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Does the Comprehensive Commercial Logging Ban Policy in All Natural Forests Affect Farmers' Income?—An Empirical Study Based on County-Level Data in China

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Abstract: The Comprehensive Commercial Logging Ban Policy in all natural forests (CCLBP) as the strictest forest conservation measure brings uncertainty to the income of farmers engaged in forest land management. Therefore, clarifying the impact and heterogeneity of the CCLBP on farmers' income has become a significant issue of current concern. Based on county-level panel data from China covering the period 2000–2020, this study uses Regression Discontinuity Design (RDD) to identify the impact of the CCLBP on farmers' income. The empirical results show that (1) the CCLBP has a significantly positive effect on farmers' income, with the policy leading to an increase in farmers' income of approximately RMB 411–582; (2) the impact of the CCLBP on farmers' income exhibits regional heterogeneity, with significant positive effects observed in Hebei, Shandong, Hubei, and Shaanxi, significant negative effects observed in Guangxi, and insignificant effects observed in other provinces; and (3) the CCLBP not only promotes the development of non-agricultural industries and labor mobility but also effectively reduces capital outflow, thereby increasing farmers' income. This study contributes to the understanding of the underlying mechanisms between the CCLBP and farmers' income, and it has significant practical implications for promoting the increase in farmers' income, narrowing the income gap among farmers, and achieving common prosperity. It can also provide valuable insights and guidance for global forest protection.

Keywords: the Comprehensive Commercial Logging Ban Policy in all natural forests; farmers' income; Regression Discontinuity Design; county-level region

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1. Introduction

As one of the main components of "natural endowment", natural forest resources are crucial for regional economic development and promoting farmers' income. However, years of excessive logging and overexploitation have severely depleted natural forest resources [1]. In 1998, China initiated the Natural Forest Resource Protection Project in crucial state-owned forest regions, encompassing the upper Yangtze and mid-to-upper Yellow River basins, along with the Northeast and Inner Mongolia regions, aimed at rejuvenating natural forests and fostering a comprehensive forest ecosystem [2]. Subsequently, China has continuously strengthened its efforts in natural forest protection [3]. The Comprehensive Commercial Logging Ban Policy in all natural forests (hereinafter referred to as the CCLBP) was successively implemented in 2014 and 2015 in major national forest areas including Heilongjiang, Inner Mongolia, and Jilin. In 2017, the CCLBP was implemented nationwide. It is undeniable that the natural forests have been fully protected by the CCLBP. According to data from the Ninth National Forest Resources Inventory, the total carbon storage has reached 9.186 billion tons, with natural forest resources contributing more than 80%. Studies conducted by Hua et al. [4] and Sun et al. [5], based on statistical data, have also confirmed that the CCLBP accelerates the restoration of the natural forest resources in China.

Income is a key factor in the improvement of people's livelihoods and quality of life [6] as well as a determinant of the quality of life of individuals and families [7]. Individual and family income levels are often influenced by political and institutional factors [8]. The government formulates and enforces the CCLBP to control human exploitation and demand for natural forests. The implementation of the CCLBP has brought about a change in farmers' production and lifestyle as the main participants, profoundly impacting on farmers' income. It has been a major policy objective in recent years to promote the ecological benefits of the CCLBP and the effect of increasing farmers' income. The contribution of the CCLBP to improving the ecological situation cannot be denied [9–11], but will such intensive policy implementation fall into the dilemma of the "forest resource curse" of "rich forest resources but slow economic growth", thus preventing an increase in farmers' income? Or will it bring new development opportunities and livelihood capital to farmers, thereby increasing farmers' income? How does the CCLBP increase farmers' income? It is important to explore these issues.

The academic community has conducted a series of discussions on the impact of the CCLBP on farmers' income. Research conducted in key state-owned forest areas, such as Heilongjiang, Inner Mongolia and Jilin in China, has shown that the income of farmers from forest-related economic activities, such as the sale of timber and the transportation of timber from forest areas, has decreased significantly due to the comprehensive logging ban [12]. This has led to a reduction in livelihood opportunities, social psychological discomfort, and an overall decline in livelihood levels [13]. In addition, the implementation of the CCLBP is likely to affect industries primarily based on timber production in forest areas [14] and limit the resource utilization of enterprises engaged in the processing of natural forest products [15–17], resulting in unemployment among forest area farmers and a decrease in income from off-farm employment. Furthermore, the conservation of natural forest resources may also escalate human–wildlife conflict. With the frequent presence of wild animals in forested areas, the incidence of damage caused by wildlife increases, leading to reduced crop yields and diminished agricultural income [18,19], thereby affecting farmers' livelihoods. On the other hand, some studies suggest that although the cessation of logging in natural forests restricts the use of timber by farmers and enterprises [20], subsidies to farmers partially compensate for their losses and enable them to transition from forest-dependent livelihoods to other livelihoods [21–24]. Simultaneously, after the protection of natural forest resources, the improvement of the ecological environment [25] promotes the rapid development of the forest-based economy and forest tourism, thereby facilitating the transformation of farmers' production methods [26,27] and increasing their income levels. In the long term, the CCLBP will gradually liberate forest farmers from exclusive dependence on forest production and management, deepen the degree of diversification of their livelihoods, and increase their incomes [28]. Moreover, some studies point out that the impact of the CCLBP on the incomes of different types of forest farmers is uneven, with high-income farmers becoming richer and low-income farmers becoming poorer, ultimately leading to polarization and widening income disparities among forest farmers [8].

The existing literature provides valuable insights into the relationship between the CCLBP and the income of farmers, but there are still several issues that need to be further explored. Firstly, the internal mechanism of how the CCLBP affects farmers' income has not been thoroughly investigated, and the conclusions of studies on this relationship are not consistent. Secondly, China has implemented a nationwide ban on commercial logging in natural forests using a "one-size-fits-all" approach [29,30]. Its impact on farmers' income, however, is likely to vary across regions, but existing research has paid limited attention to the regional heterogeneity effects of the policy. Finally, although some scholars have attempted to identify the dynamic effects of the CCLBP on farmers' income using cross-sectional data or data from specific regions [31], short-term survey data and regional-specific data are insufficient for revealing the comprehensive and long-term dynamic effects of the CCLBP. Based on these observations, to discuss the mechanism through which the CCLBP affects farmers' income, this study first constructs a logical analytical framework for examining the relationship between the CCLBP and farmers' income. Then, by using panel data at the county level in China from 2000 to 2020, the CCLBP is treated as a quasi-natural experiment, and Regression Discontinuity Design (RDD) is applied to evaluate the impact, heterogeneity, and mechanism of the CCLBP on farmers' income within counties. It is worth noting that the choice of county-level data is justified for several reasons. On the one hand, as the basic administrative units in China, counties play a crucial role in economic development, and their development and economic growth are significant driving forces for the revitalization of rural areas and common prosperity in China [32]. On the other hand, the use of county-level data can not only overcome the difficult-to-observe heterogeneity between provinces but can also overcome the lack of long-term panel data at the farmer level and increase the number of samples, providing a good balance between appropriate research units and stable heterogeneity analysis boundaries, thereby ensuring the robustness and credibility of the results [33]. Furthermore, rural areas account for a relatively high proportion of county-level regions, and the CCLBP has a strong radiation effect on rural areas. Therefore, it is reasonable to use county data to explore the impact of the CCLBP on farmers' income.

The marginal contributions of this study, in comparison to the existing literature, are as follows: first, the role of the CCLBP in increasing farmers' income is confirmed through an analysis of long-term county macro data, and the heterogeneity of its effect on income growth in different regions is identified. This provides valuable insights into China's efforts to alleviate poverty and boost farmers' income through forestry policy reform, ultimately achieving common prosperity. Second, this study reveals the mechanisms through which the CCLBP affects farmers' income from the perspective of non-agricultural industry development, labor mobility, and capital outflow. By opening the "black box" of the relationship between the CCLBP and farmers' income and understanding these fundamental mechanisms, this study also helps to explore ways to improve policy efficiency. Third, this study uses RDD to mitigate endogeneity problems in parameter estimation and bias caused by confounding factors and evaluates the differences in farmers' income before and after the implementation of the "one-size-fits-all" policy. This provides a new research method for testing the effectiveness of comprehensive bans on commercial logging in natural forests.

