	3,122	49.79	102.80	21	66.45	9.15	3,101	49.67	103.14

As observed, the GTFP of the experimental group is 42.42% higher than that of the control group and the overall average. This preliminary finding suggests that the digital city pilot has promoted the development of green finance.

3.3 Model Construction

3.3.1 Basic Regression Model

When examining the characteristics of the gradual implementation and phased pilot of the digital yuan, its "quasi-natural experiment" nature and the multi-period Difference-in-Differences (DID) approach are particularly important. These characteristics enable us to apply rigorous econometric methods to evaluate the impact of the digital yuan pilot on the development of green finance.

To analyze in depth and accurately the impact of the digital yuan pilot on Green Total Factor Productivity (GTFP), this study draws on the methodology employed by Beck et al. (2010) in multi-period DID research. We construct a two-way fixed effects DID model for the analysis. This model aims to control for other variables that might confound changes in GTFP, thereby isolating the net effect of the digital currency pilot policy on GTFP (Zhao & Toh, 2023).

The core assumption of the DID model is that, prior to the policy implementation, there are no systematic differences between the selected "experimental group" cities and the "control group" cities that did not participate in the pilot, in terms of key characteristics. However, given the significant heterogeneity in development levels and diversity across cities, validating the generalizability of this assumption is undoubtedly a complex task (Wing et al., 2018).

To address this potential limitation and enhance the precision of the evaluation of the digital city pilot effects, this study innovatively introduces the Propensity Score Matching-Difference-in-

Differences (PSM-DID) model as an analytical tool. The PSM-DID model not only effectively controls for inherent differences between cities (such as economic foundations, resource endowments, etc.) that might influence the evaluation results, but it also corrects for potential sample selection bias, ensuring that the results are more robust and reliable. Through this refined model design and data handling approach, this study aims to comprehensively reveal the true impact of the digital yuan pilot on urban Green Total Factor Productivity.

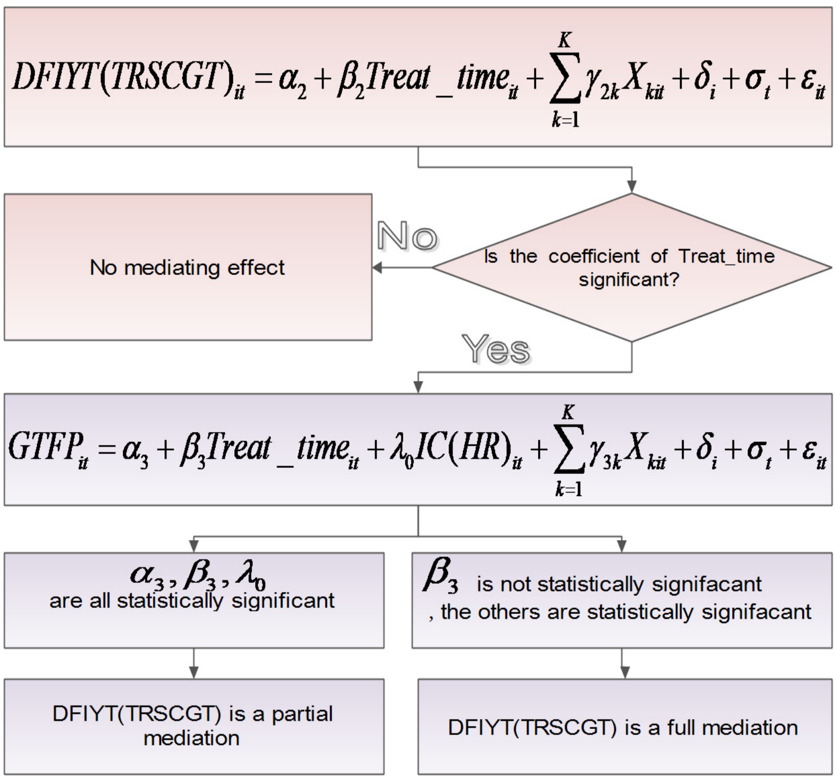
The final model is established as follows:

$$GTFP_{it} = \alpha_1 + \beta_1 Treat\_time_{it} + \sum\nolimits_{k=1}^{K} c_{1k} X_{kit} + \delta_i + \sigma_t + \varepsilon_{it}$$

In the model, $GTFP_{it}$ represents the Green Total Factor Productivity (GTFP) at time t. $Treat\_time_{it}$ is the product of the experimental dummy variable and the time dummy variable. X_{kit} refers to the k-*th* control variable affecting city i at time t, including: Education Investment (EI), Infrastructure Level (IL), Consumer Spending (CS), Financial Scale (FS), and Transportation Level (TL). δ_i denotes the city-specific fixed effect for city i, and σ_t represents the time fixed effect for year t. It is assumed that the random error term is independently and identically distributed (i.i.d.).

