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Re-Examination of the Relationship Between Digital Inclusive Finance and Urban Economic Resilience: From the Perspective of Complex Adaptive System Theory

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Abstract

Economic systems worldwide are facing an urgent need to build resilience, and digital inclusive finance (DIF), as a key component, can effectively enhance urban economic resilience (UER) through technological convergence and resource optimization. Existing research has largely examined the relationship between DIF and UER within a linear causal framework, lacking an in-depth analysis of interactions within complex systems. Drawing on complex adaptive systems (CAS) theory, this study re-examines the relationship between the two using panel data from 283 Chinese cities covering the period 2012–2024. The findings reveal that: (1) DIF significantly enhances UER, with the strongest promotional effect observed on resistance and recovery capacity, followed by innovation and transformation capacity, whilst the impact on adaptive capacity is relatively minor. (2) There are structural differences in the contributions across dimensions of DIF, and an asymmetric matching relationship exists with the subsystems of UER. (3) Mechanism tests indicate that the process by which DIF enhances UER aligns with three pathways: the reduction of transaction costs, the stimulation of consumer vitality, and the driving force of technological innovation, and that such mediation effects exhibit structural differences at the dimensional level. Furthermore, the enhancement effect of DIF is more pronounced in cities with weaker resilience, demonstrating a convergence effect. This study enriches the application of CAS theory in the field of urban economic governance and provides a reference for developing economies to enhance UER through DIF.

Keywords: digital inclusive finance; urban economic resilience; complex adaptive system theory; matching mechanism

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1. Introduction

In a complex environment marked by accelerating technological revolution, restructuring of the international order, and converging risks, enhancing urban economic resilience (UER), defined as the complex systemic capability of urban economic systems to effectively absorb, resist, and recover from external shocks, has become a key strategic issue for cities worldwide in addressing systemic risks and ensuring sustainable development [1]. As a systemic attribute, UER is not only manifested in the overall shock resistance and recovery capacity of a system, but also depends on the coordination and adaptability among its various subsystems [2,3]. In this process of systemic evolution, digital inclusive finance (DIF), as a product of the deep integration of finance and technology, has reduced transaction costs and improved the efficiency of resource allocation by restructuring service models and expanding the scope of services, thereby gradually emerging as a key driver in strengthening the resilience of urban economic systems [4–6]. According to the 2025 Financial Accessibility Survey by the International Monetary Fund (IMF), the coverage of digital financial services worldwide has continued to expand, with particularly notable growth in developing economies. China's efforts in the field of DIF have placed it among the global leaders. As the world's largest developing economy, the experience and lessons accumulated by the urban economic systems of China during the rapid digital transformation process can serve as a valuable reference for other emerging economies.

However, cities in China are facing a number of bottlenecks in promoting the synergistic development of DIF and UER, such as imbalances in service structures, insufficient integration with traditional systems, and lagging institutional adaptation, which constrain the full realization of its resilience-enhancing effects. To investigate these issues, this study employs panel data from 283 Chinese cities covering the period 2012–2024 to explore, from a systemic perspective, the multidimensional impact mechanisms and implementation pathways of DIF on UER. Our exploration not only helps to enrich the application of complex systems theory in urban economic governance, but also provides a theoretical basis and practical guidance for constructing a new model of urban development.

Although the academic community has explored the economic effects of DIF, the factors influencing UER, and their transmission mechanisms, three significant research gaps remain, which hinder further theoretical development and practical guidance.

Firstly, most studies focus on linear effects, lacking an analysis of the structural interactions between DIF and UER as complex systems. In particular, there has been little discussion regarding the nuanced relationships between the internal dimensions of DIF and UER. On one hand, scholars have demonstrated the economic effects of DIF across multiple dimensions: urban–rural regional development [7–9], corporate behavior and performance [10,11], and household income and consumption [12,13]. In recent years, some scholars began to directly examine the impact of DIF on UER, which confirmed the positive promoting effect of DIF on UER and its spatial spillover effects [14,15]. On the other hand, researchers have examined DIF from multiple dimensions, including technological innovation [16], industrial development [17], human capital accumulation [2,18], virtual agglomeration [19], digital infrastructure [20] and government governance capacity [21]. However, these studies remain confined to overall correlation analyses, overlooking the structural alignment between DIF and UER. This limitation prevents us from understanding how different dimensions of DIF precisely influence specific capacities of UER, thereby hindering the development of differentiated policy interventions.

Secondly, existing mechanism analyses are fragmented, often focusing solely on individual mediating variables, without constructing a systemic transmission framework, integrating resource allocation, technological innovation and endogenous stability, from the perspective of complex adaptive systems (CAS). Consequently, it is difficult to comprehensively explain how DIF reshapes the operational logic of urban economic systems. Although previous research has identified multiple mediating pathways, such as entrepreneurial activity [22] and industrial structural upgrading [23], as well as moderating factors including financial regulation [24] and regional credit constraints [25], these mechanisms are often examined in isolation and have not been incorporated into a unified analytical framework. This limitation of fragmented mechanism analysis makes it difficult to systematically understand the comprehensive pathways through which DIF affects UER, which motivates us to construct an integrated transmission framework based on CAS theory.

Finally, existing research has largely overlooked the potential non-linear relationship between DIF and UER, failing to reveal the differentiated impacts of DIF on cities with varying initial levels of resilience. Existing research is primarily grounded in traditional theoretical frameworks such as financial development, financial exclusion and financial inclusion [26]. Whilst these theories can partially explain the direct impact of DIF on UER through channels such as optimizing financial structures and alleviating financial exclusion [27], it is challenging to fully capture their complex relationship. Notably, CAS theory posits that the historical state of a system profoundly influences its response to external interventions through path dependence and adaptive learning [28]. This implies that DIF may produce varying effects across cities at different stages of development. Unfortunately, the limitations of traditional theoretical frameworks have confined most research to linear analyses, making it difficult to capture these heterogeneous patterns dependent on initial conditions.

To address the above research gaps, we are committed to systematically addressing the following three fundamental questions:

Q1: What are the structural and systemic relationships between DIF and UER? Specifically, how do the three dimensions of DIF, coverage breadth, usage depth and digitalization level, differentially influence the three subsystems of UER: resistance and recovery capacity, adaptive capacity, and innovation and transformation capacity?

Q2: Through which key systemic transmission mechanisms does DIF influence UER? Furthermore, do the mediating effects at the dimensional level exhibit asymmetric matching characteristics?

Q3: Does the impact of DIF on UER exhibit significant non-linear characteristics and heterogeneous patterns? More specifically, does this impact vary systematically depending on the initial level of a city's resilience?

This study aims to achieve breakthroughs in theoretical frameworks, research perspectives, and mechanism elucidation to deliver significant marginal contributions. First, regarding the theoretical framework, we ground our analysis in CAS theory, conceptualizing UER as an emergent holistic property arising from the interactions among agents within the system. On such a basis, we construct an integrated analytical framework to examine how DIF drives the evolution of UER by reshaping the internal rules of interaction among system agents. Second, concerning research perspectives, we have moved away from a holistic analytical approach and conducted a dual structural decomposition of DIF and UER. Through detailed matching tests across various dimensions, we reveal the heterogeneous patterns of correspondence between elements within the system, providing more nuanced empirical evidence for understanding the complex relationship between the two. Third, for mechanisms elucidation, we examine how three pathways, reducing transaction costs, fostering technological innovation, and stimulating consumption vitality, influence resource allocation efficiency, evolutionary dynamics, and endogenous stability foundations of the system, offering additional theoretical insights. Furthermore, at the methodological level, this study constructs a multi-layered robustness testing framework within the conventional econometric framework by employing Bartik-type instrumental variables (IVs), multidimensional clustered standard errors, and quantile regression, so as to approximate the empirical requirements of complex system analysis.

The remainder of the paper is structured as follows. Section 2 lays the theoretical groundwork and develops the research hypotheses. Section 3 outlines the research design and methodology, while Section 4 presents empirical findings. Section 5 examines effects across different dimensions. Section 6 then tests the hypothesized mediating mechanisms. Section 7 conducts heterogeneity analysis, followed by conclusions and policy implications in Section 8. Finally, Section 9 discusses theoretical and practical contributions, limitations, and suggestions for future research.

2. Theoretical Mechanism and Research Hypotheses

In this study, we move beyond the traditional linear causal analysis paradigm and examine DIF and UER within the theoretical framework of CAS. Our choice of CAS theory over traditional financial development theory as the analytical foundation is primarily motivated by the following considerations. First, traditional financial development theories (such as financial exclusion and financial inclusion theories) are built on the logic that the expansion of financial services directly promotes economic performance through channels such as easing financing constraints and optimizing resource allocation, with the implicit assumption of a relatively stable linear relationship between financial inputs and economic outputs. However, UER is not a simple aggregation of individual agents' economic performance, but rather a macro-level systemic attribute that emerges from the continuous interactions among a large number of heterogeneous agents. CAS theory is precisely capable of capturing such nonlinear interactions and systemic emergent features, thereby explaining why the effects of DIF are not uniformly distributed but instead exhibit asymmetric matching relationships across dimensions. Moreover, CAS theory emphasizes that the historical state of a system profoundly influences its responsiveness to external interventions through path dependence and adaptive learning, which provides a theoretical foundation for understanding the differentiated effects of DIF on cities with different initial resilience levels: a heterogeneous pattern that traditional financial development theories struggle to explain. Therefore, CAS theory offers systematic analytical tools for examining nonlinear interactions, structural matching, and path dependence in complex economic systems, which are exactly the core elements for understanding the complex relationship between DIF and UER.

In such a theoretical framework, we conceptualize an urban economy as a CAS composed of heterogeneous agents such as households, enterprises, financial institutions and the government [29,30]. Within this system, these agents continuously interact with each other and collectively shape the macro-level performance of the urban economic system, i.e., UER. When external shocks disrupt established interaction patterns, system resilience manifests as the capacity of agents to reorganize internal structures and operational rules through learning, adaptation and innovation, thereby maintaining key functions or achieving a more optimal state of development [31]. Meanwhile, as a socio-technical paradigm embedded within this system, DIF reshapes the modes of interaction and operational efficiency among these entities through the deep integration of information, technology and services, thereby systematically enhancing UER. Based on this framework, this study constructs an analytical framework across four levels, revealing its impact pathways layer by layer.

2.1. Impact Mechanism at the Overall System Level

DIF effectively integrates numerous micro-entities excluded by the traditional financial system, including small and micro enterprises (SMEs), self-employed individuals, and low-income households, into the modern economic cycle, thereby significantly enriching the types and scale of adaptive agents within the system [32]. According to CAS theory, system resilience fundamentally depends on the diversity of agent behavior, as well as the breadth and efficiency of interactions between agents. Moreover, the coverage breadth of DIF directly expands the reach of financial services, enhancing the heterogeneity of agents within the economic system, whilst its usage depth and digitalization level strengthen functional connectivity between agents by improving transaction efficiency and reducing interaction costs [5].

To precisely define the "agent linkages" referred to here, this study draws on the findings of Yang et al. (2025), Zhou (2025), and Zhang et al. (2026) [33–35], and decomposes the agent linkages strengthened by DIF into three specific levels. First, horizontal competition and imitation linkages, which refer to the knowledge diffusion and technological catch-up pathways that emerge among firms in the same industry through market competition and mutual learning. DIF accelerates the diffusion of best practices and technological solutions among peer firms by reducing the costs of information search. Second, vertical industrial-chain synergistic linkages, i.e., the internalization process of knowledge and technology between upstream and downstream firms in the supply chain through learning by doing and learning by using. DIF enhances the coordination and responsiveness among nodes in the industrial chain by improving payment and credit efficiency. Third, interaction linkages between agents and environment, which refers to the channels of information feedback and adaptive adjustment between micro-agents (firms, households, and government) and the system environment. DIF enhances agents' ability to perceive environmental changes and make adaptive decisions through real-time data generation and intelligent analysis. Thus, this dual effect of expanding the number of agents and strengthening connections enables the economic system to mobilize richer resource reserves and formulate more diverse response strategies when facing external shocks, thereby enhancing the overall resilience and recovery potential of a system [36].

