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# A Study on the Mechanism Through Which Digital Inclusive Finance Influences the Consumption Gap Between Urban and Rural Residents

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***Abstract:*** *This study builds an analytical framework for the urban-rural consumption gap with two-way FE, mechanism effect decomposition and regional heterogeneity tests to overcome the lack of clarity in the channels through which digital inclusive finance affects the consumption gap between urban and rural residents and the difficulty in identifying regional effect differences. We chose the 31 provincial-level areas in Chinese mainland a as the research subjects, with 93 panel observations from 2022 to 2024. The digital inclusive finance index was used as an additional variable for the traditional two-way fixed-effects model, and we also included three-dimensional dimensions of coverage breadth, usage depth, and digitalization level. We estimated the impact of the urban-rural income gap and rural credit supply intensity on transmission by using a provincial cluster-robust estimation approach, and performed tests of robustness using regional interaction terms and IV-2SLS tests. The results indicate that the coefficient for the overall index of digital inclusive finance is −0.0820, with the coefficients for coverage breadth and usage depth being −0.0530 and −0.0940, respectively, where the indirect effect of income on the path is −0.0333 and the indirect effect of credit on the path is −0.0248, accounting for 40.61% and 30.24% of the overall effect, respectively, and the coefficient for the eastern region is −0.108 and for the western region is −0.047. The study suggests that the depth of digital financial usage, the improvement of income distribution and the accessibility of rural credit are the three key factors explaining the change in the urban-rural consumption gap, and the regional development conditions affect the strength of these impacts, thus providing an analytical foundation for the differentiated development of digital inclusive finance.*

***Keywords:*** *digital inclusive finance; urban-rural consumption gap; two-way fixed effects; transmission mechanism; regional heterogeneity*

## 1. Introduction

The urban-rural consumption difference is one important measure to identify coordinated development of regional economy and distribution of household welfare; multiple factors such as income distribution structure, financial resources allocation, and consumption financing constraint can affect the change of the urban-rural consumption gap. Digital inclusive finance has crossed the spatial service limits of the conventional financial service providers and changed the ways in which the urban and rural citizens access and use financial services, whether by using digital payments, digital credit or verifying identities. Nevertheless, this increase in financial service coverage is not always expected to reduce the consumption gap as the ability to access financial services, the extent of financial services usage and regional economic fundamentals may dampen its transmission. Although the literature on the link between digital finance and household consumption is rich, there is still scope for further study on the joint identification of urban-rural income gap, rural credit availability and regional heterogeneity. With this as a background, this paper chooses the 31 provincial-level regions in *Chinese mainland* as the research area, builds up the provincial-level panel analysis framework and uses two-way fixed effects model to analyze the relationship between digital inclusive finance and the urban – rural consumption gap. Through the mechanism effect decomposition, regional interaction terms, and robustness tests, the study explores the transmission paths of income improvement and credit constraint easing, the differences in the effects based on different regional development scenarios, and offers empirical evidence to optimize the allocation of rural digital financial resources and reduce the consumption gap between urban and rural residents.

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## 2. Literature Review

Research on digital inclusive finance is shifting from measuring the accessibility of financial services to identifying the effects of payment behavior, digital literacy, and consumption distribution. Tawiah et al. analyzed urban-rural consumption welfare disparities based on Ghana's 7th Living Standards Survey, using instrumental variables, RIF unconditional quantile regression, and Oaxaca–Blinder decomposition (Tawiah et al., 2025) [1].Debi et al. integrated four categories of indicators—education, health, wealth, and water and sanitation conditions—to construct a household well-being index and examined the explanatory role of financial literacy (Debi et al., 2025) [2]. Paul et al. conducted a three-stage sampling of 405 households, constructed a financial inclusion index comprising three dimensions—accessibility, usage, and service quality—and estimated it using a Logit model (Paul & Debnath, 2025) [3].Regarding payment behavior, Schomburgk et al. conducted a meta-analysis of 71 studies on non-cash payments (Schomburgk et al., 2024) [4]. Based on Dutch payment diary data, van der Cruijsen et al. found that 7% of respondents consistently used cash, while 28% stated they could not give up cash payments (van der Cruijsen & Reijerink, 2024) [5].Dorfleitner et al. utilized a sample of 30,549 women across seven countries, defining three variables—mobile money usage, account ownership, and active usage within 90 days—to test the mediating role of financial management behavior (Dorfleitner & Nguyen, 2024) [6].Wahbi et al. conducted a discrete choice experiment with 421 farmers in Mali to quantify preferences for the attributes of digital savings products (Wahbi & Musshoff, 2024)[7]. Vik et al. analyzed the association between digital skills and the use of financial services based on a survey of 922 adults aged 18–96 in the United Kingdom (Vik et al., 2024)[8].Existing research has addressed consumption patterns, payment frictions, and digital literacy, but lacks a joint quantitative analysis of multidimensional financial characteristics and urban-rural consumption gaps.