3.3.2 Mechanism Analysis

This study uses the mediation effect method to analyze the mechanisms and explore the pathways through which the digital yuan pilot affects the development of green finance (Wang et al., 2023). The influence mechanism is illustrated in the figure below. The pathway model is established as follows:



The financial market activity and consumption level are the mediating variables in this study. In the models above, the year-end balance of RMB deposits from financial institutions in each region (DFIYT) is used as a measure of financial market activity, while the total retail sales of consumer goods (TRSCGT) is used as a measure of consumption level.

4. Empirical Results

4.1 Benchmark Regression Results

4.1.1 DID Analysis

Since the process of analyzing the impact of the digital currency pilot on green finance has a quasi-natural experiment nature, this study employs the Difference-in-Differences (DID) method to analyze the collected data (Mgammal et al., 2023). The results of the analysis are shown in the table 2 below. In the two columns of the table 2, we observe that regardless of whether control variables are included, the main explanatory variable "*Treat_time*" is positively significant at the 1% level. This indicates that, regardless of the inclusion of control variables, the digital currency pilot has a significant econometric impact on GTFP.

Table 2. Basic regression results

	(1)	(2)
	GTFP	GTFP
treat_time	0.0167***	0.0164***
	(2.77)	(2.71)
lnEI		0.0009
		(0.24)
lnIL		-0.0015
		(-1.58)
lnCS		-0.0027
		(-1.47)
lnFS		-0.0023
		(-0.64)
lnTL1		0.0145***
		(3.47)
Constant		0.3474***
	(791.16)	(25.62)
City FE	Y	Y
Year FE	Y	Y
N	3,102	3,101
R-squared	0.9562	0.9566

Note: t statistics in parentheses; * p<0.1, ** p<0.05, *** p<0.01

4.1.2 PSM-DID Analyze

To validate and enhance the robustness of the DID method, this study adopts the Propensity Score Matching (PSM) method to address potential endogeneity and bias in policy evaluation. The entire process includes the following key steps:

First, we perform propensity score estimation. After randomly sorting the dataset, we use logistic regression to estimate the propensity scores. GTFP is set as the dependent variable, and Education Investment (EI), Technology Investment (TI), Government Intervention (GI), Consumer Spending (CS), and Financial Scale (FS) are included as covariates. These covariates are incorporated into the logistic regression model to identify the factors influencing GTFP, which are then used for comparison (Zhao & Toh, 2023).

Next, kernel density matching is applied to match the scores generated by the kernel density function, removing observations that cannot be matched with the experimental group and those that do not satisfy the common support assumption. By matching the experimental group with the nearest control group, the PSM-DID model creates comparable groups and reduces potential selection bias.

A caliper distance of 0.05 is used for the matching, and if multiple matches have the same distance, one is randomly selected.

The assumption of the PSM-DID model is typically verified through what is known as a balance test, which aims to investigate whether any significant identifiable differences exist between the matched samples. As shown in the figure below, the balance test results indicate that, after matching, no substantial differences are observed between the treatment and control groups. This finding provides strong support for the validity of the PSM-DID model.

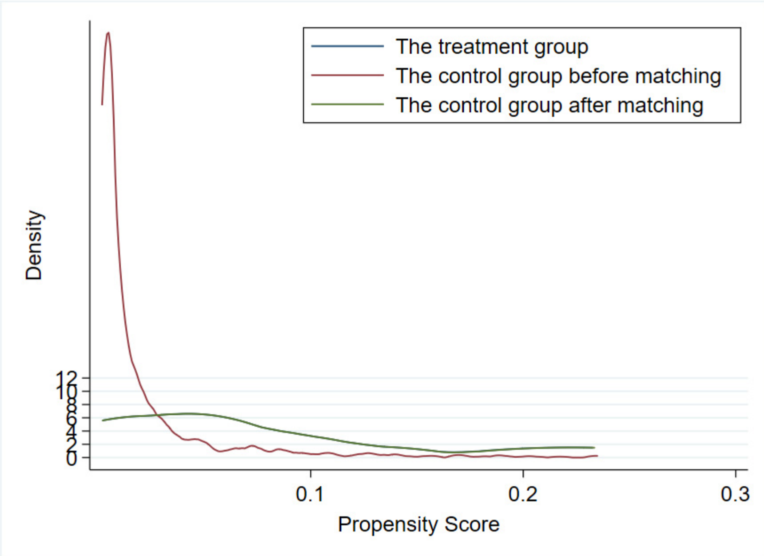


Figure 1. Balance test results

Table 3. PSM-DID results

	(1)	(2)
	GTFP	GTFP
treat_time	0.0126*	0.0130*
	(1.88)	(1.93)
lnEI		0.0014
		(0.12)
lnTI		-0.0029
		(-0.88)
lnCS		-0.0082
		(-1.28)
lnFS		0.0032
		(0.32)
lnGI		0.0260***
		(2.91)
Constant	0.3496***	0.3751***
	(442.75)	(9.47)
City FE	Y	Y
Year FE	Y	Y
N	911	909
R-squared	0.9621	0.9631

Note: t statistics in parentheses; * p<0.1, ** p<0.05, *** p<0.01

The results estimated using PSM-DID are shown in Table 3. The coefficient difference for the key explanatory variable, *Treat_time*, does not exhibit a significant difference from the DID results, and remains statistically significant.