2.2. Matching Mechanisms at the Dimensional Level

2.2.1. Differences in Demand Across Subsystems of UER

UER can be decomposed into three subsystems characterized by temporal patterns and demand differences: resistance and recovery capacity, adaptive capacity, and innovation and transformation capacity. Each subsystem corresponds to a different set of system-level demands. First, resistance and recovery capacity addresses the short-term need to maintain system functioning when external shocks occur, with the imperative being rapid response and broad coverage; the system must mobilize resources for buffering at the moment of impact and return to pre-shock operating conditions as quickly as possible thereafter [37]. Second, adaptive capacity addresses the medium-term need for structural adjustment when shocks persist or the external environment undergoes directional change, with the imperative being structural reconfiguration and dynamic equilibrium; the system must reallocate resources and optimize industrial and factor structures to adapt to changing external conditions [38]. Third, innovation and transformation capacity addresses the long-term need for transition when existing development pathways are blocked, with the imperative being path breakthrough and structural renewal; the system must introduce new technological paradigms and foster new industrial forms to open up entirely new development trajectories [13,39]. These three subsystems unfold sequentially over time and differ in their priorities on demand, jointly constituting the complete spectrum of demands underlying UER as a whole.

2.2.2. Differences in Attributes Across Dimensions of DIF

DIF, as a complex system composed of three subsystems, embeds different functional attributes across its dimensions. First, the coverage breadth dimension functions to expand the geographic and demographic reach of financial services, with its essential attribute being accessibility, that is, the availability and coverage scope of financial services [24]. Second, the usage depth dimension functions to extend financial services from basic payments to more complex activities such as credit, insurance, and wealth management, with its essential attribute being penetration, that is, the actual application depth and usage intensity of financial services [8]. Third, the digitalization level dimension functions to reduce information asymmetry, improve service efficiency, and optimize risk pricing through digital technologies, with its essential attribute being efficiency, that is, the operational efficiency and technological foundation of financial services [6]. The functional attributes of the three dimensions correspond to different aspects of the financial service system, together constituting the functional supply base through which DIF influences the economic system.

2.2.3. Formation Mechanism of Supply Demand Matching and Asymmetric Features

Based on the above definitions of the demand side of UER and the supply side of DIF, we further analyze the formation mechanism of the matching relationships between the two. Note that such matching does not reflect artificially prescribed correspondence rules, but rather emerges from nonlinear interactions among agents during system evolution.

In the initial stage of a shock (corresponding to the resistance and recovery capacity), the foremost need of a system is to mobilize resources as broadly as possible for response within a limited time frame, where the degree of accessibility determines the coverage breadth of response. Since accessibility is precisely the attribute of coverage breadth, it becomes the primary supply source to meet the needs at this stage [40]. In the medium-term stage of a sustained shock (corresponding to adaptive capacity), the challenge facing the system is no longer whether resources are sufficient, but whether resources can be channeled from low-efficiency to high-efficiency sectors, where penetration determines the precision and flexibility of structural adjustment. Since penetration is precisely the attribute of usage depth, it becomes the key supply supporting the system's medium-term adjustment [3]. In the long-term stage when current development paths are blocked (corresponding to innovation and transformation capacity), the system needs to achieve structural transition rather than incremental adjustment, where efficiency determines the growth rate of new technologies and the substitution process of new industrial forms. The digitalization level, with its efficiency attribute, plays an important role at this stage. Meanwhile, innovation activities also rely on long-term capital and risk diversification mechanisms; thus, usage depth also makes a significant contribution [41].

2.3. Analysis of Systemic Transmission Mechanisms

According to CAS theory, the impact of external interventions on a system is not directly exerted on macro-level outcomes, but rather operates through altering the behavioral rules and interaction patterns of micro-agents. On this basis, this study identifies the transmission pathways through which DIF affects UER from three dimensions: resource allocation efficiency, system evolutionary dynamics, and endogenous stability foundations. Specifically, transaction costs affect the efficiency of inter-agent interactions, technological innovation influences the direction of system evolution, and consumption vitality affects the system's endogenous stability.

2.3.1. Mechanism via Reducing Transaction Cost

Transaction cost serves as a critical constraint affecting the efficiency of interactions among agents. By applying modern information technology, DIF significantly reduces various transaction costs within the economy, including information search, contract enforcement and risk monitoring, thereby transforming the dynamic process of resource allocation [42]. The key significance of this change lies in the fact that traditional financial services, characterized by high physical branch requirements and costly credit assessments, have long excluded numerous SMEs and low-income groups from the formal financial system. As a result, it becomes difficult for resources to reach these underserved sectors, resulting in inefficient resource allocation [43]. The introduction of DIF enables the system to allocate resources across different agents at lower costs and with greater efficiency. When external shocks occur, this highly efficient resource allocation mechanism enables the economic system to rapidly reallocate capital, directing financial resources precisely towards the sectors and entities with the greatest resilience, thereby effectively preventing systemic failure caused by resource misallocation or liquidity shortages [44]. Therefore, the mechanism of reducing transaction costs essentially provides fundamental support for UER by optimizing resource allocation efficiency and enhancing the capacity of an economic system for resource reallocation and adaptation under external shocks.

2.3.2. Mechanism by Driving Technological Innovation

Technological innovation serves as the major driving force behind the structural evolution and functional upgrading in systems. Specifically, DIF provides crucial support for the accumulation and reorganization of technological factors by establishing a financial service system tailored to the innovation cycle, thereby enhancing the dynamic adaptive capacity of the economic system. However, in traditional financial systems, market entities, especially SMEs and startup teams, face severe financing constraints, which in turn severely limit their innovation and R&D activities [20]. In contrast, DIF effectively alleviates such financing constraints in the following two ways. First, by leveraging digital risk control and intelligent assessment technologies, DIF accurately identifies the growth potential of innovative entities and provides full-cycle financing services through diversified instruments such as supply chain finance and intellectual property pledges [45]. Second, as a technology-intensive service paradigm, the development of DIF itself generates demand for technologies such as artificial intelligence and blockchain, thereby expanding the application scenarios and iteration space for technological innovation [36]. Furthermore, when external shocks disrupt the existing economic structure, the system can leverage its abundant technological reserves and vibrant innovation ecosystem to drive the evolution of the economic structure towards a more advanced form through the reallocation and functional integration of technological factors, thereby achieving the transformation and upgrading of systemic functions [46].

2.3.3. Mechanism Through Stimulating Consumption Vitality

Household consumption behavior constitutes a crucial regulatory mechanism for maintaining the dynamic equilibrium of an economic system. Notably, DIF effectively strengthens the endogenous stability and adaptive capacity of the economic system by boosting household consumption capacity and optimizing their consumption decisions [47]. In particular, DIF stimulates consumer spending through two channels. At the micro-level, convenient payment services and flexible consumer credit alleviate short-term financial pressures on households, helping them maintain basic consumption levels even when their income temporarily declines [48]. At the macro-level, DIF expands the overall consumption capacity of the society by supporting entrepreneurship, creating jobs and increasing household incomes, thereby establishing a stable foundation of demand for the economy. Therefore, when the external demand environment deteriorates, a stable domestic consumption market provides local enterprises with the necessary space for survival and room for adjustment, enabling them to maintain basic operations and seek new development pathways. This, in turn, provides crucial support for the economic system to navigate the entire process from shock resistance to adaptive capacity [40].

It should be noted that various dimensions of DIF differ in their functional attributes. Consequently, the strength of their pathways through which they influence UER via the same mediating variable may vary. First, the center of coverage breadth lies in lowering financial access barriers, which makes it more likely to exert a stronger indirect effect on resistance and recovery capacity through the transaction cost mechanism. Second, usage depth involves the extension of diversified services such as credit and insurance, and therefore it may have a more pronounced impact on adaptive capacity and innovation and transformation capacity through the mechanisms of technological innovation and consumption vitality. Finally, as a fundamental technological element, the digitalization level may influence all three transmission pathways but with relatively balanced intensity.

2.4. Mechanism of Heterogeneity

The preceding analysis implicitly assumes that the effects of DIF on different cities are relatively homogeneous. However, CAS theory emphasizes the importance of path dependence and sensitivity to initial conditions, holding that the historical state of a system profoundly shapes its responsiveness to external interventions [28]. As an external intervention embedded within the economic system, the impact of DIF on UER may exhibit systemic variations depending on the initial resilience level of a city. Specifically, cities with a weaker foundation of resilience tend to have more shortcomings in areas such as financial coverage, infrastructure and consumption capacity [27]. The introduction of DIF may yield more pronounced marginal improvements in these domains. Conversely, cities with a stronger foundation of resilience already possess relatively well-developed financial ecosystems and industrial systems, meaning the scope for additional contributions from DIF may be relatively limited.

Based on the above discussion, the hypotheses below are formulated, and the research model is illustrated in Figure 1:

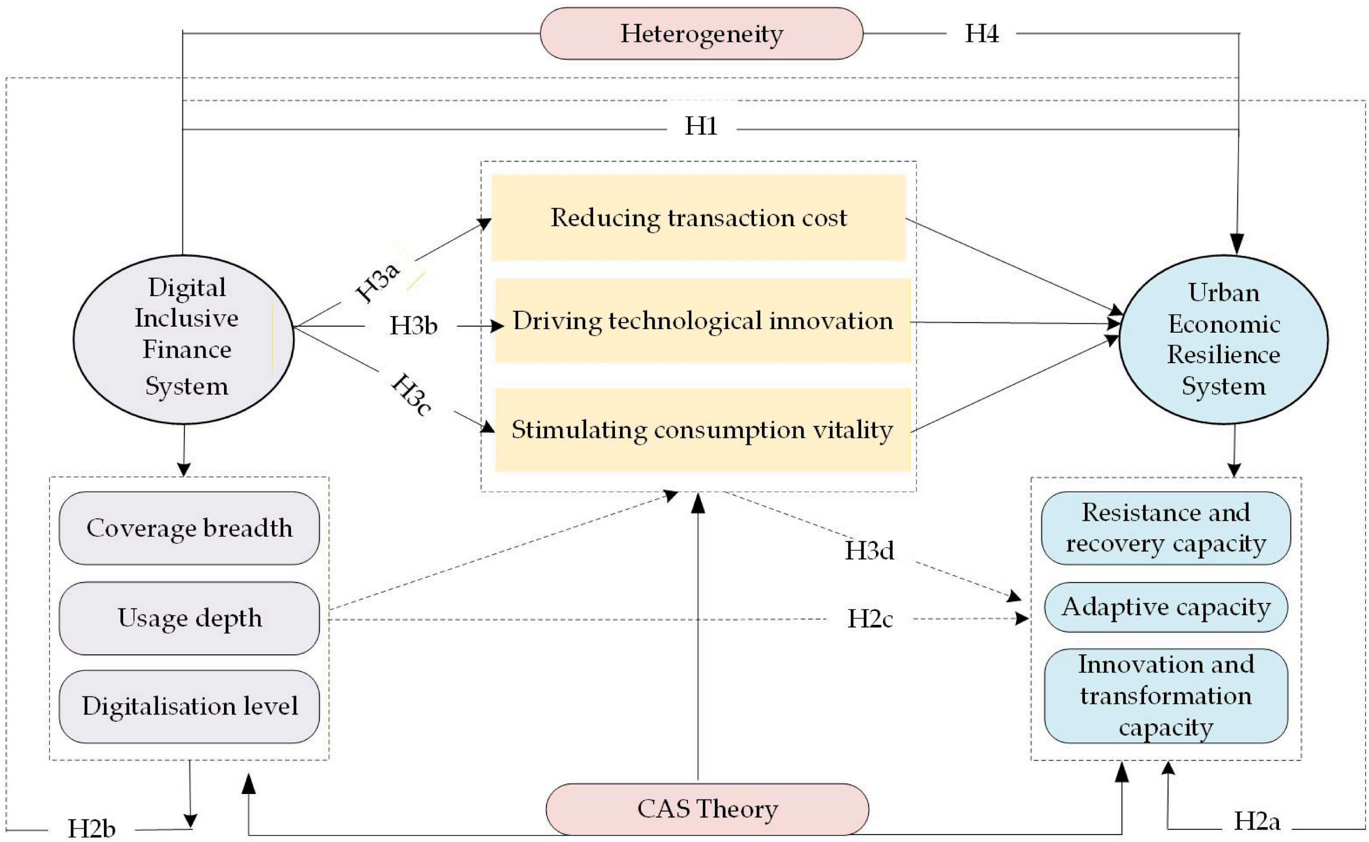

Figure 1. Research model. Source: Author's own elaboration.

