Digitalization's Effects on Income Growth and Distribution
- Evidence from the CHDES Database

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Abstract: *Using the CHDES database, we created the CIDI to comprehensively quantify digital adoption at the individual level and examine digitalization's impact on individual income. Empirical analysis results indicate that increasing the CIDI by one standard deviation (0.13) improves individual income by 5.93 percentage points, which remains true after a series of endogeneity and robustness tests. In the heterogeneity analysis, we discovered that when digital adoption grows, residents in the countryside and county seats can earn more money through internet business operations and other channels. This helps to decrease the urban-rural income divide, but it has also pushed those digitally skilled into high-paying sectors, widening the income gaps between sectors. In the mechanism analysis, we developed an income function that takes into account the individual level of digitalization to show that digitalization can boost income by increasing working hours or labor participation and adjusting the portfolio of individual material, human, and social capital. In this paper, we have expanded the system for measuring the individual levels of digitalization by offering basic data, research methodology, and policy suggestions for the digital economy's inclusive development.*

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1. Introduction

In order to foster the healthy growth of the digital economy, it is imperative to go beyond simply promoting a shift in production methods through digital transformation. It is equally important to ensure that the digital economy becomes accessible and relevant for the general public. As a cornerstone for "creating a new vision for a beautiful digital life", the Chinese government has laid out systematic plans for accelerating digitalization in its *14th Five-Year Plan for National Economic and Social Development and Long-Range Objectives for 2035*. In addition, China implemented policy guidelines including the *Digital Literacy and Skills Action Plan* and the *Overall Plan for Digital China Development*, which set up measures to raise the digital literacy of Chinese people. Given this backdrop, it is important to investigate the effects on income distribution and growth caused by disparities in digital access and digital literacy among Chinese residents, as well as to uncover basic facts about the conditions under

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which Chinese residents acquire digital skills and access the internet.

A few studies have looked at how the digital economy - which is fueled by growing internet penetration - supports inclusive development and income growth in recent years (Zhang et al., 2021; Qiu and Qiao, 2021). The effective measurement of the digital economy is a priority and challenge for this research matter. Given the absence of a Chinese household survey on the digital economy, there has been little research on a direct measurement of the digital economy's penetration in the household sector. Indirect measurement with a proxy variable cannot accurately portray the basic facts of digitalization at the individual level, thus limiting the analysis of the effects of digitalization on individual behaviors. To deepen research into the digital economy at the microscopic level, it is critical to develop a multi-dimensional individual digitalization index based on China's national and social conditions.

Using the China Household Digital Economy Survey (CHDES) from Renmin University of China, this paper develops the China Individual Digital Index (CIDI) to reflect basic facts about digital adoption at the individual level and investigates the mechanism by which the CIDI affects income under a causality identification framework. In this way, this work aims to make the following three marginal contributions: (i) The CIDI has two dimensions: "digital access" and "digital skills and usage", with five secondary indicators and 15 tertiary indicators. To compensate for the deficiencies of existing research and measurement, a total of 19 indicators thoroughly quantifies the individual level of digitalization. (ii) The CIDI presents three stylized facts concerning the relationship between individual levels of digitalization and income, as well as an empirical investigation of digitalization's effects on individual income growth and income gap reduction. When the CIDI increases by one standard deviation, individual income rises by 5.93 percentage points. On this premise, this study presents a heterogeneity analysis of the urban and rural, regional and sectoral differences that the individual level of digitalization may affect income, in order to illustrate the main aspects of "digital inequalities" in China. (iii) A discussion is offered to determine how digitalization may affect individual income via the "labor-enabling effect" and "capital multiplication effect". We found that digitalization can boost income by extending the duration of online working and learning or the likelihood of employment ("enabling effect"), or raise incomes by adjusting the portfolio of material, human and social capital ("multiplication effect"). Meanwhile, the capital multiplication effect of digitalization may widen capital endowment disparities in the digital era, necessitating policy intervention. These findings not only illuminate the mechanisms by which the digital economy affects household income, but also inspire the improvement of fairness and efficiency in the digital age.

The rest of this paper progresses as follows: Section 2 describes the creation of the CIDI. Section 3 provides stylized facts about the association between CIDI and income and proposes research hypotheses. Section 4 examines empirical methodologies and findings. Section 5 provides a mechanism analysis to determine the "labor-enabling effect" and "capital multiplication effect". Section 6 includes a summary and policy suggestions.

2. Creation of the CIDI

2.1 Explanation of Survey Data

The CHDES, which was developed by Renmin University of China throughout the years 2021-2022, is the first household-level digital economy survey in China and offers a special source of data for the CIDI. This survey, which may fully assess the growth and penetration of the digital economy at the level of individual households, covers basic household and individual information, internet access and use, use of digital equipment, digital awareness and skills, digital activities, employment situation, income and consumption, housing and transportation tools, and carbon awareness. It was carried out with the questionnaire based on the "cause-action-consequence" framework of the digital economy.