4.2 Heterogeneity Analysis

4.2.1 Analysis of Resource Heterogeneity

There are significant differences across cities in terms of natural resources, economic resources, and technological resources. As a result, Chinese cities are often classified into resource-based and non-resource-based cities. These differences directly or indirectly affect the industrial structure, economic development model, and green transition capabilities of cities. As an emerging financial tool, the promotion and application of digital currency may vary across cities with different resource endowments, thereby influencing the development path and outcomes of green finance in these cities.

Table 4. Analysis results of resource heterogeneity

	(1)	(2)	(3)	(4)
	GTFP	GTFP	GTFP	GTFP
treat_time	0.0142^{**}	0.0133^{**}	0.0279	0.0256
	(2.19)	(2.04)	(1.55)	(1.42)
lnEI		0.0041		-0.001
		(-0.63)		(-0.24)
lnTI		-0.0026^{*}		-0.0016
		(-1.77)		(-1.20)
lnCS		-0.005		-0.001
		(-1.38)		(-0.47)
lnFS		-0.0091^{*}		0.0051
		(-1.80)		(1.02)
lnGI		0.0176^{***}		0.0107^{*}
		(2.84)		(1.79)
Constant	0.3455^{***}	0.3788^{***}	0.3079^{***}	0.3065^{***}
	(632.11)	(17.46)	(476.28)	(16.71)
N	1,837	1836	1265	1265
R-squared	0.9539	0.9545	0.9565	0.9569

Note: t statistics in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Columns (1) and (2) represent data from non-resource-based cities, while columns (3) and (4) represent data from resource-based cities.

From the comparison of columns (1) and (3), and columns (2) and (4) in the table 4, it can be observed that the digital yuan pilot has a significant positive effect on the development of green finance in non-resource-based cities, while its impact in resource-based cities is minimal.

On the one hand, this is because resource-based cities often heavily rely on one or a few natural resources, which makes their economies more sensitive to external market fluctuations and lacks diversification in development drivers. When emerging financial tools such as digital currency attempt to promote the development of green finance, resource-based cities may struggle to respond quickly due to the rigidity of their economic structure, leading to insignificant results.

On the other hand, the economic structure of resource-based cities is typically more homogeneous, dominated by resource extraction and processing industries. Moreover, before 2020, their economic green transformation was generally inefficient. This lack of diversity limits the potential for development in the green finance sector, which is more focused on emerging industries like environmental protection, energy conservation, and clean energy.

4.2.2 Analysis of the Heterogeneity of Fiscal Pressure

Fiscal pressure heterogeneity refers to the imbalance between fiscal revenues and expenditures in different cities, caused by factors such as economic development level, industrial structure, and population size. Cities facing varying levels of fiscal pressure will also exhibit different levels of support for and effectiveness in promoting green finance development.

In this study, *LGPBRT* represents local general public budget revenue, and *LGPBET* represents local general public budget expenditure. Fiscal pressure is measured by the ratio *(LGPBET - LGPBRT)/LGPBRT*, with cities having a ratio above the average classified as high fiscal pressure cities, and those below the average as low fiscal pressure cities. This ratio, by comparing the relative difference between expenditure and revenue, allows for the assessment of local fiscal sustainability. A long-term fiscal deficit or a state of high expenditure and low revenue can lead to negative consequences such as the accumulation of local debt and a decline in the quality of public services, thereby exacerbating fiscal pressure.

Table 5. Analysis results of the heterogeneity of fiscal pressure

	(1)	(2)	(3)	(4)
	GTFP	GTFP	GTFP	GTFP
treat_time	0.0130**	0.0134**	0.0084	0.0069
	(1.99)	(2.05)	(0.42)	(0.35)
lnEI		0.0045		-0.0058
		(0.9)		(-1.05)
lnTI		-0.0042***		0.0009
		(-2.86)		(0.67)
lnCS		-0.0045		-0.0021
		(-1.24)		(-0.97)
lnFS		-0.0009		-0.0016
		(-0.18)		(-0.30)
lnGI		0.0163**		0.0159**
		(2.43)		(2.47)
Constant	0.3364***	0.3550***	0.3197***	0.3278***
	(643.44)	(17.39)	(468.35)	(16.70)
N	1,903	1903	1177	1176
R-squared	0.9536	0.9542	0.9635	0.964

Note: t statistics in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Columns (1) and (2) represent data from low fiscal pressure cities, while columns (3) and (4) represent data from high fiscal pressure cities.

From the comparison of columns (1) and (3), and columns (2) and (4) in the table 5, it can be seen that the digital yuan pilot has a significant positive effect on the development of green finance in low fiscal pressure cities, while its impact is minimal in high fiscal pressure cities.