H1: *The development of DIF effectively enhance UER.*

H2a: *DIF can exert positive effects on all three subsystems of UER, but the intensities of these effects vary.*

H2b: *There are systematic differences in the positive impact of the various dimensions of DIF on UER.*

H2c: *There exists an asymmetric matching relationship between the dimensions of DIF and the subsystems of UER.*

H3a: *DIF facilitates the enhancement of UER by reducing transaction costs.*

H3b: *DIF facilitates the enhancement of UER by driving technological innovation.*

H3c: *DIF facilitates the enhancement of UER by stimulating consumption vitality.*

H3d: *The extent to which each dimension of DIF affects each subsystem of UER through the same mediating variable is non-uniform.*

H4: *The impact of DIF on UER varies depending on the initial resilience level of a city.*

3. Research Design and Methodology

3.1. Econometric Model Specifications

To translate CAS theory into the practice of empirical analysis, we systematically address five core attributes of CAS theory in the design of our empirical strategy. Table 1 summarizes the mapping relationships among these attributes, their corresponding variables, the research hypotheses addressed, and the estimation strategies employed.

Table 1. Correspondence between core attributes of CAS theory and empirical strategies.

CAS Attributes	Theoretical Implication	Corresponding Variables	Corresponding Hypotheses	Empirical Counterparts
Nonlinearity	a. The effect of explanatory variables may vary across conditional distributions; b. The intensity of interactions among different elements within the system is not uniformly distributed.	a. Comprehensive UER index and three subsystem indices; b. Overall DIF index	H2a, H2b, H2c, H4	a. Panel quantile regression (Model 4) captures the heterogeneous effects of DIF across different resilience quantiles; b. Separate regressions for each dimension in Section 5.2; c. Matching matrix estimation in Section 5.3.
Path Dependence	The system's historical state affects its current response to external interventions.	a. First-order lag of DIF; b. Mediator variables; c. One period ahead of UER	H3a, H3b, H3c	a. Temporal mediation models (Models 2 and 3) establish causal timing through lag terms; b. The city's initial economic level is included as a control variable.
Adaptation	a. Agents within the system adjust internal structures in response to environmental changes; b. Different dimensions exert heterogeneous effects through distinct channels.	a. Mediator variables; b. DIF dimensional indices	H3a, H3b, H3c, H3d	a. Mediation effect model (Model 2); b. Dimensional mediation tests in Section 6.2.

Table 1. *Cont.*

CAS Attributes	Theoretical Implication	Corresponding Variables	Corresponding Hypotheses	Empirical Counterparts
Emergence	Macro-level properties cannot be reduced to a simple aggregation of individual behaviors.	a. Comprehensive UER index; b. The unit of analysis is at the level of the city, not individual firms or residents.	H1	a. The city is used as the unit of analysis, treating resilience as a systemic outcome; b. City fixed effects are controlled for to capture unobservable systemic heterogeneity.
Feedback Loops	There exists a two-way causal relationship between system states and external interventions.	a. Overall DIF index and dimensional indices; b. Comprehensive UER index	H4	a. Instrumental variable methods (Bartik IV, historical IV) mitigate reverse causality; b. Quantile regression reveals heterogeneous response patterns of cities at different resilience levels.

3.1.1. Fixed Effects Model

To capture the average net effect of DIF on UER, whilst controlling for city-specific characteristics that do not vary over time and time trends that do not vary across cities, we adopt a fixed effects model as the benchmark analytical tool, which is given by

$$\mathrm{uer}_{it} = \alpha_0 + \alpha_1 \mathrm{dif}_{it} + \beta x_{it} + r_t + \mu_i + \varepsilon_{it} \tag{1}$$

where uer_{it} represents the level of UER for city i in year t, dif_{it} denotes the level of DIF for city i in year t, and x_{it} stands for a set of control variables. α_0 is a constant coefficient, while α_1 and β are regression coefficients. The terms r_t and μ_i represent respectively time and individual fixed effects, and ε_{it} denotes the random error.

3.1.2. Temporal Mediation Model

Following the approach of Wang et al. (2025) [49], a temporal mediation model is constructed to test the mechanisms through which DIF affects UER. By introducing lagged terms, this model ensures a clear temporal ordering among DIF, the mediating mechanisms and UER, thereby better aligning with the temporal requirements of causal inference. Specifically, this model is expressed as follows:

$$M_{it} = \beta_0 + \beta_1 \mathrm{dif}_{i,t-1} + \beta x_{it} + r_t + \mu_i + \varepsilon_{it} \tag{2}$$

$$\mathrm{uer}_{i,t+1} = \gamma_0 + \gamma_1 \mathrm{dif}_{i,t-1} + \gamma_2 M_{it} + \beta x_{it} + r_t + \mu_i + \varepsilon_{it} \tag{3}$$

where M_{it} represents the mediating variable in year t, $\mathrm{dif}_{i,t-1}$ denotes the level of DIF for city i in year $t-1$, and $\mathrm{uer}_{i,t+1}$ indicates the level of UER for city i in year $t+1$. The terms β_0 and γ_0 denote constant terms (intercepts), while β_1, γ_1, and γ_2 represent the estimated coefficients for the respective variables. The other variables remain consistent with the definitions provided previously.

3.1.3. Panel Quantile Regression Model

Since significant differences exist in the initial resilience levels of urban economic systems, the effect of DIF may not be uniform but instead exhibit nonlinearity. To uncover the impact of this dependence on conditional distributions, we further employ a panel quantile regression model for a more in-depth analysis, with the aim of providing a more comprehensive understanding of the complex relationship. Specifically, the model is given by

$$Q_l(uer_{it}|dif_{it}, x_{it}, \mu_i) = \gamma_0(l) + \gamma_1(l)dif_{it} + \beta(l)x_{it} + \mu_i \quad (4)$$

where $Q_l(uer_{it}|dif_{it}, x_{it}, \mu_i)$ denotes the conditional quantile of uer_{it} at the $l \in (0,1)$ quantile, with given independent variables and individual effects. $\gamma_1(l)$ reveals the marginal effect of DIF at the l quantile of UER, serving as the key coefficient of interest in this study. $\gamma_0(l)$ is the constant term, and $\beta(l)$ represents the estimated coefficients of the control variables. The meanings of the remaining variables remain unchanged.

3.2. Variable Selection and Measurement

3.2.1. Dependent Variable

The dependent variable is UER (uer). Based on the CAS framework outlined above, UER is defined as the comprehensive capacity of an urban economic system to maintain core functions, absorb external shocks, adjust internal structures, and achieve transformation, emerging through the adaptive interactions and self-organization of heterogeneous agents within the system when facing external disturbances [21]. This definition comprises three interrelated dimensions: resistance and recovery capacity (uer_rr), i.e., the system's ability to withstand shocks and recover afterwards; adaptive capacity (uer_aa), i.e., the system's ability to respond to environmental changes through resource allocation optimization and structural reorganization; and innovation and transformation capacity (uer_it), i.e., the system's ability to achieve long-term development path transitions through technological innovation and the creation of new business forms [16,17]. These three dimensions correspond to the short-term, medium-term, and long-term response mechanisms of the system to disturbances, respectively.

To fully capture this multidimensional systemic property, this study follows the approach of Amirzadeh et al. (2022) [50], and constructs a comprehensive evaluation index system covering the above three dimensions, comprising a total of 14 basic indicators, as shown in Table 2. Both the dimensional indices and the comprehensive resilience index are calculated using the objectively weighted entropy method, with detailed calculation steps and the resulting weights available upon request.

3.2.2. Independent Variable

The independent variable is the DIF (lndif). According to CAS theory, DIF is regarded as a complex whole composed of three co-evolving subsystems: coverage breadth, usage depth and digitalization level. In terms of indicator measurement, drawing on the research by Guo et al. (2020) [51], we employ the Peking University DIF Index (PKU-DFIIC), which is jointly developed by the Centre for Digital Finance at Peking University and the Ant Group Research Institute. The three dimensions of this index, namely coverage breadth (lnbre), usage depth (lndep) and digitalization level (lndig), are consistent with the theoretical classification in this study. To satisfy the basic assumptions of the econometric model and capture growth elasticity, we take the natural logarithm of both the composite index and its sub-dimensions before incorporating them into the regression analysis.

Table 2. Evaluation index system for UER.

Objective Level	Tier-1 Indicator	Tier-2 Indicator	Tier-3 Indicator	Unit	Transformations	Data Source
UER (uer)	Resistance and recovery capacity (uer_rr)	Economic development level	GDP per capita	Chinese Yuan (CNY)	natural logarithm	EPS Data Platform—China City Database
		Living standard of residents	Disposable income of urban and rural residents	CNY	natural logarithm	
		Employment stability level	Registered urban unemployment rate	/	natural logarithm	
		Foreign trade dependence	Ratio of total exports to GDP	/	natural logarithm	
		Household saving capacity	Savings balance of urban and rural residents	CNY	natural logarithm	
	Adaptive Capacity (uer_aa)	Industrial upgrading	Ratio of tertiary industry output value to GDP	/	/	
		Household consumption level	Total retail sales of consumer goods	10 thousand CNY	natural logarithm	
		Fiscal self-sufficiency ratio	Local general budget revenue divided by local general budget expenditure	/	/	
		Asset investment scale	Fixed asset investment	10 thousand CNY		
		Financial Adjustment capacity	Year-end deposits of financial institutions divided by year-end loans of financial institutions	/	/	
	Innovation and transformation capacity (uer_it)	Fiscal education level	Local government education expenditure	10 thousand CNY	natural logarithm	
		Science and technology level	Local government science expenditure	10 thousand CNY	natural logarithm	
		Urbanization level	Urban permanent resident population divided by total permanent resident population	/	/	
		Talent support capacity	R&D personnel of industrial enterprises above designated size	Ten thousand persons	natural logarithm	

3.2.3. Control Variables

To identify the net effects of the independent variables more accurately, drawing on the research of Chao and Wang (2026) and Yan et al. (2025) [1,19], we control for a range of factors that may influence UER, specified as follows: (1) the strength of government intervention (gov), measured by the ratio of general public budget expenditure to GDP; (2) transport accessibility (lntra), measured by the logarithm of road freight volume per capita; (3) human capital level (lnhum), measured by the logarithm of the number of enrolled students in colleges per ten thousand people; (4) industrial structure level (ins), measured by the ratio of the value added of the tertiary industry to that of the secondary industry; (5) economic development level (lnpgdp), measured by the logarithm of GDP per capita; (6) population density (lnden), represented by the logarithm of the population density.