2. Theoretical Analysis and Research Hypotheses

Farmers' Behavioral Risk Theory [34] suggests that farmers face various constraints when making production decisions and will choose the optimal production method to maximize production opportunities and resources. The CCLBP restricts farmers' forestry activities and reduces the natural resource endowment available to them. According to the above theory, after the implementation of the policy, farmers will allocate production factors to more efficient sectors to maximize their income and the utility of these factors [35]. In other words, they will actively explore other livelihood strategies to adapt to the logging ban [36–38]. On the other hand, the CCLBP promotes the transformation and upgrading of the forestry industries [39]. Under the guidance of the CCLBP, the forestry industry is shifting from traditional resource consumption to a green ecological model. This transformation not only increases the added value of the forestry industry but also provides more high-quality employment opportunities for farmers. At the same time, the transformation and upgrading of the forestry industry also drive the development of related industries such as forestry machinery, forestry technology, and forestry services, providing farmers with more channels for income growth.

Considering that the CCLBP is being implemented nationwide but the volume of natural forests varies across China, there are both individual differences among farmers and disparities in agricultural management practices and income structures [40,41]. For example, in the northwestern region of China, the development model is mainly based on extensive agriculture with a relatively low level of mechanization and a comparatively smaller volume of natural forests. The advantages of developing secondary and tertiary industries are relatively limited, which may limit the mobility of labor to some extent, thereby affecting the increasing income level of farmers. On the contrary, the northeastern and southwestern regions, where natural forests are more abundant, have abundant agricultural resources and a natural environment conducive to agricultural production [42]. Farmers in these regions can transfer the production factors released by the CCLBP to agricultural production, thereby achieving intensive agricultural management and efficiency improvement to maintain stable income levels. In the regions with higher economic development in the eastern part of China, farmers also have more employment opportunities in non-agricultural industries, which allows them to earn higher incomes.

Based on this, this study proposes the following hypotheses:

Hypothesis 1 (H1). *The CCLBP contributes to increasing farmers' income.*

Hypothesis 2 (H2). *There are regional differences in the impact of the CCLBP on farmers' income.*

Through substitution effects, the CCLBP will induce adjustments in production factor allocation. First, while promoting ecological conservation, the CCLBP also actively promotes the transfer of production factors to non-agricultural industries [43]. For example, the CCLBP has created new development opportunities for the forest product processing industry [30], even though it restricts traditional logging and processing methods for natural forests. Farmers can process forest products into various higher value-added products like furniture, crafts, foods, and more, which can be sold to a wider market through e-commerce platforms. This not only increases the value of forest products but also increases farmers' income. Second, in the short term, labor is a variable factor of production, and farmers will adjust their livelihood strategies through labor mobility to achieve income growth targets. After the implementation of the CCLBP, there will be surplus labor and labor time. As rational economic actors, farmers will make livelihood choices based on comparative advantages and engage in farming or other non-agricultural production activities such as labor migration [44]. The process of labor migration can generate positive spillover effects for some farmers by optimizing the information environment for non-agricultural job opportunities and increasing non-agricultural job opportunities [45]. This is particularly beneficial for low-income farmers who lack endowment advantages, as it reduces the costs and risks of non-agricultural employment to some extent, thereby promoting common prosperity among farmers with different income levels. Third, the shortage of capital leads to a shortage of rural factor input and endogenous development ability, which has become a significant bottleneck restricting the increase in farmers' income [46]. With the implementation of the CCLBP, the government will assist farmers in transitioning from traditional logging to more environmentally friendly and economically efficient forest management models by providing financial subsidies, technical advice, and market development support. This will reduce the population and subsequent capital outflows. The increased fiscal investment and financial support from various levels of government will improve the supply of capital to farmers, fill the capital gap needed for development, and further attract external factor inflows by accelerating regional development. In addition, the increase in factor demand brought about by the industrial transformation under the CCLBP will provide more development opportunities for capital, effectively promoting rural revitalization by activating the potential of various factors, thereby effectively increasing farmers' income.

Based on the above analysis, the following hypothesis is proposed:

Hypothesis 3 (H3). *The CCLBP can increase farmers' income by promoting non-agricultural industry development and labor mobility and reducing capital outflows.*

In summary, the CCLBP can directly or indirectly affect farmers' income. The direct impact is mainly manifested as increasing the cash income or material capital of rural residents by changing the production and lifestyle of farmers, upgrading forestry industry, and promoting the increase in farmers' income. Conversely, if the CCLBP fails to effectively fulfil its role, it may result in the "forest resource curse" dilemma, prevent an increase in farmers' income. The indirect impact of the CCLBP is manifested in its promotion of non-agricultural industry development and labor mobility, as well as in reducing capital outflows, causing changes in labor supply and demand in the primary industry, secondary industry and tertiary industry, thus affecting farmers' income. This study establishes an analytical framework for the effect of the CCLBP on farmers' income, as shown in Figure 1.

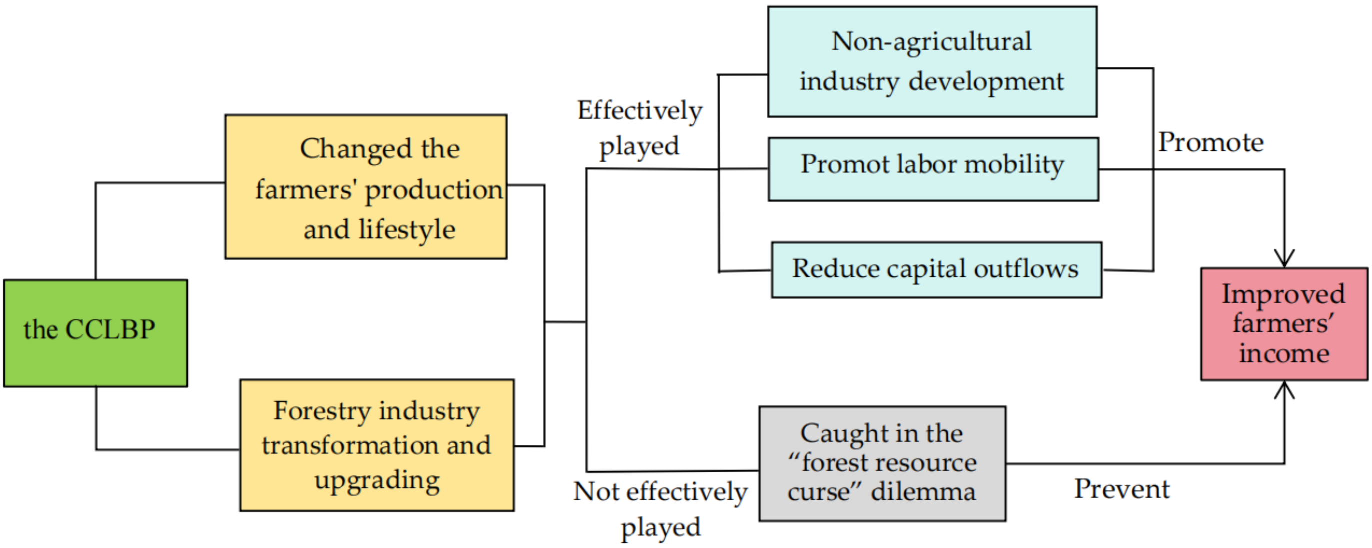


Figure 1. Analysis framework for the effect of the CCLBP on farmers' income.

3. Materials and Methods

3.1. Data Source

This study is based on data collected from various sources including the National Bureau of Statistics of China, official websites of county governments, and annual publications such as the "China Rural Statistical Yearbook", "China Agricultural Statistical Yearbook", and "China County Statistical Yearbook" for the years 2000 to 2020. A panel dataset covering 2843 counties from 31 provinces, autonomous regions, and municipalities directly under the central government was constructed. The dataset excludes regions in Hong Kong, Macao, and Taiwan. For areas that underwent renaming or reorganization into districts during the study period (2000–2020), they were treated as the same unit. Missing data were filled using the linear interpolation method.

3.2. Variable Selection

3.2.1. Dependent Variable

The dependent variable in this study is farmers' income (INC). Following previous studies [47], this study utilizes rural residents' per capita disposable income as a proxy variable for farmers' income.

Figure 2 shows the changes in farmers' income across different regions of China from 2000 to 2020. Overall, farmers' income shows a gradual increasing trend, with the highest income observed in the eastern regions, followed by the central regions, and then the western regions. In terms of fluctuation amplitude, the fluctuations in the eastern and central regions are smaller than those in the western region. The possible reason is that the rural economic development in the eastern and central regions is relatively mature, with relatively perfect rural infrastructures, and farmers' income is growing steadily. In general, there exists uneven development in farmers' income among different regions in China, and the development gap between the eastern, central, and western regions still exists.