This is because fiscal pressure directly exerts a noticeable negative effect on local productivity. High fiscal pressure cities often face considerable strain in fiscal expenditures, with more resources being allocated to rigid, essential spending or short-term revenue-generating projects, rather than long-term, forward-looking development initiatives like green finance. Therefore, despite the technical convenience provided by the digital yuan pilot, the lack of sufficient fiscal support makes it difficult to effectively promote the development of green finance.

4.2.3 Analysis of Network Development Heterogeneity

The extent of network infrastructure and the adoption of digital technologies directly affect the effectiveness of digital currency applications in green finance within cities. This study uses the number of broadband internet users to measure the local development of network infrastructure, classifying cities with values above the average as cities with good network development, and those below the average as cities with insufficient network development.

Table 6. Analysis results of network development heterogeneity

	(1)	(2)		(3)	(4)
	GTFP	GTFP		GTFP	GTFP
treat_time	0.0405^{*}	0.0418^{*}		0.0079	0.007
	(1.72)	(1.76)		(1.22)	(1.06)
lnEI		0.0021			0.0039
		(0.55)			(0.34)
lnTI		-0.0023^{**}			-0.0054^{**}
		(-1.96)			(-1.97)
lnCS		0.0004			-0.007
		(0.21)			(-1.13)
lnFS		-0.0043			0.0055
		(-1.03)			(0.66)
lnGI		0.0094^{*}			0.0270^{***}
		(1.83)			(2.74)
Constant	0.3063^{***}	0.3176^{***}		0.3734^{***}	0.3943^{***}
	(605.13)	(20.65)		(524.05)	(10.22)
N	1,941	1941		1063	1061
R-squared	0.9582	0.9584		0.953	0.9544

Note: t statistics in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Columns (1) and (2) represent data from cities with insufficient network development, while columns (3) and (4) represent data from cities with good network development.

From the comparison of columns (1) and (3), and columns (2) and (4) in the table 6, it can be observed that the digital yuan pilot has a significant positive effect on the development of green finance in cities with underdeveloped network infrastructure, while its impact is minimal in cities with more advanced network infrastructure.

This may be because cities with well-developed networks already have relatively complete financial infrastructure and higher levels of financial services, meaning the introduction of digital yuan does not generate significant marginal effects. Additionally, cities with good network development may be more inclined to adopt other advanced fintech solutions to promote green finance, thereby diminishing the impact of the digital yuan.

In contrast, in regions with relatively weak network infrastructure, the digital yuan, as a new payment tool, significantly enhances the convenience and efficiency of financial services, thereby promoting the spread and application of green finance products. Moreover, the lower levels of technological development and more rudimentary financial systems in these regions mean that the real-time settlement and traceability features of digital yuan help address issues such as information asymmetry and regulatory challenges in traditional financial systems, further driving the development of green finance in these areas.

4.3 Mechanism Analysis

In the mediation analysis model, this study uses financial market activity and consumption levels as mediating variables. The year-end balance of RMB deposits at financial institutions (DFIYT) is employed as a measure of financial development, while the total retail sales of social consumer goods (TRSCGT) is used to gauge consumption levels.

The balance of RMB deposits at financial institutions directly reflects the total funds available in the market, serving as a crucial foundation for liquidity in the financial market. A higher deposit balance indicates more funds available for investment and lending, which in turn facilitates active financial transactions. This liquidity is not only a prerequisite for the efficient functioning of financial markets but also a driving force for financial innovation and market development. As Bernanke and Blinder (1988) point out, the transmission mechanism of monetary policy largely depends on the liquidity conditions of financial markets, with financial institution deposits playing a key role in this mechanism.

Table 7. Regression results of mediator variables

	(1)	(2)
	DFIYT	TRSCGT
treat_time	0.0498^{**}	0.0589^{***}
	(2.38)	(2.81)
lnEI	-0.0867^{***}	-0.1135^{***}
	(-6.46)	(-8.45)
lnTI	0.0392^{***}	0.0558^{***}
	(10.86)	(15.43)
lnCS	-0.0320^{***}	0.9760^{***}
	(-4.64)	(141.27)
lnFS	0.4063^{***}	-0.4209^{***}
	(30.9)	(-32.01)
lnGI	-0.2256^{***}	-0.3803^{***}
	(-14.44)	(-24.33)
Constant	16.1242^{***}	16.2611^{***}
	(318.11)	(320.42)
City FE	Y	Y
Year FE	Y	Y
N	3,145	3135
R-squared	0.9941	0.9941

Note: t statistics in parentheses; * p<0.1, ** p<0.05, *** p<0.01

The total retail sales of social consumer goods refer to the value of physical goods sold directly to individuals and social groups for non-production and non-business purposes, as well as the income obtained from providing services. This indicator covers a wide range of goods and services purchased by residents in their daily lives, including food, clothing, housing, household equipment and maintenance services, healthcare and personal goods, transportation and communication, education, cultural and entertainment services, among others. Therefore, it provides a comprehensive and intuitive reflection of the consumption status and structure of regional residents, making it a key indicator for measuring the level of consumption in a region.