3.2.4. Mediating Variables

The first mediating variable is the transaction cost (cost). Following the approach of Wang et al. (2025) [49], the index of the urban business environment is used as the measure, which serves as a reverse indicator. A higher score of the index indicates a more convenient market environment and lower transaction costs for businesses. Furthermore, the reduction in transaction costs facilitates the rapid flow and efficient allocation of resources, thereby enhancing the capacity of the urban economic system to withstand external shocks, and ultimately contributing to improving UER.

The second mediating variable is the urban innovation capacity (lnino). Drawing on the approach of Buglea et al. (2026) [20], the logarithm of the number of invention patents granted per ten thousand population is used as the measure. This indicator reflects the level of technological innovation output of a city. The greater a city's innovation capacity, the more effectively its economic system can respond to external shocks and explore new pathways for growth, thereby beneficial for promoting UER.

The third mediating variable is the consumption vitality (lncon). Following the approach of Li et al. (2025) [43], the logarithm of per capita consumption expenditure of urban residents is used as the measure. As household consumption is the key driver in countering external shocks and stabilizing economic demand, stronger consumption vitality leads to higher shock resistance and self-regulation capacity of the urban economic system, thereby helping to enhance UER.

In particular, it is necessary to clarify the conceptual boundary between the mediating variables and the dependent variable. In this paper, the three subsystems of UER are defined as the stock capacity of the urban economy, i.e., the resource base and reserve level that the system possesses to cope with external shocks. By contrast, the three mediating variables capture flow processes: what the system is currently doing to respond dynamically to external changes. Stock capacity provides the foundational conditions for flow activities to occur, while the continuous accumulation of flow activities reinforces stock capacity. The logical articulation between the two constitutes the causal chain underlying the mechanism analysis in this study.

To summarize, the definitions of the variables are shown in Table 3 below:

Table 3. Definitions of Variables.

Variable Name	Variable Symbol	Variable Definition /Transformations	Unit	Data Source
DIF index	lndif	natural logarithm	/	https://www.idf.pku.edu.cn/zsbz/index.htm (accessed on 10 March 2026)
Coverage breadth	lnbre	natural logarithm	/	
Usage depth	lndep	natural logarithm	/	
Digitalisation level	lndig	natural logarithm	/	
Government intervention degree	gov	General public budget expenditure divided by GDP	/	EPS Data Platform-China City Database
Transport accessibility	lntra	Logarithm of road freight volume per capita	/	
Human capital level	lnhum	Logarithm of the number of enrolled students in ordinary higher education institutions per ten thousand population	/	
Industrial structure level	ins	Value added of tertiary industry divided by value added of secondary industry	/	
Economic development level	lnpgdp	the logarithm of GDP	CNY per person	
Population density	lnden	the logarithm of population density	Persons per square kilometer	
Transaction cost	cost	Business environment index	/	https://www.macrodatas.cn/article/1147471767 (accessed on 20 March 2026)
Urban innovation capacity	lnino	Logarithm of the number of invention patents granted per ten thousand population	Patents	EPS Data Platform-China City Database
Consumption vitality	lncon	Logarithm of per capita consumption expenditure of urban residents	/	https://www.macrodatas.cn/article/1147473746 (accessed on 25 March 2026)

3.3. Data Sources and Processing Procedures

The specific data sources for each variable in this study are detailed in the "Data Source" columns of Tables 2 and 3. City-level economic and social development indicators are drawn from the China City Database on the EPS data platform, with the initial sample covering 312 prefecture-level cities over the period 2012–2024 (sample size: 4056).

To ensure data quality, the following treatments were applied to the initial sample:

(1) A total of 29 city samples with severe data missingness were excluded.
(2) For missing values, a deterministic single-point interpolation method is employed, following the approach of Wang et al. (2025) [49] was applied. The specific procedures implemented were as follows: For isolated missing observations occurring in intermediate years, the arithmetic mean values of the preceding and subsequent

years were utilized for imputation (e.g., the 2016 and 2018 values were averaged to impute missing 2017 data). For consecutive missing values at the terminal period of the sample, the available historical growth rate of the variable was first calculated, and extrapolation based on this growth rate was subsequently applied. To evaluate the potential bias introduced, the results from a complete case analysis are provided in the robustness test section.

(3) To avoid the influence of extreme values on the reliability of the empirical results, all continuous variables were Winsorised at the 1st and 99th percentiles. Finally, a panel dataset of 283 prefecture-level cities from 2012 to 2024 is obtained, with a total sample size of 3679.

Additionally, the Winsorised descriptive statistics for all variables were reported in Table 4.

Table 4. Descriptive statistics of variables.

Variable	Observations	Mean	Median	Minimum	Maximum
uer	3679	0.26	0.23	0.09	0.69
uer_rr	3679	0.08	0.06	0.01	0.28
uer_aa	3679	0.17	0.16	0.06	0.38
uer_it	3679	0.01	0.01	0.00	0.08
lndif	3679	5.20	5.37	3.57	5.82
lnbre	3679	5.16	5.30	3.20	5.91
lndep	3679	5.15	5.36	3.56	5.74
lndig	3679	5.34	5.58	3.22	5.80
lnino	3679	1.89	0.42	0.01	30.37
lncon	3679	10.34	10.34	9.61	11.20
gov	3679	0.20	0.18	0.08	0.60
lnhum	3679	0.99	0.41	0.02	9.18
lnpgdp	3679	10.87	10.86	9.57	12.12
lnden	3679	5.76	5.89	1.61	8.12
lntra	3679	2.07	2.15	0.03	5.11
ins	3679	1.10	0.97	0.34	3.62
cost	3679	0.48	0.14	−0.47	5.56

To eliminate dimensional influences and to ensure comparability of effect sizes, standardization was performed on all continuous variables in this study prior to econometric analysis, using the means and standard deviations of the full 2012–2024 sample. The standardized variables have a mean of zero and a standard deviation of one, allowing their coefficients to be directly compared to measure the relative influence of each independent variable on the dependent variable. Note that we employ full-sample standardization rather than year-by-year standardization. This is because year-by-year standardization would eliminate the time trend information embedded in the variables, while both DIF and UER exhibit significant time trends. Applying year-by-year standardization would result in the loss of such trend information, thereby compromising the validity of causal identification.

4. Empirical Results and Analysis

4.1. Impact of DIF on UER

Prior to conducting panel estimations for Model (1), we performed F-tests, BP-tests and Hausman tests; the results indicated that the fixed effects model was more appropriate. The baseline regression results are presented in Table 5. Column (1) of Table 5 does not include any fixed effects. Column (2) introduces city-level fixed effects. Column (3) further incorporates time effects on top of Column (2). To mitigate estimation bias arising from time-varying omitted variables at the provincial level, Column (4) controls for the interaction between province and year in addition to two-way fixed effects. Due to the absence of observations for certain province-year combinations, the sample size for this column is reduced to 3600.

Table 5. Results of the baseline regression [1].

Variables	(1)	(2)	(3)	(4)
z_lndif	0.015 *** (3.53)	0.033 ** (2.29)	0.026 *** (3.05)	0.035 ** (2.23)
z_gov	−0.078 * (−1.94)	−0.028 ** (−2.49)	−0.042 * (−1.71)	−0.027 ** (−2.36)
z_lnhum	0.028 *** (4.85)	0.015 ** (2.17)	0.007 ** (2.07)	0.049 *** (4.52)
z_lntra	0.105 *** (3.02)	0.007 *** (3.19)	0.043 *** (3.90)	0.049 *** (3.82)
z_ins	0.095 ** (2.32)	0.084 ** (1.99)	0.112 ** (2.01)	0.137 ** (2.24)
z_lnpgdp	0.031 *** (3.12)	0.022 ** (2.31)	0.019 ** (2.15)	0.014 (1.45)
z_lnden	0.018 ** (2.05)	0.015 ** (2.18)	0.012 ** (2.25)	0.009 * (1.88)
Individual FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	No
Province-year FE	No	No	No	Yes
Constant	0.002 ** (2.00)	0.001 *** (9.75)	0.001 *** (5.22)	0.035 *** (10.77)
Adjusted R^2	0.026	0.182	0.182	0.066
F-statistic	5.248	0.657	1.034	1.398
Observations	3679	3679	3679	3600

[1] The values in parentheses are the *t*-test statistics; *, **, *** indicate significance levels at the 10%, 5% and 1% levels; columns (1) to (4) all use city-level clustered standard errors; the variables are standardized variables.

According to columns (1) through (4) of Table 5, the coefficients of DIF are all positive and statistically significant at least at the 5% level, supporting Hypothesis H1 of this study. Based on the estimates in column (4), a one- standard-deviation increase in the DIF index leads to a rise of 0.035 standard deviations in UER.

To facilitate interpretation on the original scale, one standard deviation of the DIF index is approximately 0.81 (before standardization), and a one-standard-deviation increase from the mean roughly corresponds to raising a city's DIF level from the national medium to the upper-middle range. The mean of the UER composite index is 0.26 with a standard deviation of 0.12, so a 0.035 standard-deviation increase translates into an approximate 0.004 increase in the original UER value, corresponding to a rise of approximately 8–10 positions in the resilience ranking among the 283 sample cities. Although the magnitude of this effect is modest in absolute terms, it is statistically significant and practically relevant in a large-sample panel data study with cities as the unit of analysis. At the same time, it also suggests that there remains room for further improvement in the promoting effect of DIF on UER.

Additionally, in Figure 2, we visualize the estimation results in Table 5 using a forest plot, where the impact coefficients of DIF along with their corresponding 95% confidence intervals (CIs) are displayed. The point estimates of the coefficients are represented by dots, while the horizontal lines indicate the associated CIs.

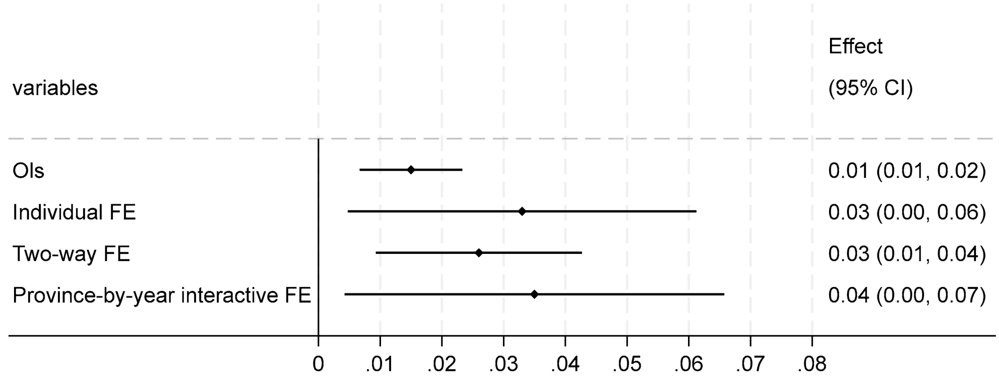

Figure 2. Forest plot for baseline regression.

4.2. Robustness Check

Robustness checks were conducted through three complementary approaches.

Firstly, sample adjustments were made to control for the influence of special groups. (1) The four municipalities directly under the central government (Beijing, Tianjin, Shanghai and Chongqing) were excluded. These cities differed significantly from other cities in terms of administrative hierarchy, economic scale and policy resources, which might bias the estimation results. After exclusion, the sample size was reduced from 3679 to 3627. (2) Years affected by major external shocks were excluded. Given the abnormal disruption of urban economic activities caused by the COVID-19 pandemic during 2020–2021, only observations from the remaining years were retained for re-estimation, resulting in a sample size of 3113.

Secondly, alternative estimation methods and data processing approaches were employed. (1) Maximum likelihood estimation (MLE) was adopted, which leverages the advantage of large sample sizes. (2) A complete case analysis was performed by removing all 43 cities with missing values and re-estimating using only fully observed samples, resulting in a total sample size of 3120. (3) Continuous variables were used directly in their raw form without Winsorisation. (4) Continuous variables were Winsorised at the 5th and 95th percentiles. (5) The level of clustering for standard errors was adjusted. To account for potential unobserved contemporaneous correlation across different cities within the same year, two-way clustering at the city and year levels was further adopted alongside the two-way fixed effects model.