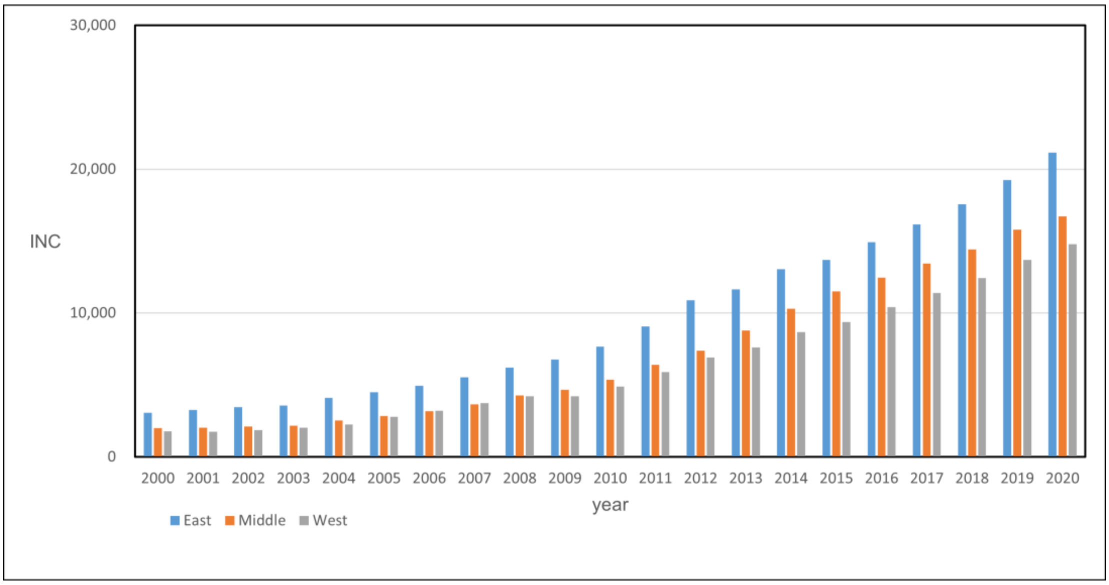


Figure 2. Changes in farmers' income in different regions of China from 2000 to 2020.

Figure 3 shows the spatial distribution and evolution of farmers' income at the county level in China for the years 2000, 2005, 2010, 2015, and 2020. The regions with high farmers' income are mainly concentrated in eastern coastal areas such as Beijing, Tianjin, Shanghai and Zhejiang, while western regions such as Yunnan and Guizhou have low farmers' income. Overall, there is a relatively stable spatial clustering pattern, with high- and low-value areas demonstrating an aggregated distribution, indicating the presence of certain spatial spillover effects.

3.2.2. Explanatory Variable

The core explanatory variable is whether the CCLBP was implemented. For each county, the CCLBP is assigned a value of 1 for the years in which the policy was implemented and for all subsequent years. Otherwise, it is assigned a value of 0.

3.2.3. Mediating Variables

Non-agricultural Industry Development (NAI): Following previous studies [48], non-agricultural industry development is represented by the proportion of the sum of value-added of the secondary and tertiary industries to GDP.

Labor Mobility (LM): Considering issues such as population births, deaths, long-term outmigration, and data availability, this study uses the annual growth rate of permanent residents in each region to represent the situation of labor mobility.

Capital Outflow (CF): Following the method proposed by Huang et al. [49], capital outflow in each year is measured using the ratio of deposits to loans in each region.

3.2.4. Control Variables

Due to the possibility of unobserved variables being correlated with the driving variables in the time breakpoint regression design, adding control variables to the model can make the results more valuable for reference. Therefore, this study selects the following control variables:

Land Area (Area): Land is a significant factor affecting farmers' income [50]. This study measures land area using the administrative division area.

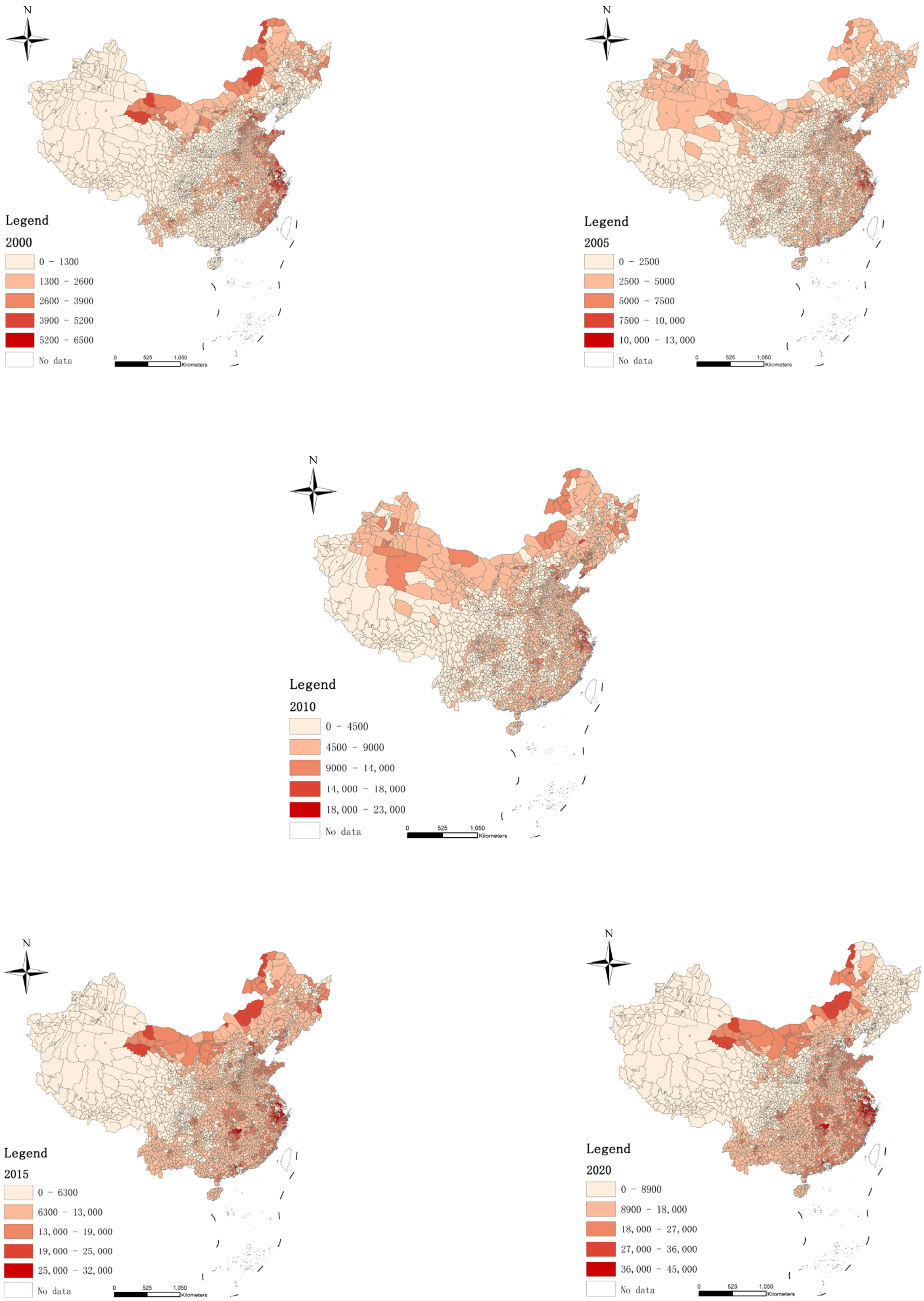


Figure 3. Geographical distribution of farmers' income at the county level in China.

Consumption Level (Consume): Consumption is closely related to income, and equal income distribution leads to an increase in total consumption. Consumption can also drive regional development and promote farmers' income growth [51]. This study uses the logarithm of the total retail sales of social consumer goods to measure residents' consumption levels.

Education Level (Edu): There is a strong correlation between education level and income [52]. This study controls for education level using the logarithm of the number of students in ordinary high schools.

Social welfare level (Welfar): The social welfare level significantly affects the income of farmers in the locality [53]. This study controls for various social welfare measures by using the logarithm of the number of adoption beds per social welfare unit.