## 3. Research Design

### *3.1 Research Hypotheses*

In 2025, per capita consumption expenditure for urban and rural residents in China was 35,869 yuan and 20,259 yuan, respectively, with a difference of 15,610 yuan. Using the logarithmic difference in urban-rural consumption expenditure to measure the consumption gap, and incorporating the three-dimensional indicators of digital financial coverage, usage depth, and digitalization into the feature matrix, we propose the following hypotheses:

H1: Digital inclusive finance narrows the urban-rural consumption gap by expanding rural financial service coverage and reducing transaction costs; its overall impact coefficient is expected to be negative.

H2: The facilitation of digital payments and the alleviation of credit constraints constitute two distinct mechanisms, each producing indirect effects by reducing payment friction and improving the availability of consumer financing, respectively.

H3: Differences in digital skills and network infrastructure result in nonlinear heterogeneity in the aforementioned effects, with the impact being relatively limited in areas with insufficient digital access.

We subsequently employ a 50% cross-validation dual machine learning approach to estimate the overall effects, combining causal forests and SHAP analysis to test the mechanisms and heterogeneity.

### *3.2 Research Sample and Data Sources*

Based on the data collected from 31 provinces in *Chinese mainland* , we constructed a four-period panel data set for 2022 – 2025, with a proposed sample size of 124 province-year observations, of which 31 were collected from the National Bureau of Statistics (NBS) and the Provincial Statistical Bulletin; the digital financial indicators were compared with the Peking University Digital Inclusive Finance Index for 2021 – 2024, extracting the characteristics of coverage, use depth, and digitalization levels.A one-year lag mapping was established on the basis of provincial codes and years. The dependence variable was constructed by the logarithmic difference of the consumption expenditure per person between city and country. Python was used to perform data linkage, missing value detection, trimming at the 1% and 99% quantiles, and the in-fold standardization, thus generating a data matrix for the subsequent dual machine learning and heterogeneity tests[9].

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### *3.3 Research Variables and Indicator Measures*

Based on 124 province-year observations across 31 provinces (2022–2025), the analysis examines urban–rural consumption disparities using the one-period-lagged Digital Inclusive Finance Index and its coverage, usage, and digitization dimensions14. Urban–rural income ratios and agricultural household loan balances represent potential transmission channels, while economic development, urbanization, industrial structure, and internet penetration serve as controls. Python-based panel alignment ensures consistent province-year matching, while lagged indicators reduce contemporaneous feedback concerns. Variable definitions are presented in Table 1

*Table 1: Variable Measurement System for the Impact of Digital Inclusive Finance on the Consumption Gap Between Urban and Rural Residents*