The household survey has collected 1,675 valid sample households (4,977 persons) across ten provincial jurisdictions of Beijing, Hebei, Zhejiang, Shanxi, Guangdong, Guangxi, Guizhou, Henan, Jilin, and Gansu. This survey adopts a stratified sampling method: Each province includes one provincial capital and one medium- or low-tier city; Beijing includes its central urban districts and suburban counties and districts; each prefectural city includes urban districts, county seats and rural villages by the ratio of 1:1:1. This simple method ensures that the samples are fully representative of the digital economy at the household level across the nation, avoiding sampling-related selection bias. Given the individual differences of education and employment, this survey has allocated samples into daytime during workdays, nighttime during workdays and weekends by the ratio of 25%:75% referencing the ratio of national employed population in 2020 to increase representative and accurate samples. In this paper, we compare the survey data of China's household digital economy with the Seventh National Demographic Census data to ensure representativeness of socioeconomic indicators[1].

2.2 Digitalization Indicators

2.2.1 Design approach

Representative studies looked for proxy indicators for the digital economy at the regional, industry/enterprise, and individual levels[2]. Since regional-level data indicators are more readily available, the measurement of regional digital economies began early, including a single or a series of indicators such as internet penetration, digital inclusive finance index, and overall digital economy development (Cheng and Zhang, 2019; Bo and Zhang, 2021), as well as methods for measuring the "broadband China" policy (Tian and Zhang, 2022). There are currently no uniform and systematic standards for measuring industrial/corporate digital transformation. Representative measurements include the number of industrial robot installations by Acemoglu and Restrepo (2020) and the analysis of annual reports of listed companies by Yuan et al. (2021). At the household level, the existing literature is still focused on a single measurement indicator, and common responses to the questions "Do you use the internet" from the CFPS database, "Do you use the internet when looking for a job or searching information?", "Frequency of using the internet" from the CGSS database, and "Do you use your mobile phone, iPad, or other mobile devices to make payments?" from the CHFS database. More recent research seeks to develop a composite score based on survey data, but the majority of such data is connected to ICT availability and use in specialized domains.

Our CIDI includes two major dimensions: "digital access" and "digital skills and usage". The first dimension, digital access, measures the most fundamental aspect of digitalization. As more users connect to the internet, there is a significant increase in internet access among the most vulnerable groups, and digital access gaps tend to narrow. Recent research, however, suggests that digital access has shifted from basic physical access to device access, which includes opportunities to access devices and peripheral devices, device diversity, and continuous expenses for hardware, software, and subscriptions, all of which influence internet skills, use, and productivity. The second dimension is digital skills and usage, which is a commonly used indicator of digitalization. After having physical and device access to the internet, it takes solid internet skills and use it properly (van Dijk, 2005; Chen and Zhou, 2022). In addition to ICT infrastructure, gaps in internet capabilities are related to material capital, social capital, and human capital (Montagnier and Wirthmann, 2011). Individuals with strong capabilities can improve their digital education through online courses or seek job and business opportunities using digital tools (DiMaggio et al., 2004; Martínez, 2020).

[1] See appendices on the *China Industrial Economics* website (http://ciejournal.ajcass.org).

[2] We searched for and examined the proxy variable "digital economy" that appears often in papers published in *Economic Research Journal*, *Management World*, *Journal of World Economy*, *China Industrial Economics*, and *Journal of Financial Research* between 2017 and 2023. Household digital economy behaviors are monitored in two dimensions: internet usage and intensity, but there is no systematic and comprehensive measurement of digitalization. See the appendices on the *China Industrial Economics* website (http://ciejournal.ajcass.org).

2.2.2 Creation of indicators

Based on the above principle, we developed the first CIDI to assess the level of individual digitalization using the measurement dimensions and determinants of digitalization from existing literature, as well as referencing the compilation method of the "Digital Financial Inclusion Index of China (DFIIC)" (Guo et al., 2020).

This index has two basic dimensions: digital access and digital skills and usage, five secondary indicators, and 15 tertiary indicators, totaling 19 distinctive indicators (see Table 1). Digital access has two dimensions: digital service and digital devices. First, digital services include internet access and net speed. Internet access is measured by whether a household has fixed broadband connection and whether fixed broadband services are adequate for daily use, while net speed is measured by uplink/downlink speed and the duration of downloading a specific app. These metrics not only indicate the availability of digital infrastructure in a region, but they also assess network quality and speed for each family, highlighting disparities in digital access at the household level. Second, digital devices are measured by subtracting idle devices from the total number of devices, and include desktop computers, laptops, tablets, smartphones, and feature phones.