The results in the first column of the table 7 show a significantly positive relationship, indicating that the digital currency pilot has a significant positive impact on the activity level of the financial market. This, in turn, supports the hypothesis in the mediation analysis model, where financial market activity serves as a partial mediator. Similarly, the second column shows a significant positive result, suggesting that the digital currency pilot also promotes the improvement of regional consumption levels, with consumption levels acting as another partial mediator.

4.4 Robustness Test

4.4.1 Parallel Trend Test

The validity of the DID model heavily relies on the fulfillment of its underlying assumptions, with the parallel trends assumption being particularly critical. The purpose of this assumption is to verify whether the treatment and control groups exhibit the same trend in the period before the policy implementation. This assumption forms the foundation for the DID model's validity; if the treatment and control groups do not share parallel trends prior to the policy intervention, the estimated policy effect may be biased, leading to distorted policy evaluation results (Roth & Sant'Anna, 2023). Therefore, in order to accurately estimate the treatment effect, it is essential to assume that the treatment and control groups would have followed the same trend in the absence of the intervention.

This test introduces a time-trend variable based on the baseline regression model, aiming to thoroughly examine the data from prior years before the policy intervention. The specific model adjustment is constructed based on the following model specification:

$$GTFP_{it} = \alpha_1 + \beta_1 Treat\_time_{it}^{-x} + \beta_2 Treat\_time_{it}^{-x+1} + \ldots + \beta_{x+y+1} Treat\_time_{it}^{y}$$

$$+ \sum_{k=1}^{K} c_{1k} X_{kit} + \delta_i + \sigma_t + \varepsilon_{it}$$

$$x, y > 0$$

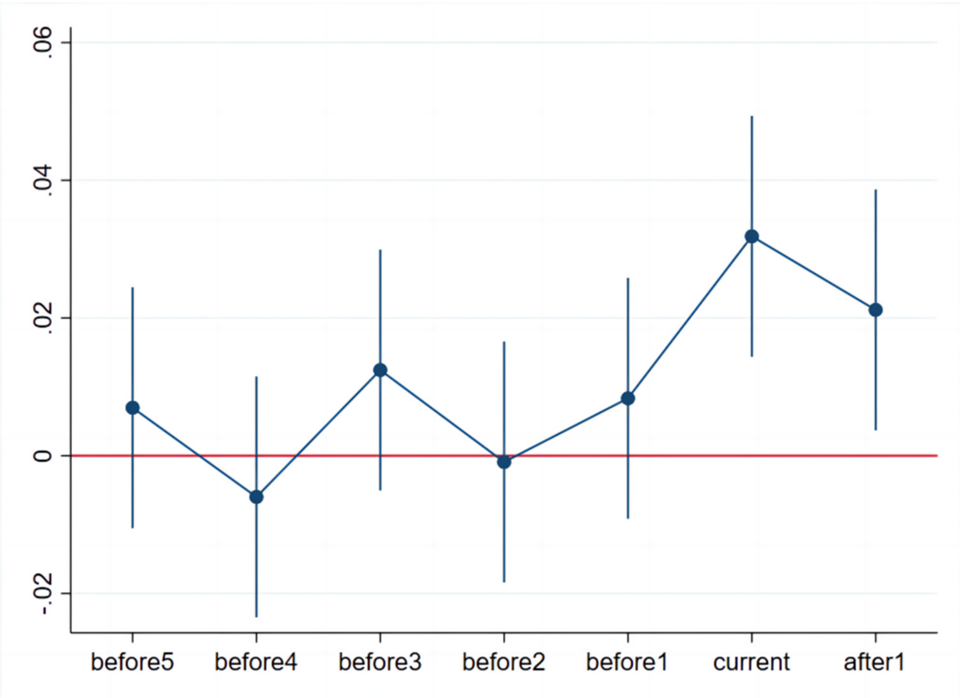


Figure 2. Parallel trend test results

The figure above presents the key results of the parallel trends test, clearly demonstrating the critical change trends before and after the policy implementation. Specifically, during the pre-policy phase (marked as "x" to "y"), the regression coefficients are not only significant but also fluctuate around zero. This phenomenon directly reflects the similarity in the change trends between the control and treatment groups before the policy intervention, thus fulfilling the basic requirement of the parallel trends assumption.

Upon further observation, it is found that after the policy implementation, the regression coefficients for the subsequent time points (marked as three points post-policy implementation) show a significant upward trend, with all coefficients being positive and their confidence intervals completely excluding zero. This significant change not only confirms the positive impact of the policy on the outcome variable, but more importantly, it strengthens the argument made by the model through the parallel trends test.

Therefore, the DID model in this study successfully passes the parallel trends test. It not only validates that the control and treatment groups followed parallel trends prior to the policy intervention but also confirms the consistency of this parallel trend across the time dimension, thus enhancing the robustness and reliability of the research conclusions.

4.4.2 Placebo Test

One of the basic assumptions of the DID method is that the treatment and control groups would follow the same time trend in the absence of policy intervention. However, in practice, the subjects may alter their behavior upon learning about the forthcoming policy implementation, leading to biased estimates of the "policy effect." The placebo test addresses this issue by simulating a scenario with no actual policy impact and observing whether the treatment effect remains significant, thus ruling out the influence of non-policy factors (Zhao & Irfan, 2023).