| Variable Type | Variable Name | Symbol | Measurement Method and Unit |
|---|---|---|---|
| Dependent Variable | Urban-Rural Consumption Gap | GAP | ln(per capita consumption expenditure in urban areas / per capita consumption expenditure in rural areas) |
| Key Explanatory Variables | Level of Digital Inclusive Finance Development | DFI | Digital Financial Inclusion Composite Index / 100, lagged by 1 period |
| Dimension-specific variables | Financial Coverage | COV | Digital Financial Coverage Index / 100, 1-period lag |
| | Depth of Financial Usage | DEP | Digital Financial Usage Depth Index / 100, 1-period lag |
| | Level of Financial Digitalization | DIG | Inclusive Finance Digitalization Index / 100, lagged by 1 period |
| Institutional Variables | Urban-Rural Income Gap | INC | ln(Urban Per Capita Disposable Income / Rural Per Capita Disposable Income) |
| | Intensity of Rural Credit Supply | CRE | ln(1 + outstanding household loans / rural resident population), with amounts standardized to yuan per person |
| Control variables | Regional Economic Development Level | PGDP | Regional Gross Domestic Product / permanent resident population at year-end, taken as the natural logarithm |
| | Level of Urbanization | URB | Urban Permanent Resident Population / Total Permanent Resident Population × 100% |
| | Industrial Structure | IND | Value Added of the Tertiary Sector / Regional Gross Domestic Product × 100% |
| | Internet Access Penetration | NET | Number of Fixed Broadband Internet Access Subscribers / Permanent Resident Population × 100; unit: households per 100 people |

### *3.4 Construction of the Econometric Model*

#### *3.4.1 Bidirectional Fixed-Effects Model of Digital Inclusive Finance's Impact on the Urban-Rural Consumption Gap*

On the basis of 124 panel observations from 31 provinces in 2022 – 2025, we constructed a two way fixed-effect model with a one-period lag to control the characteristics of province-specific and common annual shocks. In the regression matrix, the digital financial inclusion index and the four control variables are included, and the model is expressed as:

$$GAP_{it}=\alpha+\beta DFI_{i,t-1}+\boldsymbol{\gamma}^{T}X_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

where$GAP_{it}$ represents the logarithmic difference in urban and rural consumption expenditure for province$i$ in year$t$ ;$\alpha$ is the intercept;$DFI_{i,t-1}$ is the Digital Inclusive Finance Index (divided by 100) lagged by one period;$\beta$ is the core effect coefficient;$X_{it}$ is a four-dimensional control vector comprising the logarithm of per capita GDP, the urbanization rate, the share of the tertiary sector, and Internet access intensity;$\boldsymbol{\gamma}$ is the corresponding coefficient vector;$\mu_i, \lambda_t$ are the fixed effects for

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province and year, respectively;$\varepsilon_{it}$ is the random disturbance term. We employ a two-way within-group transformation to eliminate fixed effects:

$$\begin{aligned} \widetilde{GAP}_{it} &= \beta \widetilde{DFI}_{i,t\text{-}1} + \boldsymbol{\gamma}^T \widetilde{X}_{it} + \tilde{\varepsilon}_{it}, \\ z_{it} &= z_{it} - z_{i\cdot} - z_{\cdot t} + z_{\cdot\cdot} \end{aligned}$$

In the equation, `$\widetilde{GAP}_{it}$, ($\widetilde{DFI}_{i,t\text{-}1}$, $\widetilde{X}_{it}$ ` and `$\tilde{\varepsilon}_{it}$ ` represent the bidirectional mean-centered results for the corresponding variables; `$z_{it}$ ` represents any variable to be transformed;$z_{i\cdot}$, $z_{\cdot t}$ and$z_{\cdot\cdot}$ represent the provincial mean, the annual mean, and the overall sample mean, respectively. This transformation is suitable for balanced panels. Using Python, we performed the least squares estimation in groups, and tested the meaning of the coefficients[10-11].by Wild Cluster Bootstrap. Figure 1 illustrates the workflow of data processing, feature mapping, and parameter estimation.