Digital skills and usage are assigned three secondary dimensions, including digital awareness, digital skills, and digital usage. (i) Digital awareness is measured by understanding about the digital economy and network security awareness: The former evaluates whether a respondent has heard about and properly understands the concept of the digital economy and heard about the concept of smart home appliances; the latter reflects six types of behaviors, including whether a respondent has carefully read

Table 1: System of Digitalization Indicators

Primary dimension (2)	Secondary dimension (5)	Tertiary dimension (15)	Specific indicators (19)	Measurement unit / scope
Digital access (66.7%)	Digital services (66.7%)	Network access (23.4%)	Is there fixed broadband access at home?	0/1
			Are the fixed broadband services satisfactory for daily use?	0-2
		Net speed (76.6%)	Downlink speed	Mbps
			Uplink speed	Mbps
			Duration of downloading designated app	Second
	Digital devices (33.3%)	Digital devices (100.0%)	Number of digital devices in use (total number minus idle devices)	Set
Digital skills and usage (33.3%)	Digital awareness (11.7%)	Understanding of the digital economy (72.7%)	Have you ever heard about the concept of the digital economy?	0-10
			Have you ever heard about the concept of smart home appliances?	0-1
		Digital security awareness (27.3%)	Have you ever engaged in digital security protection?	0-6
	Digital skills (61.4%)	Operational skills (24.8%)	Basic skills required for the use of internet	0-10
		Information navigation skills (25.0%)	Abilities to search, select and evaluate online information sources	0-2
		Social skills (12.9%)	Abilities to acquire social capital through online communication and interaction	0-7
		Content creation skills (37.4%)	Create different types of content and publish or share such content to others via the internet	0-3
	Digital usage (26.8%)	Financial domain (12.7%)	Do you use digital financial services?	0/1
		Sales domain (7.5%)	Have you ever published any product sales information over online platforms?	0/1
		Life services domain (26.5%)	Have you ever listened to online radio, music, video, played games, bought train tickets, air tickets, or booked hotels online?	0/6
		Office domain (13.2%)	Have you stored or downloaded online resources via professional office software?	0/3
		Health domain (21.0%)	Have you ever conducted health management via online platforms?	0/1
		Education domain (19.2%)	Have you ever participated in online learning or used reading platforms to read e-books?	0/2

Note: Percentages in parentheses denote the weight of an indicator upon synthesis determined based on the subjective and objective weight assignment methods; "X-X" in the measurement unit/scope denotes the range of scores for this indicator.

the confidentiality clause when using an app, disabled a website or mobile app from accessing his or her location, deleted web browsing history, prohibited strangers from accessing moments for personal information on social media or other platforms, and used mobile storage devices rather than online storage to transfer information, documents or data. (ii) Digital skills contain 10 types of skills, including operational skills, information navigation skills, social skills, and content creation skills: operational skills include searching and downloading mobile apps, registering personal accounts at installed apps, and watching videos, listening to music or radio on online platforms. Information navigation skills are twofold: looking for and following WeChat public accounts, and accessing information using WeChat, information apps, or other online platforms. Social skills include picking up a video call or voice call initiated by others, initiating a video call or voice call with family members or friends, and five other skills. Content creation skills include publishing original content over online platforms, making a comment on a commodity or service purchased, and marketing products over an online platform. (iii) Digital usage encompasses six domains, including finance, sales, life services, office, health, and education. Questions include whether a respondent has ever used financial services, published product sales information over online platforms, listened to the radio or music, watched videos, played games, bought train tickets or air tickets, or booked hotels, over digital platforms, used office software, saved files online or downloaded online resources, carried out health management over online platforms, and used online education platforms for study or reading platforms to read e-books.

Performing non-dimensional treatment of the indicators. In this paper, we adopt the normalization method for the non-dimensional treatment of indicators based on the following equation: $x_i' = \frac{x_i - x_i^l}{x_i^h - x_i^l}$. As for the determination of the threshold value in the normalization equation, the adoption of the maximum and minimum values of each indicator as the upper and lower limits may expose the indices to extreme or outlier values. For the positive indicators, therefore, we adopt the 99% percentile of the actual values of individual indicators as the upper limit x_i^h, and the 1% percentile as the lower limit x_i^l, and vice versa for negative indicators. Further, data above the indicator limit is winsorized: if an individual indicator value is above its upper or lower limit $x_i^h(x_i^l)$, the value of this indicator is defined as its upper or lower limit $x_i^h(x_i^l)$. After the non-dimensional treatment, the numerical value of each indicator is between 0 and 1, and higher score means a higher level of development.