The placebo test involves multiple randomizations of the treatment and control groups, simulating an estimated result distribution under the assumption of no real policy impact. If the actual observed treatment effect falls far beyond this random distribution, then we can be more confident that the estimated result reflects a true policy effect, rather than being due to random factors. In this study, a rigorous testing procedure is employed, which involves randomly sampling the treatment group variables a specific number of times, followed by 500 regression analyses.

The figure below visually presents the key results of the placebo test, specifically the distribution of t-values. This distribution, centered around zero, exhibits typical normal distribution characteristics, revealing that the t-values generated by randomly selected samples do not exhibit statistically significant differences from zero. This finding not only strengthens the robustness of the study's conclusions but also further confirms that the positive effect of the digital RMB pilot on green growth is not the result of random factors or arbitrary variables, but rather a genuine policy effect.

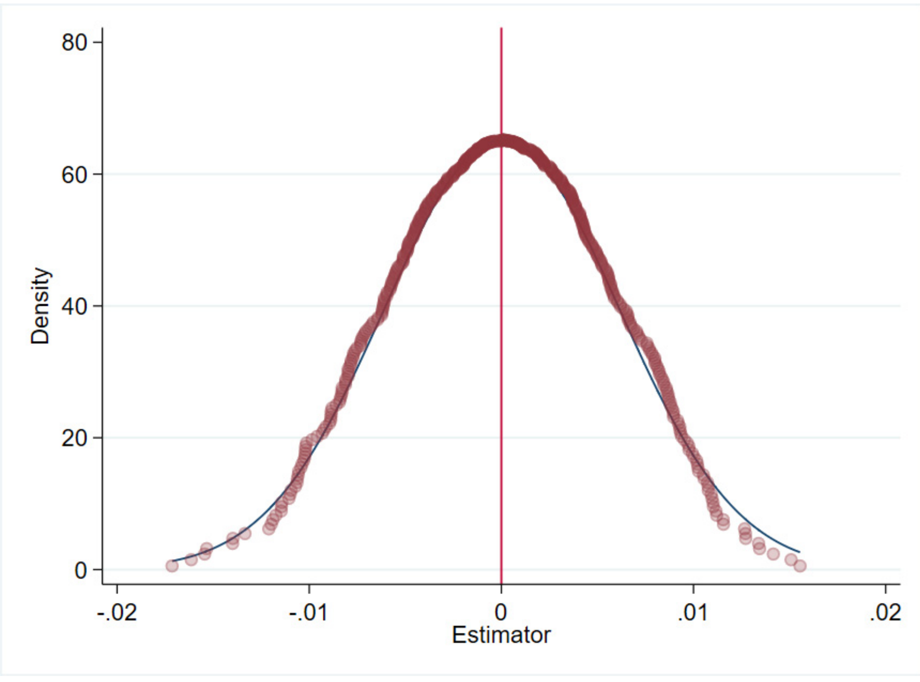


Figure 3. Placebo Test results

4.4.3 Impact of Outliers

To minimize the impact of potential outliers that may interfere with the research results, this study employs a 2% tail trimming method for data cleaning and conducts a re-regression analysis. As shown in the table 8, the regression coefficient for the treatment time (Treat_time) remains significantly positive. This indicates that after excluding outliers, the results of this study remain robust.

Table 8. Regression results excluding the influence of outliers

	(1)	(2)
	GTFP	GTFP
treat_time	0.0167***	0.0165***
	(2.77)	(2.73)
lnEI		-0.0003
		(-0.07)
lnTI		-0.0012
		(-1.07)
lnCS		-0.0049
		(-1.55)
lnFS		0.0003
		(0.08)
lnGI		0.0143***
		(2.95)
Constant	0.3302***	0.3409***
	(791.16)	(20.89)
City FE	Y	Y
Year FE	Y	Y
N	3,102	3101
R-squared	0.9562	0.9566

5. Discussion

5.1 Conclusion

The DID (Difference-in-Differences) regression analysis results provide strong support for Hypothesis 1, clearly demonstrating the significant positive effects of digital currency pilot programs in promoting green growth. During the empirical analysis, government intervention was included as a control variable, showing a significant positive impact. This strongly supports the argument that the active involvement of government in digital currency pilot initiatives is crucial for enhancing their positive role in advancing the green growth agenda.

Furthermore, by employing the PSM-DID (Propensity Score Matching-Difference-in-Differences) method, we conducted a more refined treatment of the sample data to eliminate potential selection bias. Even after implementing propensity score matching, the estimated coefficients remained highly significant. This finding not only consolidates the conclusions drawn from the DID analysis but also reveals that, even after controlling for sample selection bias, the promotion effect of the digital currency pilot on green growth remains robust and significant. This further strengthens the reliability and generalizability of the research findings. Additionally, the government intervention factor remains significant in the PSM-DID results, corroborating the DID findings.