3.3. Empirical Model

The probability change in the CCLBP implementation from 0 to 1 before and after its implementation meets the requirements of the sharp RDD. Therefore, in this study, a sharp RDD model was employed to measure the impact of the CCLBP on farmers' income. This method is closer to a randomized experiment compared to other methods, providing estimation results similar to randomized controlled trials (RCT) [54,55]. It can also avoid endogeneity issues in causal estimation and restore causal effects from experimental benchmarks, and has stronger causal inference capabilities, reflecting the true causal relationships between variables [56]. Therefore, RDD is one of the most reliable quasi-experimental methods for causal inference and policy evaluation [57]. The formula is as follows:

$$INC_i = \alpha + \beta CCLBP_i + \beta_1(x_i - c) + \beta_2(x_i - c)CCLBP_i + \beta_3 C_i + \varepsilon_i \tag{1}$$

where INC_i represents rural residents' income. c is the breakpoint, representing the year in which the CCLBP was implemented, that is, 2017. x_i is the grouping variable, and $(x_i - c)$ is the standardization of x_i. $CCLBP_i$ is the time dummy variable. When $x_i - c \geq 0$, $CCLBP_i$ = 1; otherwise, $CCLBP_i$ = 0. The cross-term $\beta_2(x_i - c)CCLBP_i$ allows for different slopes on both sides of the breakpoint. C_i represents control variables. ε_i is the random disturbance term. β is the local average treatment effect at the breakpoint $x_i = c$, representing the measure of CCLBP's impact on farmers' income. β_1 represents the magnitude of the effect of the time variable on the dependent variable. β_2 represents the slope coefficient of $(x_i - c)CCLBP_i$. β_3 represents the coefficient value of control variables.

It is necessary to estimate the local average treatment effect (LATE) between the treatment group and the control group at the breakpoint in order to obtain the effect of the CCLBP. To estimate the LATE, this study employs a non-parametric estimation method, conducting kernel density estimation. The estimation equation is as follows:

$$\min_{|\alpha,\beta,\beta_1,\beta_2|} \sum_{i=1}^{n} K\left[\frac{x_i - c}{h}\right]\left[INC_i - \alpha - \beta CCLBP_i - \beta_1(x_i - c) - \beta_2(x_i - c)CCLBP_i - \beta_3 C_i\right]^2 \tag{2}$$

In Equation (2), K(·) represents the kernel function, h denotes the bandwidth, and the remaining variables have the same meanings as in Equation (1). In this study, the triangular kernel is primarily used to estimate the local average treatment effect in the baseline regression and subsequent exploratory analyses because it is more appropriate for estimating the kernel density at the breakpoint. Additionally, the estimation results using the Epanechnikov and Uniform kernels are reported as part of robustness checks.

Furthermore, to elucidate the potential mechanisms through which the CCLBP affects farmers' income, this study constructs a mediation effects model as follows:

$$M_i = \lambda_0 + \lambda CCLBP_i + \lambda_1(x_i - c) + \lambda_2(x_i - c)CCLBP_i + \lambda_3 C_i + \varepsilon_i \tag{3}$$

$$INC_i = \lambda_0 + \lambda CCLBP_i + \lambda_1(x_i - c) + \lambda_2(x_i - c)CCLBP_i + \delta M_i + \lambda_3 C_i + \varepsilon_i \tag{4}$$

In Equations (3) and (4), M_i represents the mechanism variables under investigation in this study, namely non-agricultural industry development, labor mobility, and capital outflow. Other variables are defined in the same manner as in Equation (1).

3.4. Data Processing

The data were examined for the Variance Inflation Factor (VIF) before analysis. The results indicated that all VIF values were below 4.02. With 10 being the threshold for detection, the analysis excluded the possibility of multicollinearity among the variables. Descriptive statistics for the main variables of this study are presented in Table 1.

Table 1. Descriptive statistics of variables.

Variable Category	Name	Variable	N	Mean	SD	Min	Max
Dependent Variable	Farmers' income	INC	39,965	7760.987	5854.32	498	44,117
Explanatory Variable	the CCLBP Dummy Variable	the CCLBP	59,862	0.228	0.419	0	1
Mediating Variables	Non-agricultural Industry Development	NAI	51,260	0.781	0.151	0.111	5.593
	Labor Mobility	LM	47,240	0.503	7.728	−100	328.571
	Capital Outflow	CF	46,965	1.438	8.910	0	1770
Control Variables	Land Area	Area	50,255	7.56	1.14	2.079	12.246
	Consumption Level	Consume	46,943	12.17	1.55	4.007	16.627
	Education Level	Edu	50,408	9.75	1.08	2.890	12.319
	Social Welfare Level	Welfare	45,834	6.14	1.51	0	9.942

4. Empirical Testing and Results Analysis

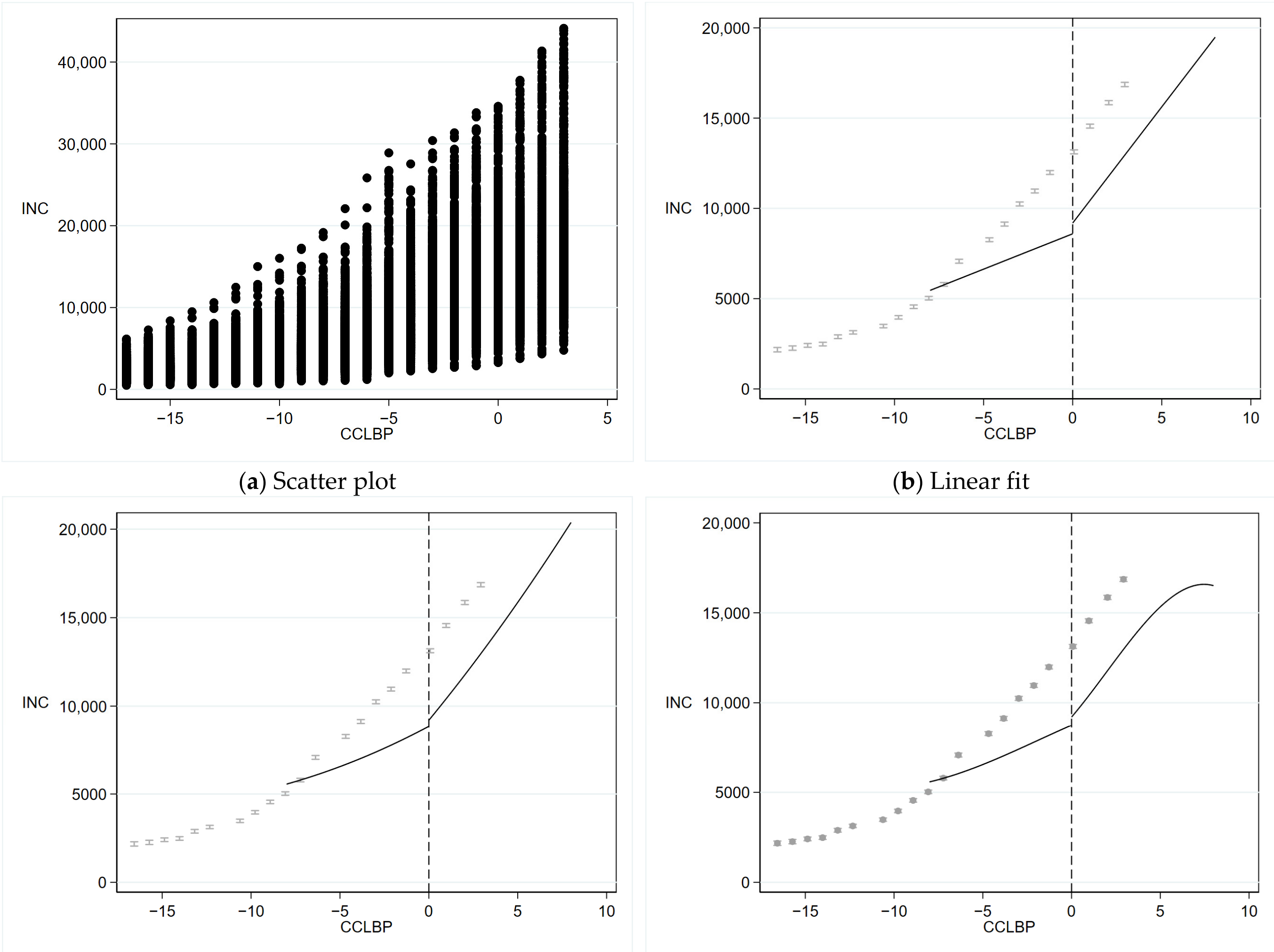
4.1. Validity Test of the Regression Discontinuity Design

4.1.1. Test for the Existence of the Breakpoint in the Dependent Variable

When using the RDD for testing, it is first necessary to determine whether there is a jump phenomenon in the dependent variable at the breakpoint, that is, the breakpoint effect. Figure 4 shows the scatterplot and fit situation of farmers' income before and after the implementation of the CCLBP. It can be seen that the scatterplot, linear fit, quadratic fit, and cubic fit all show significant jumps on both sides of the breakpoint, indicating that farmers' income at the breakpoint increases significantly due to the policy effect. Thus, it can be inferred from the breakpoint effect that the implementation of the CCLBP has a significant impact on farmers' income.