Thirdly, the measurement of the dependent variable was replaced. The comprehensive index of UER was recalculated using Principal Component Analysis (PCA) as an alternative weighting method.

The estimation results of the robustness checks are presented in Table 6. The coefficients of the variable across all columns remain consistent in sign with the baseline regression, with only minor differences in significance levels and magnitudes. This finding supports the reliability of the baseline conclusions.

In addition, the estimation results in Table 6 are visualized using a forest plot in Figure 3, where the impact coefficients of DIF along with their corresponding 95% CIs are displayed.

Table 6. Results of Robustness Check [1].

Variables	(1) Excluding Municipalities	(2) Excluding 2020 and 2021	(3) Maximum Likelihood Estimation	(4) Complete-Case Analysis	(5) Without Winsorizing the Sample	(6) Winsorized at the 5% Level	(7) Two-Way Clustering at City and Year Levels	(8) Alternative Weighting Method
z_lndif	0.028 *** (4.22)	0.006 ** (2.05)	0.005 *** (3.04)	0.017 ** (2.21)	0.038 ** (2.18)	0.016 *** (3.33)	0.006 *** (4.07)	0.007 *** (2.82)
Constant	0.034 *** (3.08)	0.015 ** (1.99)	0.024 *** (5.08)	0.018 ** (2.44)	0.022 *** (5.79)	0.005 *** (3.68)	0.001 *** (4.19)	0.019 ** (2.13)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.075	0.180		0.198	0.179	0.077	0.182	0.154
F-statistic	0.919	1.220		1.178	1.205	1.189	2.040	2.168
Observations	3627	3113	3679	3120	3679	3679	3679	3679

[1] The values in parentheses are the *t*-test statistics; **, *** indicate significance levels at the 5% and 1% levels; columns (1) to (6) and column (8) all use city-level clustered standard errors; all variables are standardized variables.

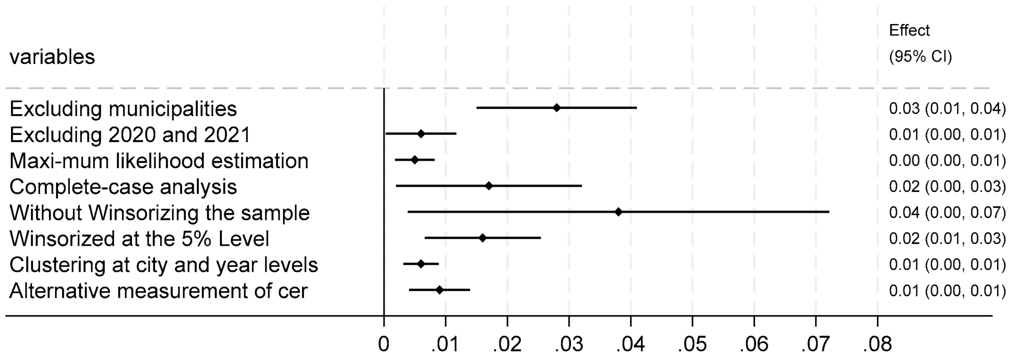

Figure 3. Forest plot for robustness check.

4.3. Endogeneity Test

The potential endogeneity in this study may arise from two sources: a possible reverse causality between DIF and UER, and the omission of relevant variables in the model. To mitigate estimation bias, two IVs are constructed as follows:

(1) The first IV is designated as lnpt. Following Zhang and Hu (2023) [42], the logarithm of the total volume of postal and telecommunications services in each city in 1999 (lnpt) is selected as an IV for the DIF index. The reasons for such a choice are as follows. First, the relevance condition is satisfied. Modern internet technology has gradually evolved from historical traditional communication infrastructures such as postal and telecommunications services. Given that DIF is fundamentally predicated on internet technology, regions with historically higher levels of postal and telecommunications development tend to possess better accumulation of information infrastructure and greater acceptance of digital technologies. Consequently, a significant positive correlation exists between historical postal and telecommunications development and the contemporary level of DIF. Second, the exogeneity condition is satisfied. The 1999 data on postal and telecommunications services are historical statistics, and their direct impact on current UER has largely dissipated over time. Thus, lnpt influences UER only indirectly through its effect on the development of DIF.

(2) The second IV is designated as dis_ave. Following the approach of Han and Peng (2023) [44], this IV is constructed by multiplying the spherical distance (logarithm) from a given city to Hangzhou by the annual national average of DIF (excluding the focal city). The rationale is twofold. First, relevance is satisfied. Hangzhou is the birthplace of DIF in China. Cities closer to Hangzhou are subject to stronger spillover effects and therefore tend to exhibit higher levels of DIF. Meanwhile, the national average captures the overall trend of DIF, and its combination with the distance measure strengthens the correlation between the IV and local DIF. Second, exogeneity is satisfied. Spherical distance is a geographic variable that is not influenced by economic characteristics of a city and has no direct bearing on UER. The national average, as a macro-level aggregate indicator, is exogenous to any individual city. Consequently, this IV meets the exogeneity requirement.

(3) The third IV is designated as Bartik_it. Following the approach of Zhou and Miao (2023) [52], this IV is constructed as follows: $\text{Bartik}_{it} = \text{L.dif}_{it} \times \text{D.dif}_{ijt}$, where L.dif_{it} denotes the first-order lag of the DIF index for city i in year t, and D.dif_{ijt} denotes the first difference in the DIF index for province j (in which city i is located) in year t. The reasons for this selection are as follows: First, relevance is satisfied. The current level of DIF is influenced by its previous level, and the city-level lagged term is highly correlated with the endogenous variable. Second, exogeneity is satisfied. The provincial level difference term captures the macro-level variation in DIF within the province, which constitutes an external shock to any individual city within that province, thereby meeting the exogeneity requirement. Consequently, this IV affects the dependent variable primarily through its impact on the city-level DIF, thus satisfying the exclusion restriction.

Table 7 reports the validity test results for the three IVs. Across all columns, the Kleibergen–Paap rk Wald F statistics are substantially larger than 10, leading to rejection of the weak instrument assumption. The Anderson–Rubin 95% CIs do not contain zero, further supporting the significance of the key variable. Moreover, when all IVs are used simultaneously, the *p*-value of the Hansen J test is 0.228, failing to reject the exogeneity of the IVs. The regression results show that, regardless of whether a single IV or the joint set is employed, the coefficient of z_lndif remains significantly positive, consistent with the baseline conclusion. This indicates that the enhancing effect of DIF on UER is robust.

Table 7. Estimation results of endogeneity test.

Variables	lnpt	dis_ave	Bartik	All
z_lndif	0.038 *** (3.52)	0.045 *** (4.11)	0.041 *** (3.79)	0.029 *** (2.74)
Conley spatial SE	0.011	0.018	0.039	0.024
Chi-sq(1) *p*-val	0.000	0.000	0.000	0.000
Kleibergen–Paap rk Wald F statistic	26.37	30.12	27.89	35.46
Anderson–Rubin 95% CI	[0.016, 0.060]	[0.024, 0.066]	[0.019, 0.063]	[0.018, 0.081]
Hansen J statistic (*p*-value)				0.228
Control variables	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.158	0.065	0.164	0.047
F-statistic	1.487	1.621	1.512	1.435
Observations	3679	3679	3393	3393

*** indicates 1% significance level; t-statistics in parentheses; LM statistic *p*-value (Chi-sq(1)) tests instrument relevance; Kleibergen–Paap rk Wald F statistic evaluates weak instruments; Hansen J statistic (*p*-value) examines overidentification restrictions; all variables are standardized variables; the standard errors are robust and clustered at the city level.

Despite the preliminary satisfaction of the relevance and exogeneity requirements for the IVs discussed above, further robustness analyses are conducted in this study to address potential identification challenges such as common trends and spatial dependence. (1) Leave-one-province-out tests are performed by sequentially excluding all city samples from each province and re-estimating the regressions, in order to examine whether the main conclusions are driven by any particular province and to avoid estimates being dominated by abnormal regions. (2) A placebo test is conducted by constructing a pseudo-Bartik IV, which interacts an unrelated national shock (the growth rate of national grain output) with $L.dif_{it}$. The results from the above tests consistently support the robustness of the main conclusions of this study.

5. Dimensional Deconstruction and Association Analysis

5.1. Impact of DIF on the Subsystems of UER

To investigate at which stage of UER formation DIF primarily exerts its influence, we conducted regression analyses using resilience and recovery capacity, adaptive capacity, and innovation and transformation capacity as dependent variables. Columns (1) to (3) of Table 8 report the regression results of the above three subsystems, respectively. It is shown that DIF exerts a significantly positive effect on all three subsystems, albeit with varying intensities, thereby supporting Hypothesis H2a.

Table 8. Regression results for subsystems [1].

Variables	Subsystems of UER			Dimensions of DIF		
	(1)	(2)	(3)	(4)	(5)	(6)
z_lndif	0.103 *** (5.73)	0.055 ** (2.46)	0.080 *** (2.78)			
z_lnbre				0.023 *** (4.31)		
z_lndep					0.031 ** (2.41)	
z_lndig						0.038 *** (6.57)
Constant	0.006 ** (2.06)	0.003 *** (8.27)	0.002 *** (5.56)	0.004 *** (6.40)	0.008 *** (8.25)	0.005 *** (9.33)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.188	0.204	0.285	0.182	0.182	0.182
F-statistic	1.209	0.893	1.593	1.074	1.031	1.109
Observations	3679	3679	3679	3679	3679	3679

[1] The values in parentheses are the *t*-test statistics; **, *** indicate significance levels at the 5% and 1% levels; all variables are standardized variables; the standard errors are robust and clustered at the city level.

Figure 4 visualizes the estimation results in Table 8 using a forest plot, where the impact coefficients of subsystems along with their corresponding 95% CIs are displayed.

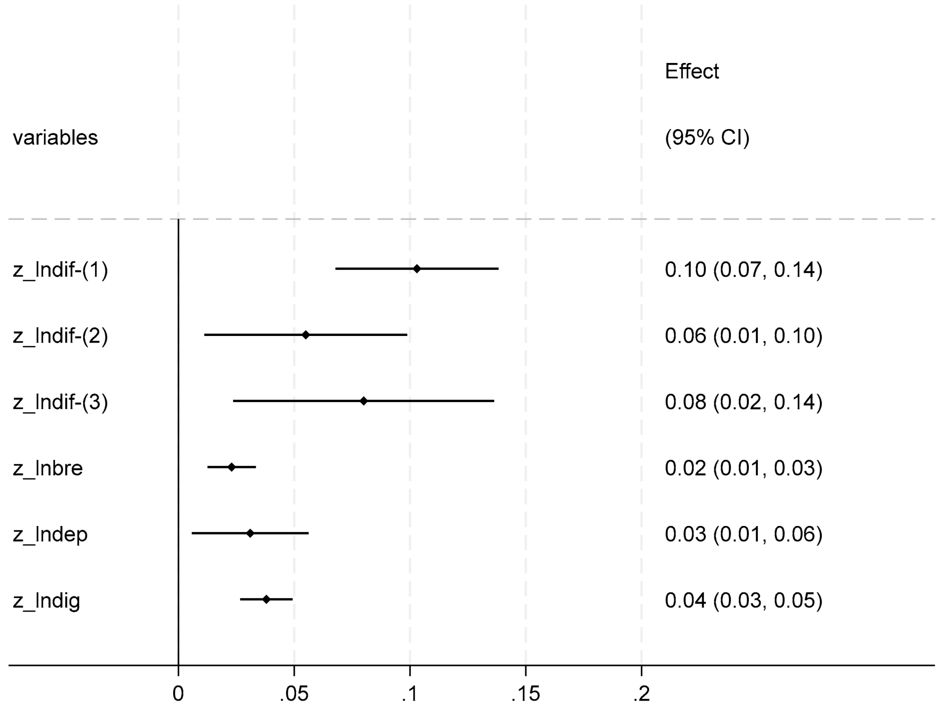

Figure 4. Forest plot for subsystems.