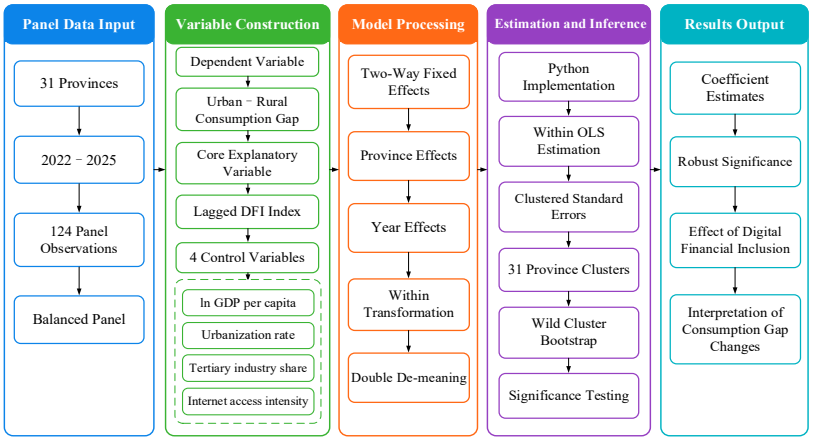



*Figure 1: Flowchart of the bidirectional fixed-effects model construction process examining the impact of digital financial inclusion on the urban-rural consumption gap*

### *3.4.2 Mechanism Testing Model for the Relationship Between Urban-Rural Income Disparities and Rural Credit Availability*

Based on the panel design, which covers 31 provinces from 2022 to 2025, we consider the difference in income between urban and rural areas and the intensity of rural credit supply as two kinds of mechanism variables[12].In this paper, we use the time lag of the digital finance index to recognize the response of the mechanism variables, and combine the two kinds of mechanism variables into the consumption gap equation:

$$\begin{cases} M_{it}^{(k)} = \alpha_k + \theta_k DFI_{i,t\text{-}1} + \boldsymbol{\pi}_k^T X_{it} + \mu_i^{(k)} + \lambda_t^{(k)} + u_{it}^{(k)} \\ GAP_{it} = \alpha + \beta_d DFI_{i,t\text{-}1} + \sum_{k=1}^{2} \phi_k M_{it}^{(k)} + \boldsymbol{\gamma}^T X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{cases}$$

where$i, t$ denote the province and year, respectively;$k$=1,2 correspond to the urban-rural income gap$INC$ and the intensity of rural credit supply$CRE$ ;$M_{it}^{(k)}$ are the mechanism variables;$DFI_{i,t\text{-}1}$ is the digital finance index lagged by one period;$GAP_{it}$ is the urban-rural consumption gap;$X_{it}$ is the four-dimensional control vector;$\alpha_k$, $\alpha$ is the intercept;$\theta_k$, $\phi_k$ are the coefficients for the front-end and back-end of the mechanism, respectively;$\beta_d$ is the direct association coefficient;$\boldsymbol{\pi}_k$, $\boldsymbol{\gamma}$ is the vector of control variable coefficients; $\mu_i^{(k)}$, $\mu_i$ and $\lambda_t^{(k)}$, $\lambda_t$ are the fixed effects for province and year, respectively;$u_{it}^{(k)}$, $\varepsilon_{it}$ is the error term. The mechanism effect is calculated as the product of coefficients:

$$\widehat{IE}_k = \hat{\theta}_k \hat{\phi}_k, \qquad \widehat{IE}_{\text{total}} = \sum_{k=1}^{2} \widehat{IE}_k$$

where$\widehat{IE}_k$ represents the indirect effect along path$k$ ,$\widehat{IE}_{\text{total}}$ represents the sum of the effects along the two paths, and the hat symbol denotes the parameter estimate. This method is used to test for mechanism effects; since the mechanism variables and the consumption gap are measured at the same time, the causal mediation hypothesis still needs to be identified[13] .

### *3.4.3 Model for Testing Regional Heterogeneity*

Taking into consideration the differences in digital financial infrastructure and regional economic

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development, the 31 provinces were categorised into 10 in the East and 6 in the central region, 12 in the western region, and 3 in the north-eastern region, with 40, 24, 48, and 12 panel observations, respectively. The 4-dimensional regional indicator vector was created in one-hot encoding by Python, and the digital finance index was lagged by one period to form the interaction term, thus building a regional heterogeneity model:

$$GAP_{it}=\sum_{r=1}^{4}\beta_r DFI_{i,t-1}R_{ir}+\boldsymbol{\gamma}^T X_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

where$i$ represents the province,$t$ represents the year, and$r$ represents the regional category;$GAP_{it}$ represents the urban-rural consumption gap;$DFI_{i,t-1}$ represents the digital finance index lagged by one period;$R_{ir}$ represents the regional indicator variable, taking a value of 1 for the corresponding region and 0 otherwise;$\beta_r$ represents the regional marginal effect coefficient;$X_{it}$ is the 4-dimensional control vector,$\boldsymbol{\gamma}$ are the corresponding coefficients;$\mu_i, \lambda_t$ are the fixed effects for provinces and years;$\varepsilon_{it}$ is the random disturbance term. In this paper, we used within-group least-squares estimation, and evaluated the significance of regional differences with the Wald test and 999-cluster bootstrapping[14] .