4.1.2. Manipulability Test of Driving Variables

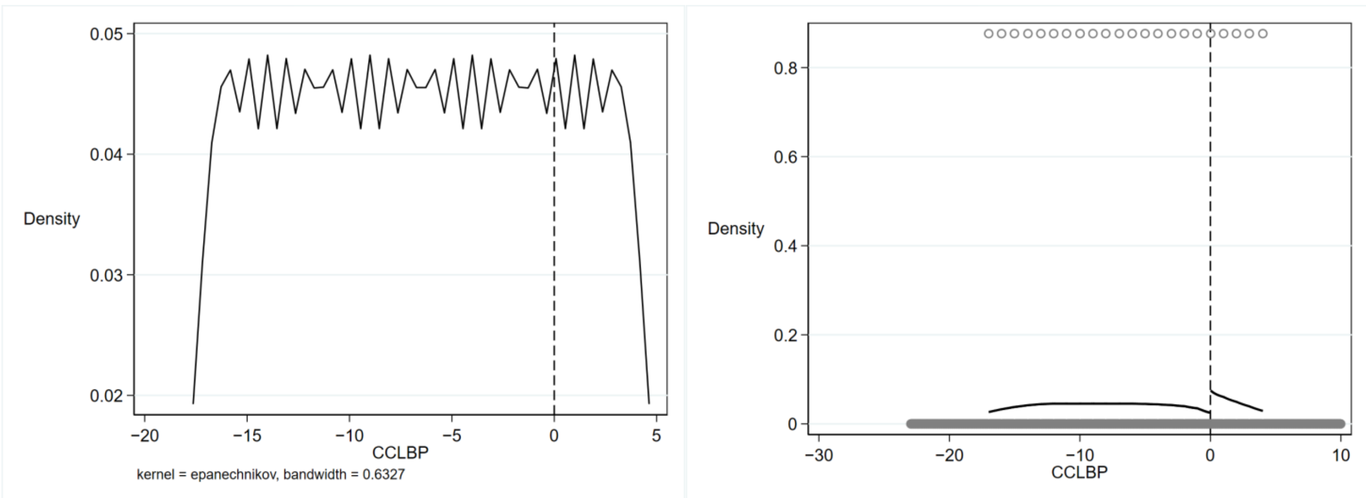
The local randomization assumption requires that the driving variables are not subject to potential human manipulation. If their response to policy interventions is largely influenced by human manipulation, the final estimation results will be biased. To examine the potential manipulation of individual driving variables near the breakpoint, the following tests were conducted in this study. First, we tested the continuity of the density function of the driving variables [58]. As shown in Figure 5a, there is no significant difference in the density function of the distribution of driving variables on both sides of the breakpoint. Second, we used local polynomial density estimation (local quadratic approximation) to test for discontinuities in the breakpoint regression estimates and plotted the corresponding density functions (Figure 5b), following Cattaneo et al. [59]. From Figure 5b, it can be seen that the change in the driving variables at the breakpoint is relatively smooth. The results of the above tests indicate that there is no evidence of manipulation in the selection of the driving variables.



(**a**) Scatter plot (**b**) Linear fit

(**c**) Quadratic fit (**d**) Cubic fit

Figure 4. Breakpoint of farmers' income before and after the CCLBP.



(**a**) Continuity test of density function (**b**) Density distribution plot

Figure 5. Manipulability test of the driving variables.

4.1.3. Balance Test of Control Variables

In this study, if the conditional density function of county-level characteristic variables exhibits a jump at the breakpoint, then the entire treatment effect cannot be attributed solely to the CCLBP. Therefore, an implicit assumption is that county-level characteristic variables are continuous at the breakpoint. Table 2 presents the results of a balance test on the continuity of control variables using different standard errors. The results show that the county-level characteristic variables have no significant impact on farmers' income.

Table 2. Balance test.

Variables	**Area (1)**	**Consume (2)**	**Edu (3)**	**Welfare (4)**
Conventional	0.041	−0.010	0.026	0.019
	(1.340)	(−0.357)	(1.118)	(0.532)
Bias-corrected	0.045	−0.005	0.005	0.047
	(1.472)	(−0.183)	(0.237)	(1.275)
Robust	0.045	−0.005	0.005	0.047
	(1.493)	(−0.179)	(0.229)	(1.172)
Control	NO	NO	NO	NO
Kernel Function	Triangular	Triangular	Triangular	Triangular
N	39,380	39,380	39,380	39,380
Eff. N	20,209	12,292	14,225	20,200

Note: values in parentheses are *t*-statistics; Conventional refers to conventional standard errors, i.e., OLS standard errors; Bias-corrected refers to bias-corrected robust standard errors; Robust refers to robust standard errors.

4.2. Baseline Regression Results

The regression parameters in RDD are highly sensitive to the choice of bandwidth, and the estimated results often lack robustness. Imbens and Kalyanaraman (2012) [60] proposed a method to choose the optimal bandwidth by minimizing the expected mean squared error of two functions at the breakpoint. However, Cattaneo et al. (2019) [57] argued that the bandwidth generated by this criterion is too large relative to the approximate distribution values used, resulting in biased RDD estimates. Therefore, they corrected the IK2012 criterion in two ways: re-estimating parameters and standard errors to correct asymptotic bias and then selecting smaller bandwidths. Thus, this study used the CCT2019 criterion for estimation and conducted sensitivity analysis using different bandwidths near this criterion.

Table 3 presents the regression results of the impact of the CCLBP on farmers' income. Columns (1), (2), and (3) show the regression results without controlling for other variables, while columns (4), (5), and (6) report the regression results after controlling for additional variables. The results indicate that under the Triangular kernel setting, farmers' income is significantly positive across conventional standard errors, bias-corrected robust standard errors, and robust standard errors. Similar results are observed under the Epanechnikov and Uniform kernel settings, indicating that the CCLBP can increase farmers' income, consistent with H1.

In terms of coefficient estimation, after controlling for additional variables, farmers' income can increase by approximately RMB 411–582. Compared with the average level of the counties in the sample, the implementation of the CCLBP can increase farmers' income by about 5.3%–7.5%.

Table 3. Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	202.904	261.086 *	287.050 *	411.436 ***	435.073 ***	466.560 ***
	(1.286)	(1.653)	(1.817)	(3.112)	(3.279)	(3.497)
Bias-corrected	465.919 ***	577.398 ***	553.206 ***	513.297 ***	581.973 ***	537.236 ***
	(2.952)	(3.656)	(3.501)	(3.886)	(4.387)	(4.026)
Robust	465.919 ***	577.398 ***	553.206 ***	513.297 ***	581.973 ***	537.236 ***
	(2.946)	(3.656)	(3.497)	(3.836)	(4.330)	(3.957)
Control	NO	NO	NO	YES	YES	YES
Kernel Function	Triangular	Epanechnikov	Uniform	Triangular	Epanechnikov	Uniform
N	39,965	39,965	39,965	33,022	33,022	33,022
Eff. N	23,892	21,714	21,714	17,194	17,194	17,194

Note: values in parentheses are *t*-statistics; ***, * are significant at the 1%, 10% statistical levels; Conventional refers to conventional standard errors, i.e., OLS standard errors; Bias-corrected refers to bias-corrected robust standard errors; Robust refers to robust standard errors.

4.3. Robustness Test

4.3.1. Sensitivity Test of Bandwidth

This study attempts to test the robustness by altering the bandwidth setting for the breakpoint estimation. Table 4 reports the effect of the CCLBP on farmers' income under different bandwidths. It can be observed that the impact of the CCLBP on farmers' income remains significantly positive across different bandwidths, thus maintaining consistent conclusions.

Table 4. Robustness test: sensitivity test of bandwidth.

Variables	(1) 0.75 CCT	(2) 1.34 CCT	(3) 1.68 CCT
Conventional	395.646 ***	225.032 *	227.190 *
	(2.990)	(1.689)	(1.695)
Bias-corrected	516.152 ***	456.535 ***	258.010 *
	(3.901)	(3.426)	(1.925)
Robust	516.152 ***	456.535 ***	258.010 *
	(3.867)	(3.406)	(1.922)
Control	YES	YES	YES
Kernel Function	Triangular	Triangular	Triangular
N	33,022	33,022	33,022
Eff. N	19,179	23,111	13,460

Note: values in parentheses are *t*-statistics; ***, * are significant at the 1%, 10% statistical levels; Conventional refers to conventional standard errors, i.e., OLS standard errors; Bias-corrected refers to bias-corrected robust standard errors; Robust refers to robust standard errors.