Specifically, the coefficient for resistance and recovery capacity is 0.103 (significant at the 1% level), the highest among the three subsystems, indicating that DIF has the most prominent effect on promoting short-term shock resistance and rapid recovery capacity of urban economic systems, confirming its short-term emergency function of providing liquidity support through mobile payments and emergency credit to enhance recovery capacity. The coefficient for innovation and transformation capacity is 0.080 (significant at the 1% level), suggesting that DIF has significant value in shaping long-term resilience by supporting innovation and entrepreneurship and fostering new business forms. The coefficient for adaptive capacity is 0.055 (significant at the 5% level), which has only a limited contribution. This could be because adaptive capacity involves resource allocation optimization and cross-sectoral factor flows, whose improvement requires more complex institutional coordination, and the direct impact of DIF is difficult to materialize rapidly in the short term. This is consistent with the finding of Yabe et al. (2025) [3] that medium-term system adjustment depends on coordinated responses among multiple agents, and external financial interventions alone cannot effectively activate this process in the short term.

5.2. The Role of Various Dimensions of DIF in Enhancing Resilience

To investigate which dimension of DIF serves as the primary driver of UER, regression analyses are conducted using coverage breadth, usage depth and digitalization level as the independent variables, respectively. Columns (4) to (6) of Table 8 report the regression results of these three dimensions, respectively. As we can see, all three dimensions of DIF exert significantly positive effects on UER, albeit with different magnitudes, thereby supporting Hypothesis H2b.

In particular, the digitalization level exhibits the most prominent driving effect among the three dimensions, with a coefficient of 0.038 (significant at the 1% level), indicating that it significantly amplifies the overall promoting effect of DIF on UER by reducing information asymmetry, improving service efficiency, and lowering transaction costs. The coefficient for usage depth is 0.031 (significant at the 5% level), suggesting that through the actual penetration of diversified services such as credit and insurance, usage depth provides functional support for resource allocation optimization and risk diversification within the system. The coefficient for coverage breadth is 0.023 (significant at the 1% level), with a relatively smaller contribution, reflecting its role as a network foundation. It integrates more micro-agents into the financial system, enhancing agent diversity and connection scale. However, compared with functional deepening and technological optimization, its direct enhancing effect on resilience is limited.

5.3. A Detailed Analysis of the Relationship Between DIF and UER

To precisely identify the independent contribution of each dimension of DIF to the different subsystems of UER, a regression strategy that simultaneously includes all three-dimensional variables is adopted. Specifically, resistance and recovery capacity, adaptive capacity, and innovation and transformation capacity are used as the dependent variables, respectively. Coverage breadth, usage depth and digitalization level are entered into the model simultaneously, while city fixed effects, year fixed effects and the baseline control variables are also controlled for. This specification avoids omitted variable bias and isolates the net effect of each dimension, thereby revealing the fine-grained matching relationships between dimensions and subsystems.

The regression results presented in Table 9 indicate that fine-grained matching relationships exist between the three dimensions of DIF and the three subsystems of UER, thereby supporting Hypothesis H2c. Specifically, the matching relationships are as follows.

Table 9. Matching matrix estimation results [1].

Variables	Resistance and Recovery Capacity (z_uer_rr) (1)	Adaptive Capacity (z_uer_aa) (2)	Innovation and Transformation Capacity (z_uer_it) (3)
coverage breadth (z_lnbre)	0.052 *** (3.58)	0.004 ** (2.05)	0.006 ** (2.13)
usage depth (z_lndep)	0.010 (1.11)	0.056 *** (6.85)	0.098 *** (4.52)
digitalization level (z_lndig)	0.021 ** (2.00)	0.040 ** (2.16)	0.033 *** (3.67)
Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	3679	3679	3679

[1] The values in parentheses are the *t*-test statistics; **, *** indicate significance levels at the 5% and 1% levels; all variables are standardized variables; the standard errors are robust and clustered at the city level.

First, coverage breadth predominantly affects resistance and recovery capacity. Its coefficient for resistance and recovery capacity is 0.052 (significant at the 1% level), which is considerably larger than its contributions to adaptive capacity (0.004, significant at the 5% level) and to innovation and transformation (0.006, significant at the 5% level). This indicates that the main function of coverage breadth is to construct a financial safety net, enhancing the foundational stability and rapid recovery capacity of a system when shocks occur by integrating more micro-agents into the formal financial system.

Second, usage depth exhibits the strongest driving effect on innovation and transformation. Its coefficient for innovation and transformation is 0.098 (significant at the 1% level), and its coefficient for adaptive capacity is 0.056 (significant at the 1% level), whereas its coefficient for resistance and recovery capacity is not statistically significant. This suggests that usage depth, through the actual penetration of diversified services such as credit and insurance, provides the system with support for resource allocation optimization and risk diversification, and is particularly effective in driving structural transformation and evolutionary upgrading.

Finally, digitalization level exerts significantly positive effects on all three subsystems, albeit with relatively balanced magnitudes. Its coefficient for resistance and recovery capacity is 0.021 (significant at the 5% level), its coefficient for adaptive capacity is 0.040 (significant at the 5% level), and its coefficient for innovation and transformation is 0.033 (significant at the 1% level). This indicates that digitalization level, as a foundational technological underpinning, permeates the entire process of resilience building, yet its marginal contribution is more pronounced during the medium-term adaptation and long-term transformation stages.

Moreover, we visualize the estimation results in Table 9 using a heatmap as shown in Figure 5, where the coefficients of the three dimensions of DIF on the three subsystems of UER are displayed. Darker blue indicates larger coefficient values, such that the strength of the net contribution of each dimension to the corresponding subsystem is highlighted.

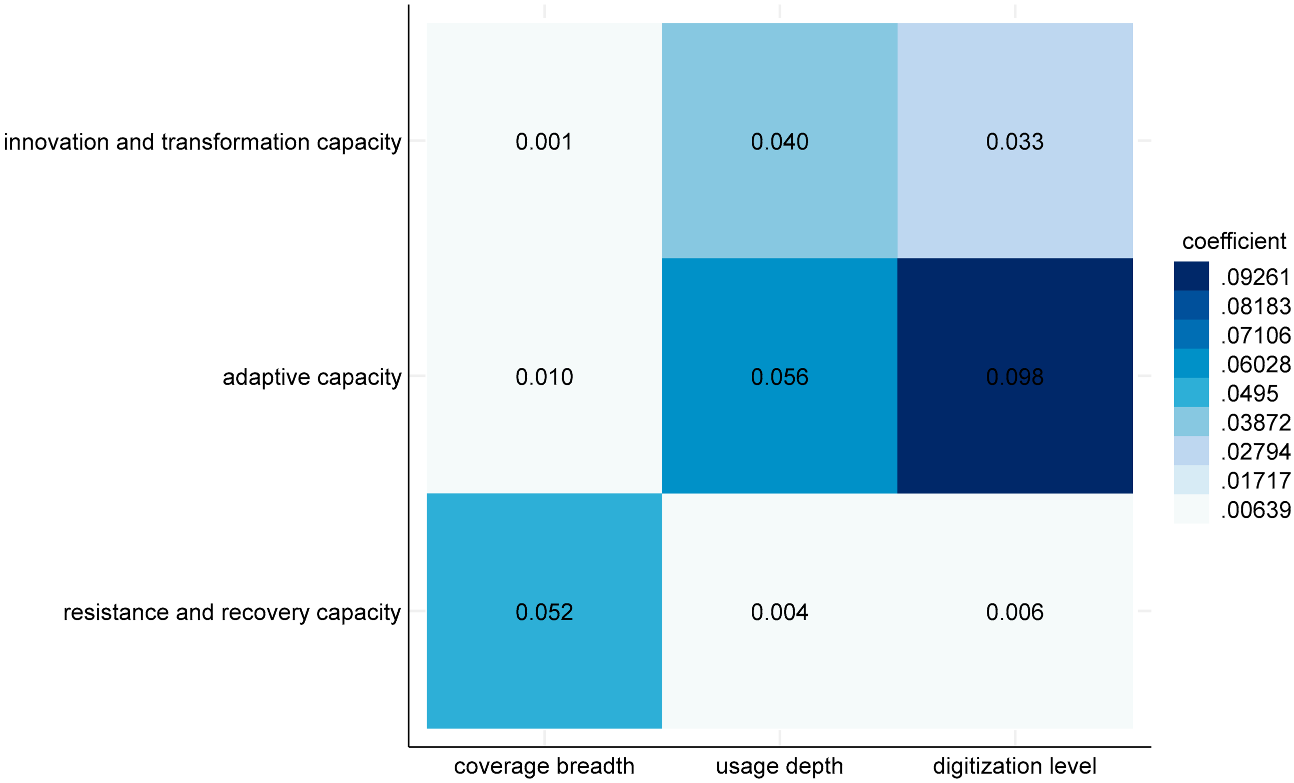

Figure 5. Heatmap of coefficients across various dimensions.

6. Mechanism Tests

6.1. Mechanism Tests of the Impact of DIF on UER

6.1.1. Analysis of Mechanism Test Results

To test the mechanisms through which DIF affects UER, a temporal mediation model is employed to examine three pathways: transaction cost, technological innovation and consumption vitality. Table 10 reports the regression results. The baseline regression results in column (3) of Table 5 show that the total effect coefficient of DIF on UER is 0.026 ($t = 3.05$), which is significant at the 1% level.

Table 10. Results of the mechanism test [1].

Variables	Testing the Mechanism of Transaction Cost (1)	(2)	Testing the Mechanism of Technological Innovation (3)	(4)	Testing the Mechanism of Consumption Vitality (5)	(6)
L.z_lndif	0.470 *** (4.22)	0.013 * (1.75)	0.808 *** (4.75)	0.024 ** (2.04)	0.055 *** (5.07)	0.020 ** (2. 38)
z_cost		0.028 *** (3.44)				
z_lnino				0.003 *** (4.05)		
z_lncon						0.105 *** (2.96)
Constant	0.011 *** (3.13)	0.025 ** (2.19)	0.055 *** (3.86)	0.027 * (1.85)	0.122 *** (4.42)	0.021 *** (6.02)
Bootstrap 95% CI		[0.006, 0.024]		[0.001, 0.004]		[0.002, 0.010]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.905	0.191	0.828	0.191	0.967	0.192
F-statistic	22.956	1.271	13.562	1.162	8.435	1.212
Observations	3395	3111	3395	3111	3395	3111

[1] The values in parentheses are the *t*-test statistics; *, **, *** indicate significance levels at the 10%, 5% and 1% levels; all variables are standardized variables; the standard errors are robust and clustered at the city level.

Regarding the transaction cost pathway, the coefficient of lagged one-period DIF on transaction cost is 0.470 (t = 4.22, significant at the 1% level), and the coefficient of transaction cost on one-period-ahead UER is 0.028 (t = 3.44, significant at the 1% level). After the inclusion of the mediating variable, the direct effect of DIF declines to 0.013 (t = 1.75, significant at the 10% level). This result is consistent with the hypothesized mechanism that DIF enhances UER by reducing transaction costs, thereby supporting Hypothesis H3a.

Regarding the technological innovation pathway, the coefficient of DIF on urban innovation capacity is 0.808 (t = 4.75, significant at the 1% level), and the coefficient of innovation capacity on UER is 0.003 (t = 4.05, significant at the 1% level). The direct effect is 0.024 (t = 2.04, significant at the 5% level). The statistical significance of this pathway supports technological innovation as a plausible transmission channel through which DIF affects UER, thereby supporting Hypothesis H3b.