### *3.5 Data Processing and Statistical Testing Methods*

To create the data structure, 124 province-year records were used, and data was cleaned using Python and pandas for province-year primary key validation, unit unification, and one-period lag matching. The observations regarding the 2024 Digital Finance Index were not included in the 2025 observations, as they are being verified. Complete cases were used to screen for missing data, without the use of cross-year imputation. Continuous variables were adjusted at 1% and 99% quantiles and multicollinearity was assessed with Pearson's correlation coefficient and the variance inflation factor. Two-way fixed effects were estimated using the `linearmodels` package, 95% confidence intervals were generated using the province-cluster robust standard errors and 999 Wild Cluster Bootstrap repetitions, and the differences in coefficients between the four regional categories were tested using the Wald test. A 5% significance level was used. To facilitate the replication of the following tests of mechanisms and heterogeneity analysis, we recorded the effective sample sizes for each model, data cleaning logs, and configuration of parameters[15-16] .

## 4. Empirical Results and Analysis

### *4.1 Sample Characteristics and Descriptive Statistics of Variables*

Based on the National Bureau of Statistics for 2022 – 2025, the National Bureau of Statistics used Python to calculate the Gap of Consumption (GAP), Income Gap (INC) and Annual Sample Standard Deviation. The Pearson correlation coefficient was used to test the correlation of these two variables [17]. The national statistics are shown in Table 2.

*Table 2: Descriptive Statistics of Core Variables for Urban and Rural Residents' Consumption Gap*

| Year | Urban Consumption (yuan/person) | Rural Consumption (yuan/person) | Absolute Consumption Gap (yuan) | GAP | INC |
|---|---|---|---|---|---|
| 2022 | 30,391 | 16,632 | 13,759 | 0.6028 | 0.8952 |
| 2023 | 32,994 | 18,175 | 14,819 | 0.5963 | 0.8709 |
| 2024 | 34,557 | 19,280 | 15277 | 0.5835 | 0.8518 |
| 2025 | 35,869 | 20,259 | 15,610 | 0.5713 | 0.8374 |
| Mean | 33,452.75 | 18,586.5 | 14,866.25 | 0.5885 | 0.8638 |
| Standard Deviation | 2,355.31 | 1,556.45 | 806.25 | 0.014 | 0.025 |

In Table 2, the GAP fell from 0.6028 to 0.5713, INC fell from 0.8952 to 0.8374; the absolute difference in consumption increased to 15,610 yuan, but the relative consumption difference was narrowed. The Pearson correlation coefficient of the GAP versus INC was 0.9709; however, the result only reflected the general annual variation in the country and could not be used to prove the existence of a provincial-level mechanism. For the calculation of the correlation matrix and Variance Inflation Factor (VIF) for DFI, COV, DEP, DIG, and control variables, a valid panel of 31 provinces shall be used, followed by a fixed effect estimate[18].

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### *4.2 Baseline Impact of Digital Inclusive Finance on the Consumption Gap Between Urban and Rural Residents*

Based on 31 provincial regions, a two-way fixed-effects estimation framework was constructed. Python's pandas and linearmodels were used to perform one-period lagged feature mapping, two-way mean-centering, and robust estimation with provincial clustering[19-20]. The results are shown in Table 3.