4.3.2. Placebo Test

To mitigate the estimation bias resulting from non-random sample selection and ensure that the effect captured in this study is indeed attributable to the CCLBP, we conducted a placebo test following the approach outlined by Baker [61]. Since the "pseudo" treatment group is generated randomly and does not have a significant effect on the explained variable, its estimated coefficient should be near 0. Figure 6 depicts the kernel density distribution of the regression coefficients of the CCLBP on farmers' income from 1000 placebo estimations. As shown, the results exhibit a symmetric inverted U-shaped distribution centered around 0, resembling a standard normal distribution. This suggests that the coefficients estimated in the 1000 random processes are indeed concentrated around 0. Therefore, we can reasonably conclude that the results of the baseline estimation are not affected by non-random sample selection bias, providing evidence for the credibility of our research findings.

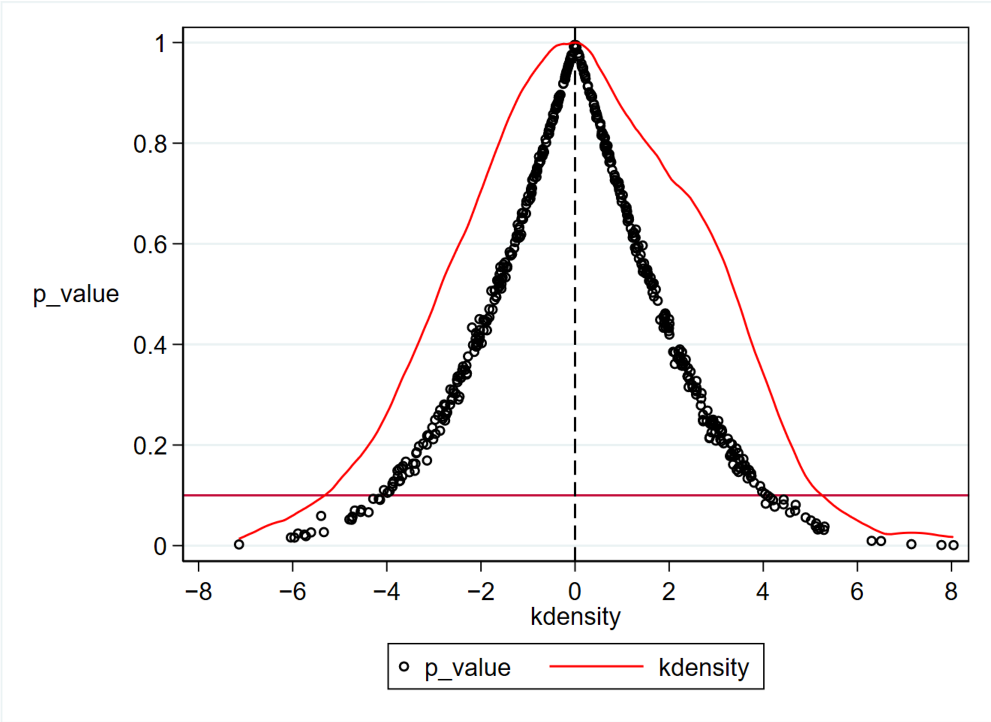


Figure 6. Placebo test.

4.3.3. Sensitivity Test for Sample Selection

The motivation for manipulation being stronger for samples closer to the breakpoint may affect the estimation results of this study [62]. Therefore, this study removed samples within 4%, 8%, 12%, 16%, 20%, and 24% around the breakpoint and conducted a donut hole RDD test. Figure 7 shows the regression coefficients and 95% confidence intervals. It can be seen that even after removing up to 24% of the samples, the regression results remain robust.

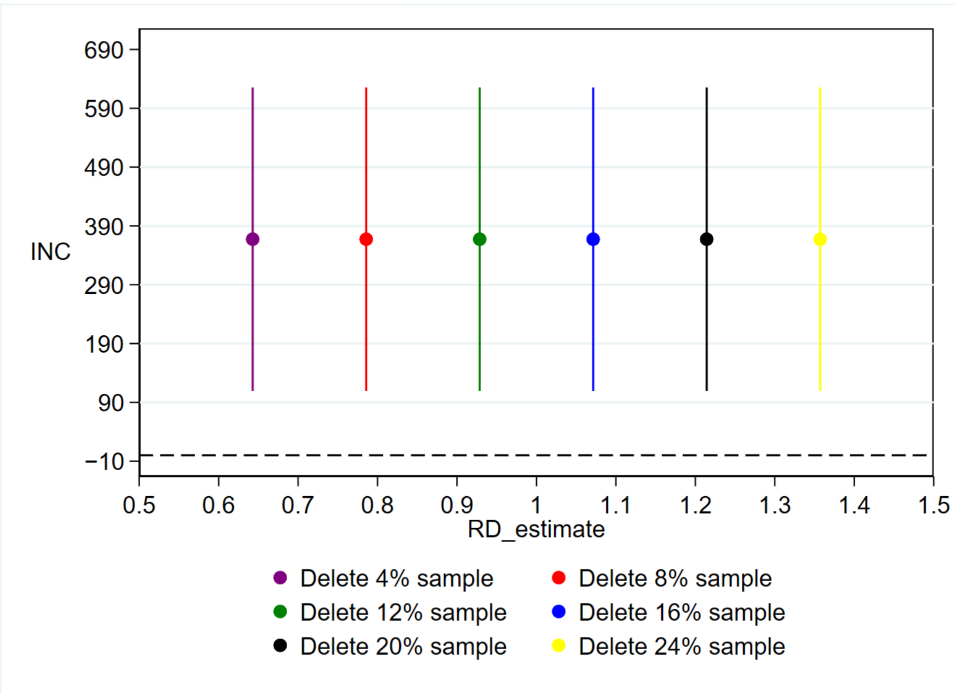


Figure 7. Sensitivity test for sample selection.

4.3.4. Other Robustness Tests

This study also conducted the following robustness tests: ① Excluding Special Samples. There are significant differences among different districts, county-level cities, and their subordinate counties in terms of political resources, economic resources, and decision-making autonomy. If all counties (districts, county-level cities) are estimated together, it may affect the results. Therefore, this study attempted to exclude all district and county-level city sample data, and the estimation results are shown in columns (1), (2), and (3) of Table 5. After excluding the above samples, the regression coefficient remains significantly positive, confirming the robustness of the research conclusions. ② Changing the Sample Interval. Different sample intervals may affect the baseline conclusions of this study. The implementation of the CCLBP was in 2017, while the data sample spanned from 2000 to 2020, making the period before the CCLBP implementation relatively long, which may affect the research conclusions. To address this concern, the data from the first five years were excluded, and the sample interval was set to 2005–2020 for regression analysis. The results are shown in columns (4), (5), and (6) of Table 5. The regression coefficient remains significantly positive, indicating that the long period does not affect the research conclusions, and the conclusions of this study remain robust after changing the sample interval. ③ Lagged Effects. Considering that the policy implementation may have a certain time lag effect, referring to Acemoglu et al. [63], this study used lagged explanatory variables as alternative variables for the current explanatory variables to examine the impact of the CCLBP on farmers' income. The results are shown in columns (7), (8), and (9) of Table 5. The results indicate that the regression coefficient of the lagged period of the CCLBP's impact on farmers' income is positive and significant, demonstrating the robustness of the research conclusions.

Table 5. Other robustness tests.

Variables	Excluding Special Samples			Changing the Sample Interval			Lagged Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Conventional	393.555 ***	227.638 *	449.991 ***	411.136 ***	435.073 ***	368.917 ***	218.882 *	299.105 **	283.778 **
	(3.010)	(1.694)	(3.410)	(3.112)	(3.279)	(2.734)	(1.836)	(2.502)	(2.371)
Bias-corrected	495.796 ***	299.627 **	700.474 ***	375.009 ***	430.088 ***	472.667 ***	470.831 ***	482.443 ***	549.591 ***
	(3.792)	(2.230)	(5.309)	(2.839)	(3.242)	(3.503)	(3.949)	(4.036)	(4.593)
Robust	495.796 ***	299.627 **	700.474 ***	375.009 ***	430.088 ***	472.667 ***	470.831 ***	482.443 ***	549.591 ***
	(3.746)	(2.220)	(5.255)	(2.777)	(3.167)	(3.452)	(3.855)	(3.935)	(4.362)
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
Kernel Function	Triangular	Epanechnikov	Uniform	Triangular	Epanechnikov	Uniform	Triangular	Epanechnikov	Uniform
N	33,022	33,022	33,022	19,179	19,179	19,179	31,907	31,907	31,907
Eff. N	17,194	13,400	17,194	17,194	17,194	19,179	17,603	15,616	15,616

Note: values in parentheses are *t*-statistics; ***, ** and * are significant at the 1%, 5% and 10% statistical levels; Conventional refers to conventional standard errors, i.e., OLS standard errors; Bias-corrected refers to bias-corrected robust standard errors; Robust refers to robust standard errors.