Regarding the consumption vitality pathway, the coefficient of DIF on consumption vitality is 0.055 (t = 5.07, significant at the 1% level), and the coefficient of consumption vitality on UER is 0.105 (t = 2.96, significant at the 1% level). The direct effect is 0.020 (t = 2.38, significant at the 5% level). This provides empirical evidence for the role of consumption vitality in the transmission mechanism, thereby supporting Hypothesis H3c.

Before interpreting the sum of the effects across the three pathways, it is necessary to verify whether there is a significant collinearity among the three mediating variables. The Pearson correlation coefficients among transaction cost, technological innovation and consumption vitality are 0.21, 0.18 and 0.29, respectively, all below 0.30. Furthermore, the variance inflation factors (VIFs) for the three variables are 1.35, 1.42 and 1.28, well below the commonly used threshold of 5. These results indicate that there is no significant collinearity among the three mediating variables, and thus the summation of the mediation effects is justified.

The summary of the indirect effects of the three pathways is presented in Table 11. The indirect effect of the transaction cost pathway is approximately 0.013, accounting for 50.6% of the total effect, which is the highest proportion among the three pathways. A possible explanation for this finding is that transaction costs directly reflect the level of frictions in the operation of market institutions, and the improvements brought by DIF to activities such as information search and contract enforcement are relatively direct and tend to materialize within the sample period. The indirect effect of the consumption vitality pathway is approximately 0.0058, accounting for 22.3%, indicating that the expansion of household consumption is an important intermediate link in resilience enhancement. The indirect effect of the technological innovation pathway is approximately 0.0024, accounting for 9.3%, which is relatively low. One possible explanation is that the transition from innovation input to enhanced UER typically requires a longer transformation period and depends on conditions such as industrial supporting systems and human capital. The one-period-ahead specification adopted in this study may not fully capture its long-term effects. Overall, the sum of the indirect effects of the three pathways accounts for approximately 81% of the total effect, which aligns with the systemic framework in which DIF affects UER through multiple channels.

Table 11. Summary of mediation effect test results [1].

Path	Total Effect	Direct Effect	Indirect Effect
Transaction cost	0.026 ***	0.013 *	0.013
Technological innovation	0.026 ***	0.024 **	0.0024
Consumption vitality	0.026 ***	0.020 **	0.0058

[1] The values in parentheses are the *t*-test statistics; *, **, *** indicate significance levels at the 10%, 5% and 1% levels.

Given that consumption vitality is measured by the absolute level of per capita consumption expenditure of urban residents in the baseline regression, which may be influenced by the city's economic development level and residents' income, we further employ the ratio of per capita consumption expenditure to per capita disposable income as an alternative indicator of consumption vitality for additional testing. The results show that the mediation effect of this relative indicator remains significant and consistent with the baseline findings, suggesting that our conclusion regarding the consumption vitality transmission mechanism is not driven by the interference of absolute income levels.

6.1.2. Placebo Test

To alleviate concerns about potential reverse causality in the mediation effect analysis, a placebo test is conducted. Specifically, the one-period-ahead mediating variable $M_{i,t+1}$ is regressed on the contemporaneous DIF (dif_{it}). The model specification remains consistent with the baseline mediation equations, while city and year fixed effects are controlled for and standard errors are clustered at the city level. If contemporaneous DIF exhibits no significant predictive power for future mediating variables, the possibility of estimation bias arising from reverse causality can be partially excluded. As shown in Table 12, the coefficients for DIF are statistically insignificant across all cases, suggesting that the likelihood of endogeneity due to reverse causality is low, thereby providing further robust support for the mechanism analysis results presented above.

Table 12. Results of the placebo test [1].

Variables	Testing the Mechanism of Transaction Cost (1)	Testing the Mechanism of Technological Innovation (2)	Testing the Mechanism of Consumption Vitality (3)
z_lndif	0.447 (1.15)	0.788 (1.59)	0.063 (1.26)
_cons	0.019 * (1.71)	0.025 *** (4.64)	0.119 *** (3.62)
Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adjusted R^2	0.905	0.828	0.966
F-statistic	23.366	13.785	8.044
Observations	3395	3395	3395

[1] The values in parentheses are the *t*-test statistics; *, *** indicate significance levels at the 10% and 1% levels; all variables are standardized variables; the standard errors are robust and clustered at the city level.

6.2. Dimension-Based Mediation Effect Test

To identify the mediating mechanisms through which various dimensions of DIF influence the subsystem of UER, we continued to employ a time-series mediation model for analysis. This analysis involved a total of 36 regression models, yielding a large number of results, most of which showed no significant indirect effects. To simplify the presentation, we have summarized only the main pathways that were statistically significant. These results support research hypothesis H3d.

6.2.1. Dimensional Matching Analysis with Transaction Costs as the Mediator

The results of the tests using transaction costs as the mediating variable are shown in Table 13. We see that coverage breadth exerts a significant indirect effect on resilience by reducing transaction costs, with an indirect effect of 0.00704, a mediation proportion of 13.6%, and a Bootstrap 95% CI of [0.003, 0.012]. This finding is consistent with theoretical expectations that coverage breadth builds a financial safety net and lowers entry barriers. Therefore, it supports the conclusion that the transaction cost reduction mechanism primarily operates at the short-term resilience stage.

Table 13. Dimensional test results based on transaction cost [1].

Dimensions of DIF	Mediator	Resilience Subsystem	Indirect Effect	Mediation Proportion	Bootstrap 95% CI
Coverage breadth	Transaction cost	Resistance and recovery capacity	0.00704	13.6%	[0.003, 0.012]
Usage depth	Transaction cost	Adaptive capacity	0.00663	11.8%	[0.005, 0.016]
Usage depth	Transaction cost	Innovation and transformation capacity	0.00702	7.2%	[0.001, 0.008]
Digitalization level	Transaction cost	Adaptive capacity	0.00378	9.5%	[0.012, 0.063]
Digitalization level	Transaction cost	Innovation and transformation capacity	0.00346	10.5%	[0.010, 0.059]

[1] The indirect effects are standardized coefficients estimated using the product of coefficients method. The mediation proportion is the ratio of the indirect effect to the baseline total effect. Bootstrap CIs are calculated based on 1000 replications.

Usage depth exerts significant indirect effects on both adaptive capacity and on innovation and transformation through transaction costs. Specifically, the indirect effect on adaptive capacity is 0.00663 (accounting for 11.8%), while that on innovation and transformation is 0.00702 (accounting for 7.2%). This suggests that usage depth not only supports system structural adjustment through the optimization of resource allocation, but may also indirectly promote long-term transformation capacity by reducing transaction costs, albeit with a relatively weaker effect.

The digitalization level also exerts a significant indirect influence on adaptive capacity and innovation and transformation capacity via transaction costs, with indirect effects of 0.00378 (accounting for 9.5%) and 0.00346 (accounting for 10.5%), respectively. This result suggests that the digitalization level can reduce market frictions by mitigating information asymmetry and other factors, thereby playing a role in the medium-term adaptation and long-term transformation stages.

6.2.2. Dimensional Matching Analysis with Technological Innovation as the Mediator

The results of the tests using technological innovation as a mediating variable are shown in Table 14. The digitalization level exerts a significant indirect influence on both adaptive capacity and innovation and transformation capacity by promoting technological innovation. The indirect effect on innovative transformation capacity (0.00836) is greater than that on adaptive capacity (0.00148), accounting for 8.5% and 2.6%, respectively. This result is consistent with theoretical expectations.

Table 14. Dimensional test results based on technological innovation [1].

Dimensions of DIF	Mediator	Resilience Subsystem	Indirect Effect	Mediation Proportion	Bootstrap 95% CI
Usage depth	Technological innovation	Adaptive capacity	0.00148	2.6%	[0.004, 0.025]
Usage depth	Technological innovation	Innovation and transformation capacity	0.00836	8.5%	[0.032, 0.035]
Digitalization level	Technological innovation	Adaptive capacity	0.00083	2.1%	[0.002, 0.014]
Digitalization level	Technological innovation	Innovation and transformation capacity	0.00431	13.6%	[0.018, 0.068]

[1] The indirect effects are standardized coefficients estimated using the product of coefficients method. The mediation proportion is the ratio of the indirect effect to the baseline total effect. Bootstrap CIs are calculated based on 1000 replications.

Additionally, the digitalization level also exerts a significant indirect influence on adaptive capacity and innovation and transformation capacity through technological innovation. Notably, the indirect effect on innovation and transformation capacity (0.00431, accounting for 13.6%) is greater than that on adaptive capacity (0.00083, accounting for 2.1%). This reflects how the digitalization level promotes technological innovation by reducing information costs, thereby exerting a positive influence on the UER. It is worth noting that the proportion of the mediating effect of digitalization level on innovation and transformation capacity via technological innovation (13.6%) is higher than the corresponding proportion for usage depth (8.5%). Such a result implies that digital technology itself makes an independent contribution to driving the transformation process.

6.2.3. Dimensional Matching Analysis with Consumption Vitality as the Mediator

The results of the tests using consumption vitality as the mediating variable are shown in Table 15. It is shown that coverage breadth exerts a significant indirect effect on resistance and recovery capacity by enhancing consumption vitality, with an indirect effect of 0.00202 (accounting for 3.9%). This indicates that, when facing short-term shocks, coverage breadth can stabilize basic needs by expanding access to payment services and reducing transaction costs for consumption, thereby enhancing resistance and recovery capacity. However, its contribution is relatively small.

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Table 15. Dimensional test results based on consumption vitality [1].

Dimensions of DIF	Mediator	Resilience Subsystem	Indirect Effect	Mediation Proportion	Bootstrap 95% CI
Coverage breadth	Consumption vitality	Resistance and recovery capacity	0.00202	3.9%	[0.011, 0.030]
Usage depth	Consumption vitality	Resistance and recovery capacity	0.00410	40.9%	[0.023, 0.059]
Usage depth	Consumption vitality	Adaptive capacity	0.00909	16.2%	[0.062, 0.120]
Digitalization level	Consumption vitality	Resistance and recovery capacity	0.00227	10.8%	[0.013, 0.033]
Digitalization level	Consumption vitality	Adaptive capacity	0.00508	12.7%	[0.030, 0.072]

[1] The indirect effects are standardized coefficients estimated using the product of coefficients method. The mediation proportion is the ratio of the indirect effect to the baseline total effect. Bootstrap CIs are calculated based on 1000 replications.

The usage depth exerts significant indirect effects on both resilience and adaptive capacity through consumption vitality. The indirect effect on adaptive capacity (0.00909) is greater than that on resilience (0.00410), although the mediation proportion for the latter (40.9%) is higher than that for the former (16.2%). This suggests that, when external shocks occur, the depth of digital adoption enhances residents' purchasing power through services such as installment payments, thereby preventing a sharp decline in demand and making a significant contribution to resilience. At the same time, sustained consumer vitality provides businesses with stable market expectations, which helps them to adjust their medium-term structures, thus corresponding to the indirect effect on adaptive capacity.

The digitalization level also exerts a significant indirect influence on both resilience and adaptive capacity via consumer vitality. The indirect effect on adaptive capacity (0.00508, accounting for 12.7%) is greater than that on resilience and recovery capacity (0.00227, accounting for 10.8%). Such a result indicates that the digitalization level exerts indirect influences on the resilience and recovery capacity and the adaptive capacity respectively by lowering consumption barriers and enhancing consumption convenience.