In the heterogeneity analysis, this study found that the impact of digital currency pilot programs on green financial development varies significantly. In non-resource-based cities and cities with low fiscal pressure, the digital currency pilot significantly boosts green finance development. This is attributed to the diversified economic structure of non-resource-based cities and the greater financial capacity of low fiscal pressure cities to support long-term development projects. In contrast, in resource-based cities and high fiscal pressure cities, the impact is weaker, mainly due to the lack of economic diversification, challenges in transformation, and fiscal constraints.

Regarding network development, the digital currency pilot program significantly promotes green finance development in cities with underdeveloped network infrastructure by improving financial service convenience and efficiency, addressing issues like information asymmetry and regulatory challenges. However, in cities with well-developed networks, the impact is more limited. These cities already possess robust financial infrastructure and may be more inclined to adopt other advanced financial technologies.

In the mechanism analysis model, this study uses financial market activity and consumption levels as mediating variables, measured by the year-end RMB deposit balances of financial institutions (DFIYT) and total retail sales of social consumer goods (TRSCGT), respectively. Financial institution deposit balances directly reflect the total amount of market funds, serving as an important foundation for financial market liquidity, influencing financial transaction activity and market innovation. Total retail sales of social consumer goods comprehensively reflect residents' consumption status and structure, making it a key indicator for measuring consumption levels. The results show that the digital currency pilot has a significant positive impact on both financial market activity and consumption levels, suggesting that both act as partial mediators in the process.

5.2 Policy Recommendations

Based on the findings of this study, the following policy recommendations are proposed to further enhance the positive role of the digital yuan pilot in promoting the development of green finance.

1. Expand the Scope of the Digital Yuan Pilot

The study shows that the digital yuan pilot significantly promotes the development of green finance, especially in non-resource-based cities. Therefore, it is recommended that the government further expand the scope of the digital yuan pilot, particularly in economically dynamic, non-resource-based cities. Increasing the number of pilot cities can accelerate the adoption and application of the digital yuan, thereby promoting green finance on a broader scale.

2. Enhance Support for the Transformation of Resource-Based Cities

The study finds that the digital yuan pilot has a less significant impact in resource-based cities. To address this issue, it is recommended that the government strengthen support for the transformation of these cities. By providing fiscal subsidies, tax incentives, and technical assistance, the government can encourage resource-based cities to accelerate industrial restructuring and diversify their economies. At the same time, fostering cooperation between resource-based cities and emerging industries related to green finance, such as environmental protection, energy efficiency, and clean energy, can enhance their participation and potential in the green finance sector.

3. Optimize Policy Support Measures

In the process of promoting the digital yuan pilot, the government should focus on optimizing complementary policy measures. This includes formulating and improving relevant laws and regulations, strengthening financial infrastructure, and enhancing financial supervision to ensure robust support for the promotion and application of the digital yuan. Furthermore, it is essential to enhance policy advocacy and education to raise public awareness and acceptance of the digital yuan and green finance.

4. Strengthen Support for Cities with Lower Fiscal Pressure

The study indicates that cities with lower fiscal pressure show better performance in the digital yuan pilot. Therefore, it is recommended that the government increase support for these cities by providing additional fiscal resources and policy incentives to encourage them to better leverage the digital yuan in advancing green finance. Simultaneously, the government should enhance guidance and support for high-fiscal-pressure cities, helping them reduce their fiscal burdens and improve the efficiency of their investments and outputs in green finance.

5. Strengthen Cross-Departmental Collaboration and Information Sharing

The promotion and application of the digital yuan involve multiple sectors and agencies, requiring strengthened cross-departmental collaboration and information sharing. It is recommended that the government establish a cross-departmental coordination mechanism to clarify responsibilities and divisions of labor among departments, while promoting information sharing and resource integration. Strengthening collaboration will create synergies in advancing both the digital yuan and green finance, thereby improving the effectiveness of policy implementation.

6. Implement Continuous Monitoring and Evaluation

Continuous monitoring and evaluation should be conducted throughout the digital yuan pilot. A scientific monitoring framework should be established to periodically assess and analyze the impact of the digital yuan pilot on the development of green finance. Timely identification and resolution of issues during the pilot phase will help optimize policies and implementation strategies, ensuring that the digital yuan pilot yields more significant results in promoting green finance development.

References

[1] Acquah, I. S. K., Baah, C., Agyabeng-Mensah, Y., & Afum, E. (2023). Green procurement and green innovation for green organizational legitimacy and access to green finance: The mediating role of total quality management. Journal of Environmental Management, 331, 114456. https://doi.org/ 10. 1016/ j. jenvman.2023.114456.

[2] Akomea-Frimpong, I., Adeabah, D., Ofosu, D., & Tenakwah, E. J. (2022). A review of studies on green finance of banks, research gaps and future directions. Journal of Sustainable Finance & Investment, 12(4), 1241-1264.

[3] Beck, T., Levine, R., and Levkov, A., 2010. Big bad banks? The winners and losers from bank deregulation in the United States. The Journal of Finance, 65: 1637-1667.