4.4. Heterogeneity Analysis

Policies are usually implemented under the coordination of provincial governments, and different counties within the same province are often constrained within a unified framework [64]. Therefore, this study conducts heterogeneity analysis by province. Table 6 presents the results of the heterogeneity analysis. The results show that the policy effect is significantly positive in Hebei, Shandong, Hubei and Shaanxi, while it is significantly negative in Guangxi. The policy effect in other provinces is insignificant, indicating significant regional heterogeneity and supporting Hypothesis 2.

Table 6. Heterogeneity analysis.

Variables	(1) Heilongjiang	(2) Jilin	(3) Inner Mongolia	(4) Hebei	(5) Shanxi	(6) Liaoning	(7) Beijing	(8) Anhui
Conventional	396.117	329.955	76.775	492.723 **	186.355	643.428	61.572	149.349
	(0.689)	(0.903)	(0.114)	(2.020)	(0.536)	(0.705)	(0.080)	(0.278)
Bias-corrected	520.721	666.224 *	421.635	652.012 ***	400.260	887.683	533.153	157.001
	(0.905)	(1.823)	(0.627)	(2.673)	(1.151)	(0.972)	(0.689)	(0.292)
Robust	520.721	666.224 *	421.635	652.012 ***	400.260	887.683	533.153	157.001
	(0.905)	(1.863)	(0.630)	(2.636)	(1.159)	(0.963)	(0.680)	(0.287)
Control	YES	YES	YES	YES	YES	YES	YES	YES
Kernel Function	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
N	1606	836	1749	2869	1925	2200	105	1310
Eff. N	949	485	1008	1493	1041	1300	60	758

Variables	(9) Fujian	(10) Gansu	(11) Guangdong	(12) Guangxi	(13) Guizhou	(14) Hainan	(15) Henan	(16) Hubei
Conventional	114.164	126.243	133.542	−459.714 *	161.785	45.540	−38.618	738.251 **
	(0.445)	(0.238)	(0.226)	(−1.795)	(0.804)	(0.210)	(−0.140)	(2.141)
Bias-corrected	256.593	−220.528	63.799	−605.423 **	161.579	346.615	92.382	1070.410 ***
	(1.000)	(−0.416)	(0.108)	(−2.363)	(0.803)	(1.595)	(0.334)	(3.104)
Robust	256.593	−220.528	63.799	−605.423 **	161.579	346.615 *	92.382	1070.410 ***
	(0.998)	(−0.416)	(0.105)	(−2.342)	(0.802)	(1.682)	(0.335)	(2.955)
Control	YES	YES	YES	YES	YES	YES	YES	YES
Kernel Function	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
N	1137	1405	1463	1850	1958	319	2289	1394
Eff. N	634	795	869	1100	1157	186	1206	736

Variables	(17) Hunan	(18) Jiangsu	(19) Jiangxi	(20) Ningxia	(21) Qinghai	(22) Shandong	(23) Shaanxi	(24) Sichuan
Conventional	165.483	910.548	86.392	123.344	−170.431	964.222 ***	648.745 **	172.942
	(0.333)	(1.330)	(0.236)	(0.188)	(−0.240)	(3.055)	(2.321)	(0.416)
Bias-corrected	463.739	963.306	220.152	220.244	4.702	1594.552 ***	923.291 ***	96.244
	(0.932)	(1.407)	(0.601)	(0.337)	(0.007)	(5.052)	(3.304)	(0.232)
Robust	463.739	963.306	220.152	220.244	4.702	1594.552 ***	923.291 ***	96.244
	(0.947)	(1.463)	(0.602)	(0.343)	(0.007)	(4.846)	(3.252)	(0.232)
Control	YES	YES	YES	YES	YES	YES	YES	YES
Kernel Function	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
N	1835	1279	2199	293	968	3058	1751	3143
Eff. N	968	772	1300	156	572	1807	957	1920

Variables	(25) Tianjing	(26) Xinjiang	(27) Yunnan	(28) Zhejiang	(29) Chongqing
Conventional	600.595	14.936	−327.857	764.711	86.018
	(0.577)	(0.014)	(−1.219)	(1.543)	(0.380)
Bias-corrected	784.496	−145.187	−42.199	868.005 *	39.842
	(0.754)	(−0.134)	(−0.157)	(1.752)	(0.176)
Robust	784.496	−145.187	−42.199	868.005 *	39.842
	(0.761)	(−0.132)	(−0.158)	(1.715)	(0.174)
Control	YES	YES	YES	YES	YES
Kernel Function	Triangular	Triangular	Triangular	Triangular	Triangular
N	352	1745	2360	1196	545
Eff. N	176	999	1409	724	286

Note: values in parentheses are *t*-statistics; ***, ** and * are significant at the 1%, 5% and 10% statistical levels; Conventional refers to conventional standard errors. i.e., OLS standard errors. Bias-corrected refers to bias-corrected robust standard errors. Robust refers to robust standard errors.

4.5. Mechanism Analysis

Results from baseline regression suggest that the CCLBP can help raise farmers' income. But how does this policy affect farmers' income? We first tested whether the CCLBP would influence non-agricultural industrial development, labor mobility, and capital outflow and then estimated how the CCLBP would work.

The results in columns (1), (3), and (5) of Table 7 show that there are significant differences in the mechanism variables on both sides of the breakpoint and indicate that the CCLBP can significantly promote non-agricultural industrial development and labor mobility and reduce capital outflows. The results in columns (2), (4), and (6) show that after adding the mechanism variables, the effect of the CCLBP on farmers' income decreases compared to the baseline regression results, indicating that the impact of the CCLBP on farmers' income can be explained by the above mechanism variables. Therefore, the CCLBP can indeed increase farmers' income by promoting non-agricultural industrial development and labor mobility and reducing capital outflows. Hypothesis 3 is supported.

Table 7. Mechanism analysis.

Variables	NAI (1)	INC (2)	LM (3)	INC (4)	CF (5)	INC (6)
Conventional	0.014 ***	411.136 ***	1.112 **	410.719 ***	−0.095 **	403.235 ***
	(4.864)	(3.112)	(2.273)	(3.109)	(−2.046)	(3.052)
Bias-corrected	0.014 ***	517.710 ***	1.500 ***	532.642 ***	−0.430 ***	548.059 ***
	(4.847)	(3.919)	(3.066)	(4.032)	(−9.241)	(4.148)
Robust	0.014 ***	517.710 ***	1.500 ***	532.642 ***	−0.430 **	548.059 ***
	(4.659)	(3.871)	(2.734)	(3.988)	(−2.405)	(4.105)
NAI		YES				
LM				YES		
CF						YES
Control	YES	YES	YES	YES	YES	YES
Kernel Function	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
N	39,029	33,022	36,521	33,022	38,452	33,022
Eff. N	22,149	17,194	19,140	19,179	19,692	17,194

Note: values in parentheses are *t*-statistics; ***, ** are significant at the 1%, 5% statistical levels; Conventional refers to conventional standard errors, i.e., OLS standard errors; Bias-corrected refers to bias-corrected robust standard errors; Robust refers to robust standard errors.