7. Heterogeneity Test

To examine the heterogeneous responses of cities with different resilience levels to DIF, this study employs a panel quantile regression model. We adopt the fixed-effects panel quantile regression framework proposed by Koenker (2004) [53], which is a commonly used estimation method for static panel quantile regression. In this method, estimation bias caused by the incidental parameters problem is mitigated through imposing a penalty term on individual fixed effects. Regarding the selection of quantiles, we choose three representative quantiles, 0.25, 0.50, and 0.75, to represent cities with low, medium, and high resilience, respectively. The choice of these three quantiles is based on three considerations: at the theoretical level, 0.25, 0.50, and 0.75 can effectively capture the trend of DIF's effects across the conditional distribution of resilience; at the methodological level, three quantiles are sufficient to reveal differences across low, medium, and high levels while avoiding redundancy caused by too many quantiles; at the comparability level, this combination is a common choice in the empirical quantile regression literature, facilitating comparison of our results with those of comparable studies. Table 16 reports the estimation results.

The regression results show that DIF exerts significantly positive effects on UER at all three quantiles, but the coefficients exhibit a decreasing trend. At the 0.25 quantile (low resilience cities), the coefficient is 0.032, significant at the 1% level. At the 0.50 quantile (medium resilience cities), the coefficient is 0.019, significant at the 5% level. At the 0.75 quantile (high resilience cities), the coefficient is 0.006, significant at the 5% level. This pattern indicates that DIF has a more pronounced enhancing effect on cities with weaker resilience, demonstrating a convergence effect. The above findings support research hypothesis H4.

Table 16. Panel quantile model estimation results [1].

Variables	q = 0.25 (1)	q = 0.5 (2)	q = 0.75 (3)
z_lndif	0.032 *** (4.27)	0.019 ** (2.08)	0.006 ** (2.19)
Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	3679	3679	3679

[1] The values in parentheses are the *t*-test statistics; **, *** indicate significance levels at the 5% and 1% levels; all variables are standardized variables; the standard errors are robust and clustered at the city level.

This finding is consistent with theoretical expectations and aligns with the view of Tesfatsion (2003) [28]. Low-resilience cities typically face more severe financial exclusion, weaker infrastructure and greater consumption constraints, and the marginal benefits of DIF in alleviating these bottlenecks are consequently higher. In contrast, high-resilience cities already possess a relatively sound financial ecosystem and industrial base, leaving limited additional room for improvement through DIF.

8. Conclusions and Policy Implications

8.1. Conclusions

Based on CAS theory, we have reached the following conclusions through theoretical analysis and empirical testing:

First, from a systemic perspective, DIF has a significant positive impact on UER. Specifically, DIF has the strongest effect on promoting resistance and recovery capacity, followed by innovation and transformation capacity, whilst its impact on enhancing adaptive capacity is relatively weaker. This gradient pattern indicates that DIF primarily strengthens the short-term stability of the economic system in response to external shocks, thereby driving long-term transformation capacity, whilst medium-term structural adjustments require more complex institutional conditions to support them.

Second, from the perspective of subsystems, the contributions of the dimensions of DIF to the subsystems of UER differ, and asymmetric matching relationships are formed with the subsystems. In terms of the magnitudes of contributions from the three dimensions of DIF, digitalization level is the most prominent, followed by usage depth, while coverage breadth is relatively minor. Therefore, promoting the application of technology and enhancing service capabilities are more important than simply expanding coverage breadth. In terms of matching relationships, coverage breadth primarily affects resistance and recovery capacity, usage depth mainly influences adaptive capacity as well as innovation and transformation capacity, while digitalization level exerts a balanced positive effect on all three resilience subsystems.

Third, from the perspective of transmission mechanisms, the process by which DIF enhances UER aligns with three pathways: the reduction of transaction costs, the driving force of technological innovation, and the stimulation of consumer vitality. Moreover, the mediating effects at the dimensional level exhibit asymmetric characteristics. In terms of the aggregate index, these three pathways collectively account for approximately 81% of the total effect. At the dimensional level, coverage breadth primarily influences resilience through reduced transaction costs; usage depth drives innovation and transformation capacity via technological innovation, whilst also influencing resilience and recovery capacity and adaptive capacity through consumption dynamism; and digitalization exerts a balanced influence across all three pathways.

Finally, heterogeneity analysis shows that the enhancement effect of DIF is more pronounced in cities with lower resilience, exhibiting a convergence effect. Specifically, the marginal effect for low-resilience cities is 0.032, whereas for high-resilience cities it is only 0.006.

8.2. Policy Implications

Based on the above conclusions, the following targeted policy recommendations are proposed:

First, differentiated development strategies should be implemented such that each dimension of DIF can precisely address the specific needs of different cities in enhancing UER. Specifically, for cities with insufficient financial coverage but a sound economic foundation, priority should be given to expanding the reach of basic financial services to enhance their ability to withstand shocks; for cities with a monolithic industrial structure and significant pressure to transform, the focus should be on developing businesses such as lending and insurance to support industrial restructuring and innovation; for cities with a high level of technological advancement and digital infrastructure, the practical application of digital technologies should be further promoted to improve UER more effectively.

Second, differentiated policy priorities should be established according to the specific resilience weaknesses of each city. Cities with different resilience capacities should adopt different entry points for promoting DIF development. For cities with weak resistance and recovery capacity, such as those prone to natural disasters or experiencing large economic fluctuations, priority should be given to building a financial safety net through tools such as mobile payments and emergency credit, so as to enhance the system's rapid response and recovery capabilities when shocks occur. For cities with insufficient adaptive capacity, the focus should be on leveraging big data risk control and intelligent pricing to improve the precision and flexibility of resource allocation. For cities lagging in innovation and transformation capacity, efforts should concentrate on supporting innovation and entrepreneurship through instruments such as venture capital and intellectual property pledges, thereby fostering new business forms and new growth paths.

Third, differentiated support policies should be implemented based on the initial resilience level of cities. For cities with a weak resilience foundation (e.g., resource-based cities), policies should focus on reducing the thresholds and costs of adopting digital finance through measures such as fiscal subsidies, digital infrastructure development, and technical training, so as to fully leverage their substantial room for marginal improvement. For cities with a relatively sound resilience foundation, the policy priority should shift from expanding financial coverage to improving the institutional environment and enhancing the quality of financial services, rather than continuing to merely pursue expansion of coverage.

9. Discussion

9.1. Comparison with Existing Literature

We first systematically compare the findings of this study with those of the existing literature. The convergence lies in that our findings align with those of Feng and Lai (2025) [14], both confirming the positive effect of DIF on UER. Meanwhile, our results are also consistent with the findings of Wang and Chen (2025) [37], who confirmed that DIF enhances UER by improving resource allocation efficiency. Building on this, our study further identifies three specific transmission channels and their structural differences.

However, our findings differ substantively from existing studies in the following two aspects. First, at the dimensional matching level, most previous studies have focused on the overall effect of DIF on UER [38], failing to identify the differentiated functions across dimensions. We find that coverage breadth primarily affects resistance and recovery capacity, while usage depth mainly drives innovation and transformation capacity, an asymmetric matching pattern that has not been systematically revealed in the existing literature. This finding suggests that researchers should not focus solely on the aggregate or average level of financial services, but rather distinguish the differentiated roles of various dimensions at different stages, which offers general implications for understanding the correspondence between structure and function in complex systems. Second, at the heterogeneity level, we find that DIF exerts a more pronounced enhancing effect on cities with lower resilience, which complements the perspective of studies focusing on the moderating role of industrial structure [54]. This finding directly responds to the debate over whether digital technologies exacerbate or narrow regional disparities, indicating that DIF has a stronger marginal improvement effect in regions with weaker initial conditions, thus providing new empirical evidence for evaluating the inclusive features of digital finance.

9.2. CAS Framework and Its Differentiating Theoretical Insights

The deeper reason why our findings differ from those of existing studies lies in the fact that the CAS framework introduces an analytical logic distinct from that of traditional financial development theory. Traditional theories tend to treat DIF as a homogeneous whole, focusing on its average effects on economic output, whereas the CAS framework understands UER as an emergent outcome of system evolution, emphasizing the matching of different elements at different stages of system development. From this perspective, both the asymmetric matching pattern and the convergence effect identified in this study can be reasonably explained. The former stems from the system's differentiated sensitivity to accessibility and penetration at different stages, while the latter can be attributed to the greater room for marginal improvement in low-resilience cities under the mechanism of path dependence. As described in Section 2.1, DIF influences system operation by reshaping the three layers of linkages among agents, competition, collaboration, and environmental interaction. It is precisely this analysis of internal interaction processes within the system that enables the CAS framework to uncover the dimensional structural patterns that traditional theories have obscured.

9.3. Theoretical Contributions and Open Research Questions

Based on the above analysis, this study makes theoretical contributions in the following two aspects. First, the asymmetric matching pattern at the dimensional level suggests that coupling among system elements is constrained by the demands at different stages of system evolution, rather than being a one-to-one precise correspondence. This finding offers general implications for understanding the relationship between structure and function in complex systems, and extends the discussion of path lock-in and path breakthrough in evolutionary economics from the firm or industry level to the urban economic system level. Second, the convergence effect indicates that the effectiveness of external interventions at the system level depends on the system's initial conditions, providing empirical evidence for understanding the two directions of system evolution, convergence and divergence.

These theoretical advancements also give rise to several research questions. First, given that DIF has a greater marginal effect on cities with low resilience, is it possible that such cities may over-rely on external financial interventions while overlooking the cultivation of internal institutional capacity? Second, our study indicates that usage depth contributes most prominently to innovation and transformation capacity. More specifically, which type of services within usage depth contributes the most to this effect? Third, will the asymmetric matching pattern identified in this study be adjusted as the stage of system evolution changes? Answering these questions calls for more refined data and the introduction of research methods that better align with the logic of system evolution.

9.4. Limitations and Future Research Directions

Despite the findings obtained in this study, several limitations remain, which also imply directions for future research.

First, a limitation arises from the scope of the sample coverage. Although this study is based on panel data from Chinese cities, caution should be exercised when generalizing the conclusions to other countries. Institutional environments, levels of financial development and digital infrastructure vary considerably across countries, and the mechanisms through which DIF affects UER may differ accordingly. Specifically, the asymmetric matching pattern identified in this study may be less pronounced in countries with highly mature financial systems, while it may be more salient in economies undergoing rapid financial market transformation. Therefore, future research could employ cross-country panel data to test the generalizability of this pattern and examine the moderating role of institutional differences on the matching relationships.

Second, a limitation pertains to the contemporaneity of variable measurement. As the Peking University DIF Index is primarily based on traditional digital financial services such as mobile payments and credit, it may not fully capture the potential impact of frontier technologies such as blockchain and artificial intelligence. This may lead to an underestimation of the contribution of frontier technologies to innovation and transformation capacity through the efficiency channel. Future research could incorporate these emerging digital financial sectors to optimize the indicator system for DIF, thereby enabling a more comprehensive assessment of its effects across various dimensions of resilience.

Third, there is a limitation in the alignment between the methodology and the theoretical framework. Standard linear panel models struggle to capture the key features of CAS, such as nonlinear interactions among multiple agents, threshold effects, and structural shifts in the long-term evolution of the system. The asymmetric matching relationships identified in this study only reflect the static associations during the sample period and fail to reveal the potential path transitions that these relationships may trigger over the long-term evolution of the system. Therefore, future research could employ agent-based models to directly simulate the adaptive behaviors of various agents under different DIF policies and the dynamic evolution of UER systems. This would allow the methodology to be more closely aligned with CAS theory.

Fourth, there is a concern regarding the conceptual boundary between the mediating variables and the dependent variable. In this study, they are distinguished based on a framework of stock capacity (resilience subsystems) and flow processes (mediating variables), and concerns about reverse causality are alleviated through the lagged structure of the temporal mediation model and placebo tests. However, the validity of this distinction ultimately depends on the accuracy of the theoretical specification. If certain mediating variables indeed have a closer co-constitutive relationship with the resilience dimensions, it may lead to an overestimation of the mediation effects. Future research could employ instrumental variable approaches to address the endogeneity of mediating variables, or utilize panel data with a longer observation window to test the robustness of this boundary distinction.

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