[4] Bernanke, B. S., & Blinder, A. S. (1988). Credit, money, and aggregate demand. American Economic Review, 78(2), 435-439.

[5] Buckley, R., Arner, D., Zetzsche, D., Lammer, T., & Gazi, S. (2022). Regional Solutions to Global Payments Challenges: Toward a Single Rulebook. Banking & Finance Law Review, 38, 81-X.

[6] Cheng, P. (2022). Decoding the rise of Central Bank Digital Currency in China: designs, problems, and prospects. Journal of Banking Regulation, 24(1), 156-170. https://doi.org/10.1057/s41261-022-00193-5.

[7] State Council of the People's Republic of China, 2013. National Sustainable Development Plan for Resource-Based Cities (2013-2020). Guofa [2013] No. 45. Retrieved from Central Government Portal: https://www.gov.cn/zwgk/2013-12/03/content_2540070.htm.

[8] Huang, P., & Chen, X. (2024). The impact of data factor-driven industry on the green total factor productivity: Evidence from China. Scientific Reports, 14(1), 25377. https://doi.org/10.1038/s41598-024-77189-w.

[9] Iulia Monica, Oehler-Șincai, I. M. (2023). Central bank digital currencies-the future backbone of the international payment system? CES Working Papers, 15(4).

[10] Li, Y., Sun, R., & Rao, Y. (2024). Digital technology and green total factor productivity. Polish Journal of Environmental Studies, 33(2), 1251-1265. https://doi.org/10.15244/pjoes/172849.

[11] Lin, Y., & Zhong, Q. (2023). Does green finance policy promote green total factor productivity? Evidence from a quasi-natural experiment in the green finance pilot zone. Clean Technologies and Environmental Policy, 26(2661-2685). https://doi.org/10.1007/s10098-023-02729-3.

[12] Meng, Y., Wu, J., & Tu, Y. (2024). Central bank digital currency, financial technology level and regional financial stability. International Review of Economics & Finance, 96(Part A), 103598.

[13] Mgammal, M. H., Al-Matari, E. M., & Alruwaili, T. F. (2023). Value-added-tax rate increases: A comparative study using difference-in-difference with an ARIMA modeling approach. Humanities and Social Sciences Communications, 10(1), 1-17.

[14] Moradi, F., Ziapour, A., Abbas, J., Najaf, S., Rezaeian, S., Faraji, O., Moayeri, E., & Soroush, A. (2023). Comparing the associated factors on lifestyle between type 2 diabetic patients and healthy people: A case-control study. Communications in Health Equity, Research, and Policy, 43, 293-299.

[15] Náñez, S. (2023). CBDCs and green finance: A model to assess the environmental sustainability of central bank digital currencies. Green Finance, 5(4), 603–623. https://doi.org/10.3934/GF.2023023.

[16] Roth, J., & Sant'Anna, P. H. (2023). When is parallel trends sensitive to functional form?. Econometrica, 91(2), 737-747.

[17] Rusiawan W, Tjiptoherijanto P, Suganda E, Darmajanti L (2015) Assessment of green total factor productivity impact on sustainable Indonesia productivity growth. Procedia Environ Sci 28:493–501.

[18] Spulbăr, L. F., & Mitrache, L. A. (2023). DEVELOPMENTS AND PERSPECTIVES OF CENTRAL BANK DIGITAL CURRENCIES. A COMPREHENSIVE ANALYSIS OF BLOCKCHAIN AND DISTRIBUTED LEDGER TECHNOLOGY. Revista Tinerilor Economiști (The Young Economists Journal), 41, 139-147.

[19] Taghizadeh-Hesary, F., & Hyun, S. (Eds.). (2022). Green Digital Finance and Sustainable Development Goals. Economics, Law, and Institutions in Asia Pacific. Springer Nature Singapore.

[20] Tone K, Tsutsui M (2010) Dynamic DEA: A slacks-based measure approach. Omega 38:145–156.

[21] Wang, A., Si, L., & Hu, S. (2023). Can the penalty mechanism of mandatory environmental regulations promote green innovation? Evidence from China's enterprise data. Energy Economics, 125, 106856.

[22] Wang, R., & Zhao, W. (2024). Synergistic dance of digital economy and green finance on carbon emissions: Insights from China. Chinese Journal of Population, Resources and Environment, 22(3), 213-229.

[23] Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing difference in difference studies: best practices for public health policy research. Annual review of public health, 39(1), 453-469.

[24] Xu, C., & Jin, B. (2022). Digital currency in China: pilot implementations, legal challenges and prospects. Juridical Tribune, 12(2), 177-193.

[25] Zhao, W., & Irfan, M. (2023). Does healthy city construction facilitate green growth in China? Evidence from 279 cities. Environmental Science and Pollution Research, 30(46), 102772-102789.

[26] Zhao, W., & Toh, M. Y. (2023). Impact of Innovative City Pilot Policy on Industrial Structure Upgrading in China. Sustainability, 15(9), 7377.