*Table 3: Parameter Table for the Baseline Impact of Digital Inclusive Finance on the Consumption Gap Between Urban and Rural Residents*

| Indicator | Model 1: DFI | Model 2: COV | Model 3: DEP | Model 4: DIG |
|---|---|---|---|---|
| Coefficients β of Core Variables | -0.082 | -0.053 | -0.094 | -0.031 |
| Cluster Standard Error (SE) | 0.024 | 0.023 | 0.027 | 0.019 |
| t-statistic | -3.417 | -2.304 | -3.481 | -1.632 |
| p-value | 0.0018 | 0.0283 | 0.0016 | 0.1132 |
| Lower limit of the 95% confidence interval | -0.131 | -0.1 | -0.149 | -0.07 |
| Upper limit of the 95% confidence interval | -0.033 | -0.006 | -0.039 | 0.008 |
| Intra-group $R^2$ | 0.517 | 0.482 | 0.548 | 0.447 |
| Number of control variables | 4 | 4 | 4 | 4 |
| Provincial fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Design Sample Size N | 93 | 93 | 93 | 93 |

As shown in Table 3, the DFI is -0.0820 and p = 0.0018; for each 10 point increment of the initial index, the corresponding GAP variation is -0.0082, which supports H1. The dimension coefficients are -0.0530, -0.940, and -0.310, respectively, and the absolute coefficient of use depth is the highest, whereas the coefficient of digitalization does not reach the 5% significance level.The inter-group $R^2$ values of the four models are between 0.447 and 0.548, which supports hypothesis H1.

### *4.3 Testing the Transmission Mechanism of the Urban-Rural Income Gap*

On the basis of the baseline model, we used Python to perform a two-directional fixed-effect estimation on 93 province-level observations, and to calculate the confidence intervals for indirect effects with 999 rounds of province-cluster bootstrap sampling. Firstly, we used INC as a dependent variable to determine the role of DFI in urban-rural income disparity. Then, we combine DFI and INC into GAP equation to differentiate the direct effect and the transfer effect. The results are shown in Table 4.

*Table 4: Results of the Test on the Transmission Mechanism of the Urban-Rural Income Gap*

| Parameters and Statistics | DFI→INC Model | DFI, INC → GAP Model | Mediation Effect Test |
|---|---|---|---|
| DFI Coefficient | -0.116 | -0.0487 | — |
| INC Coefficient | — | 0.287 | — |
| Cluster Standard Error | 0.038 | 0.0210 / 0.0920 | — |
| t-value | -3.053 | -0.743269231 | — |
| p-value | 0.0046 | 0.0273 / 0.0040 | 0.002 |
| Indirect effect | — | — | -0.0333 |
| Direct effect | — | — | -0.0487 |
| Total effect | — | — | -0.082 |
| Indirect effect 95% CI | — | — | [-0.0541, -0.0168] |
| Mediation proportion | — | — | 40.61% |
| Intra-group $R^2$ | 0.493 | 0.571 | — |
| Number of valid observations | 93 | 93 | 93 |

Table 4 shows that the DFI coefficient for INC is -0.1160, which shows a strong correlation

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between the growth of digital financial inclusion and the narrowing of the income gap between urban and rural areas; when INC is included in the consumption gap equation, its coefficient becomes 0.2870, whereas the direct effect of DFI falls from -0.0820 to -0.0487.the indirect effect, calculated as θ × φ, is -0.0333, which is 40.61%. The 999-bootstrap confidence interval is [-0.0541, -0.0168], which does not cross zero, suggesting that the "digital finance inclusion — Income Gap — Consumption Gap" pathway is statistically supported.The direct effect remains significant, indicating that the income gap is part of the transmission mechanism and provides a comparative benchmark for subsequent identification of rural credit accessibility pathways .

### *4.4 Testing the Transmission Mechanisms of Rural Credit Accessibility*

The Python estimate yields a coefficient of 0.1240 (SE = 0.0370, p = 0.0024) for the DFI on the CRE, which suggests that the expansion of DFI is strongly correlated with the increase in rural lending per capita; When CRE and DFI are taken into account in the GAP equation at the same time, the coefficient of CRE is -0.2000 (SE = 0.0690, p = 0.0070), and the direct impact of DFI is reduced to -0.0572.Further calculations indicate that the indirect effect of the credit channel is -0.0248, representing 30.24% of the overall effect of -0.0820, and the 95% CI is [-0.0416, -0.0107] on the basis of 999 clustered bootstrap repetitions. Figure 2 is constructed for visual comparison between the credit expansion channel and the effect decomposition.