5. Discussion

5.1. Reflections on How the CCLBP Promotes Increases in Farmers' Income

This study confirms that the CCLBP can improve farmers' income and shows regional heterogeneity. However, it is interesting to note that the CCLBP did not significantly affect Heilongjiang, Jilin, Inner Mongolia, Yunnan, Sichuan, Qinghai, Shaanxi, Gansu, or Xinjiang, which are the main distribution areas of natural forests. Instead, it had a negative impact on Guangxi and a significant positive impact on only four provinces: Hebei, Shandong, Hubei, and Shaanxi. This result differs significantly from previous studies [8,31]. We believe the reasons are as follows: first, Heilongjiang, Jilin, Inner Mongolia, Yunnan, Sichuan, Qinghai, Shaanxi, Gansu, and Xinjiang are significant state-owned forest areas in China. While the CCLBP was being implemented, the government also took several measures to ensure the livelihoods of forest farmers and forest workers. For example, after the end of logging in Heilongjiang, the province actively promoted the transformation of forest farmers' roles from "loggers" to "forest guardians", which resulted in minimal fluctuations in farmers' income. In addition, Cheng, K et al. [65,66] found a significant increase in artificial forests in these areas. After the implementation of the CCLBP, some farmers may switch to logging and processing artificial forests, resulting in no significant change in income. Second, the annual harvesting volume of natural forests in Guangxi was only about 100,000 cubic meters, accounting for 4.6% of the natural forest harvesting quota and 0.3% of the total harvesting volume before the implementation of the CCLBP. In terms of total volume and proportion, the commercial logging intensity of natural forests in Guangxi was not high, and the CCLBP seemed to have little impact on farmers' income. However, Guangxi is the leading province in the cultivation of fast-growing eucalyptus trees, with an industrial scale of tens of billions, affecting the livelihoods of tens of millions of farmers. The implementation of the CCLBP closely coincided with the "eucalyptus ban" by the Guangxi Forestry Department. Under the double impact of these policies, the papermaking and wood processing industries in Guangxi have been significantly impacted. Moreover, the decline in the price of imported wood pulp has exerted further adverse effects on the industrial chain clusters related to eucalyptus seedlings, planting, processing and transportation in Guangxi, ultimately resulting in a reduction in farmers' income. Third, following the implementation of the CCLBP in Hebei, Shandong, Hubei, and Shaanxi, various industries focused on green food, animal husbandry, and traditional Chinese medicine as well as forest tourism and non-timber forest products. This shift from "relying only on forestry" to "diversified industries" and from "forestry economy" to "forest economy" promoted an increase in farmers' income. For example, Saihanba Mechanized

Forest Farm in Hebei has rapidly developed surrounding rural tourism, farm stays, and specialty product processing industries, driven by a good ecological environment, with a total annual social income of more than RMB 600 million. Mulan Forest Farm provides more than 240,000 direct labor services for forest protection and management every year. It also supports the development of industries such as forest harvesting and forest recreation in the surrounding areas and helps residents increase their annual income by more than RMB 150 million.

5.2. Further Reflections on the CCLBP

The effectiveness of China's CCLBP in protecting natural forests can be attributed to its robust legal provisions and strict "top-down" government regulatory mechanism, which provide an effective solution for global forest conservation. Evidence indicates that governments and social organizations worldwide are actively seeking solutions to address land degradation and forest loss caused by human activities [67–71]. Examples include Pakistan's "Billion Tree Afforestation Project" (BTAP) [72]; the European Union's approval of the "EU Deforestation Regulation" (EUDR) on 16 May 2023 to address forest cutting and degradation in Europe and globally; and the 2021 forest conservation agreement signed by representatives from over 100 countries, including Brazil and China, committing to eliminate deforestation by 2030. Notably, Brazil's commitment has garnered significant international attention. However, data released by the Brazilian National Institute for Space Research show that from August 2020 to July 2021, deforestation in the Brazilian Amazon reached a 15-year high, increasing by 22% compared to the previous year, with approximately 13,235 square km of rainforest disappearing from the Amazon. This indicates that deforestation remains a "challenge" for Brazil. Meanwhile, on-site law enforcement in Brazil is a high-cost method for forest protection [73]. Therefore, the Brazilian government can draw lessons from China's CCLBP and enhance the implementation of existing regulatory measures as a crucial part of its action plan against deforestation.

Furthermore, through research, many scholars have found that logging bans issued by governments in countries such as Indonesia and Thailand have promoted an increase in farmers' income [74–78]. However, unlike these bans, China's CCLBP has fundamentally transformed the production and lifestyle of local people, achieving the dual goals of increasing farmers' income and enhancing the quality of natural forest protection. Through mechanism analysis, this study finds that the CCLBP promotes farmers' income through the development of non-agricultural industries, labor mobility, and reduced capital outflows. Specifically, first, following the implementation of the CCLBP, the Chinese government provided numerous employment opportunities in forest management, tree planting, and afforestation, transforming former loggers into forest protectors and thereby avoiding deforestation due to unemployment and the need to earn a living. Second, after the implementation of the CCLBP, the favorable ecological environment has promoted the development of under-forest economic industries in forest areas, driving farmers to shift towards non-agricultural industries and accelerating the economic and industrial transformation of forest areas. Third, following the implementation of the CCLBP, the Chinese government has invested heavily in ecological compensation funds, stimulating the enthusiasm of farmers to participate in policy implementation and compensating for the capital gap needed for farmers' development. Fourth, the Chinese government's adherence to the CCLBP does not sacrifice regional development equity but seeks new economic development models, helping regions dependent on forests to transform through green transitions, namely, demanding new economic growth by realizing the value of ecological products [79]. As for Brazil, agricultural expansion is the primary culprit behind deforestation and forest degradation in the Amazon [80,81], making it urgent to transform the production and lifestyle of local people. With the development of non-agricultural industries and green finance, it is believed that Brazil can help farmers break their dependence on forests, achieve coordinated economic and ecological development, and reach the goal of eliminating deforestation by 2030.

6. Conclusions

Based on county-level panel data in China from 2000 to 2020, this study effectively identified the impact of the CCLBP on farmers' income using RDD. The empirical results of the study show that the CCLBP has a significant effect on farmers' income, increasing it by about RMB 411–582. Moreover, the CCLBP has heterogeneous effects on increasing farmers' income in different regions. The CCLBP significantly promotes the development of non-agricultural industries and labor mobility while reducing capital outflows, which has significantly increased farmers' income. Based on these findings, two policy implications are proposed to further enhance the CCLBP's promotion effect on farmers' income. First, we have interpreted the positive effects of the CCLBP on farmers' income, but the effects vary across different regions, indicating that fully exploiting the effectiveness of the CCLBP is a prerequisite for promoting farmers' income. Therefore, first of all, it is essential to establish complementary employment policies for farmers based on the existing CCLBP, providing them with vocational training, specific non-agricultural job opportunities, and preferential employment policies. The second important step is to develop characteristic industries tailored to local resource endowments that encourage farmers to start their businesses. For example, the development of activities such as picking tourism and rural homestays can diversify farmers' sources of income sources. Lastly, it is necessary to establish a long-term ecological compensation mechanism. Provinces and counties (cities) can implement a dynamic adjustment mechanism for compensation standards based on the local economic development levels and financial capacity, on top of the national minimum compensation standards, targeting different compensation regions and populations. Second, we have explained how the CCLBP promotes farmers' income through the development of non-agricultural industries, labor mobility, and reduction in capital outflow. Thus, based on the ecological resources of forests, it is necessary to vigorously develop non-agricultural industries such as forest tourism, rural e-commerce and forest recreation and encourage the adjustment and upgrading of the industrial structure in rural areas to create more employment opportunities, guide the local transfer of surplus rural labor, and reduce the loss of capital due to population migration. Simultaneously, some scholars [82] have found that land rights for farmers can improve agricultural productivity. Therefore, it is essential to establish a sound rural property rights protection system, improve the rural financial services system, and raise the level of rural public services. These measures will provide investors with a stable, fair, and transparent investment environment, promote the continuous inflow of factors, support rural industrial development, and increase farmers' income. This will ultimately build a development system characterized by ecological sustainability and prosperity for the people, tailored to local conditions.

Despite using long-term county-level macro-level statistical data, which effectively avoids potential biases associated with the use of micro-level household surveys and partial regional data in previous research, this study addresses the shortcomings of previous studies on the comprehensive and dynamic effects of the CCLBP, provides a new perspective for analyzing the CCLBP, and offers significant additions to the existing literature. However, it may not capture all the details of micro-level survey data. For example, it cannot determine the impact of the CCLBP on different components of farmers' income, such as agricultural and non-agricultural income. Secondly, this study used county-level data from 2000 to 2020 due to data availability. Although this covers a long period, the CCLBP was implemented nationwide in 2017 in a "one-size-fits-all" manner. Therefore, our observation period after policy implementation is not long enough, and further research is needed to dynamically track and observe changes in farmers' income. Thus, as data availability increases, future research can match micro-level survey data with macro-level statistical data to explore the dynamic effects of the CCLBP from a longer-term perspective. Finally, quantitative analysis alone is not enough to obtain universal policy recommendations suitable for each region, but the development of a logically consistent and complementary policy system is outside the purview of this study. Therefore, future research could use case studies to explore this aspect, which would help uncover more powerful mechanisms of the CCLBP effects and ultimately achieve sustainable development in a truly meaningful sense.

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