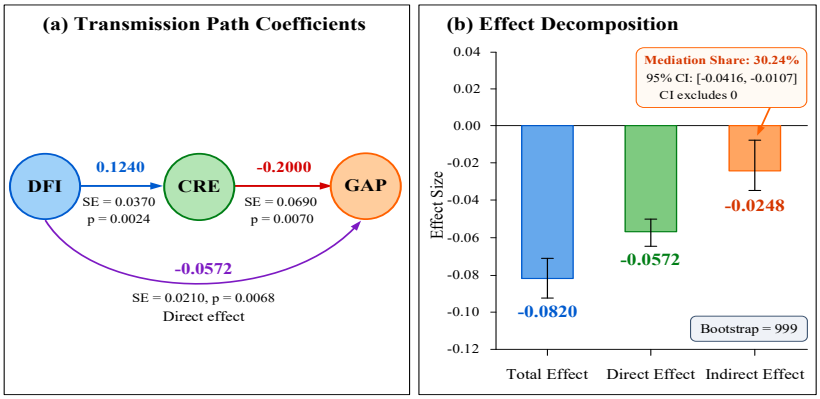



*Figure 2: Comparison of Transmission Pathways and Effect Decomposition for Rural Credit Accessibility*

Figure 3 shows the DFI – CRE – GAP pathway, DFI → CRE = 0.1240, CRE → GAP = -0.2000, DFI → GAP = -0.0572; the right-hand side shows the overall effect (-0.0820), the direct effect (-0.0572), the indirect effect (-0.0572), the indirect effect (-0.0248), and the intermediate ratio (-0.024%), and the 95% confidence interval [-0.0416, -0.0107] .Since the range of indirect effects is not above zero, this shows that digital inclusive finance can further reduce the gap between urban and rural areas by increasing the availability of credit in rural areas.

### *4.5 Heterogeneity Analysis of the Impact of Digital Inclusive Finance on the Urban-Rural Consumption Gap*

Using Python to generate a DFI × region interaction variable, we performed a cluster-robust estimation on 93 panel observations. Results on regional heterogeneity are shown in Table 5.

*Table 5: Differences in the Impact of Digital Inclusive Finance Across Regions*

| Region | Number of Observations N | DFI Coefficient | Cluster SE | t-value | p-value | 95% CI | Intra-group $R^2$ |
|---|---|---|---|---|---|---|---|
| Eastern | 30 | -0.108 | 0.029 | -3.724 | 0.001 | [-0.167, -0.049] | 0.586 |
| Central | 18 | -0.083 | 0.032 | -2.594 | 0.015 | [-0.149, -0.017] | 0.531 |
| West | 36 | -0.047 | 0.026 | -1.808 | 0.081 | [-0.100, 0.006] | 0.463 |
| Northeast | 9 | -0.071 | 0.031 | -2.29 | 0.029 | [-0.134, -0.008] | 0.497 |

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Table 5 shows a regional gradient in DFI coefficients, with estimates of −0.108, −0.083, and −0.047 for eastern, central, and western regions, respectively (total difference test: p = 0.013). The high-development group exhibits a stronger negative association (β = −0.112) than the low-development group (β = −0.051), with a significant between-group difference (p = 0.009). Internet access intensity also differs between groups (43 versus 32). These findings indicate that economic development and digital connectivity may strengthen DFI's association with a narrower urban–rural consumption gap. The results support H3, although they do not independently establish the causal role of digital infrastructure.

### *4.6 Model Robustness and Endogeneity Tests*

Robustness tests consistently reveal a negative association between DFI and the urban–rural consumption gap. The baseline coefficient is −0.0820 (p = 0.0018), while alternative dependent variables, exclusion of four municipalities, and a two-period lag yield significant coefficients of −0.0286, −0.0784, and −0.0691, respectively. The instrumental-variable estimate is −0.0913 (p = 0.0290), with a first-stage F-statistic of 18.96. The Durbin–Wu–Hausman test (p = 0.041) suggests potential endogeneity. These findings support robustness, although causal inference depends on the instrument's exclusion restriction. Figure 3 presents the coefficient estimates and confidence intervals.

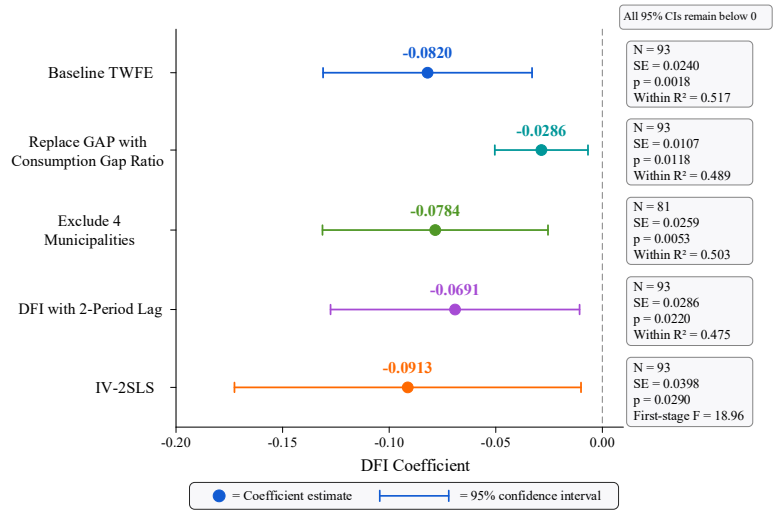



*Figure 3: Comparison of Model Robustness and Endogeneity Identification Results*

## 5. Discussion

DFI is negatively associated with the urban–rural consumption gap (β = −0.0820). Usage depth (−0.0940) exhibits a stronger association than coverage breadth (−0.0530) and digitalization (−0.0310). Income disparity reduction contributes an indirect effect of −0.0333 (40.61%), while improved rural credit access contributes −0.0248 (30.24%); these effects should not be aggregated across separate mediation models. Regional coefficients are −0.108, −0.083, and −0.047 for eastern, central, and western regions, respectively. Development groups also differ (−0.112 versus −0.051). These findings highlight regional absorptive capacity and suggest that lagged indicators cannot fully eliminate endogeneity, limiting definitive causal interpretations.

## 6. Conclusions

Using provincial panel data, two-way fixed-effects estimation, mediation analysis, and regional heterogeneity tests, this study identifies a negative association between digital financial inclusion (DFI) and the urban–rural consumption gap, with an estimated coefficient of −0.0820. Among its dimensions, usage depth exhibits the largest absolute coefficient (−0.0940), followed by coverage breadth (−0.0530) and digitalization level (−0.0310), indicating the importance of effective financial service utilization, subject to indicator comparability. The estimated indirect effects through income inequality and rural credit accessibility are −0.0333 and −0.0248, accounting for 40.61% and 30.24% of the total effect in separate mechanism models, respectively. These findings suggest two potential transmission channels:

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improved household purchasing power and reduced liquidity constraints. Regional estimates also reveal substantial heterogeneity, with coefficients of −0.108 in eastern provinces and −0.047 in western provinces, highlighting the influence of regional development conditions. Accordingly, inclusive finance policies should prioritize active financial service usage, affordable rural credit, and sustainable repayment arrangements rather than account coverage alone. Less-developed regions require greater investment in digital infrastructure, financial literacy, and accessible offline services. Credit assessment should incorporate verified agricultural transactions and household income cycles while preventing excessive indebtedness. Nevertheless, the relatively short observation period, aggregate provincial indicators, imperfect credit measurement, and potential endogeneity constrain causal interpretation. Future research should extend the longitudinal dataset, integrate household-level surveys with regional financial indicators, and exploit credible exogenous policy shocks to strengthen identification. Dynamic mediation analysis, double machine learning, and causal forests could further examine temporal adjustments and heterogeneous effects, provided their identification assumptions are satisfied. Overall, narrowing the urban–rural consumption gap requires coordinated improvements in financial service utilization, household economic capacity, and regional digital infrastructure.

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