Weight of indicators: Referencing Guo et al. (2020), we determined the weight of each indicator based on a combination of subjective and objective weights, i.e. the coefficient of variation method is employed to calculate the weight of each indicator at the bottom layer versus its upper criterion layer, and the weights of indicators at the criterion layer versus the upper layer objectives are calculated based on the stratified analysis method in order to obtain the total index. Our final CIDI weight vector is shown in the parentheses in Table 1[3]. In practice, indicator synthesis is performed by aggregating each layer from the bottom to the top, i.e. the grouping index of each layer is calculated first before conducting a weighted aggregation of the grouping indices of various layers.

2.2.3 Statistical description of the CIDI

Based on the above set of indicators and method for indicator creation, we compiled the Chinese Individual Digitalization Index (CIDI) using household survey samples from 102 counties, 22 prefectural cities, and 10 provinces on the Chinese Mainland. We also created the digital access index and the digital skills and usage index (see Table 2), both of which measure different aspects of digitalization. For 2021, the CIDI's average value is 0.41 with a standard deviation of 0.13. The mean value of digital access is 0.32, and the minimum value is 0.01, i.e. there was almost no resident without digital access. This reflects China's moderately advanced infrastructure development on a massive scale in recent years, which has

[3] Weights are expressed in rounded numbers.

generally achieved universal access to basic digital services. The mean value of digital skills and usage is 0.59, the minimum value is 0.00, and the maximum value is 0.98. This implies that despite a fairly high level of digital skills and usage for the vast majority of people, certain groups of people still have a very low level of digital skills and usage, which is a weakness for China to improve individual digital literacy and reduce "digital poverty".

Table 2: Statistical Description of Digitalization Index System Variables

Name of variable	Symbol of variable	Sample size	Mean	Standard deviation	Min.	Max.
Digitalization index	*CIDI*	1675	0.4115	0.1283	0.0275	0.8978
Digital access	*Digtal_connect*	1675	0.3218	0.1252	0.0074	0.8837
Digital skills and usage	*Digtal_skill_uses*	1675	0.5910	0.2384	0.0000	0.9840

Source: CHDES database.

3. Stylized Facts and Hypotheses

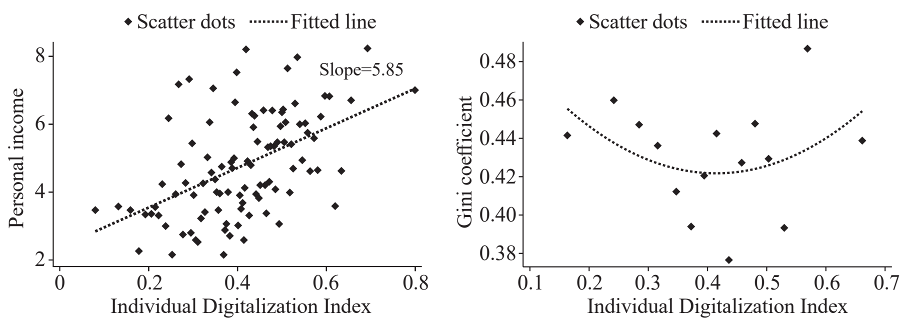
3.1 Three Stylized Facts and Hypotheses of the Digital Economy and Household Income

In this paper, we use the CIDI to depict the basic facts about the relationship between the individual level of digitalization and household income, putting forth a hypothesis about the digital economy's impact on household income.

3.1.1 Stylized fact 1: Positive correlation between the level of household digitalization and household income[4]

First, we divide the CIDI into 100 equal shares in ascending order to calculate each equal share of the CIDI and mean household income and draw a scattered plot with fitted line, as shown in Figure 1 (a). The chart reveals a positive correlation between the CIDI and individual income at the societal level. Recent years have seen fast adoption of digital technologies in various sectors, spawning new business models and paradigms. Deep labor market changes have created new jobs and incomes, potentially leading to a positive correlation between the CIDI and income.

Based on this stylized fact, existing research has identified and verified the individual income growth effect of digitalization in several ways. First, digital technologies not only improve agricultural productivity and quality, but also help farmers overcome information asymmetry and sell farm produce through e-commerce sites or livestreaming, thereby raising their incomes. Second, the digital economy creates jobs such as data analysis, R&D and platform operations, stabilizing the job market and thereby



(a) CIDI and individual income
(b) CIDI and income distribution

Figure 1: Relationship between the CIDI and Household Income Level and Income Distribution

Source: CHDES database.

4 The subsequent section will focus on a mechanism analysis of the Stylized Fact 1 "Positive correlation between the level of household digitalization and individual income".

raising wage incomes. Third, a rising level of digitalization may expand informal employment and raise other incomes. According to the Research Report on Employment and Entrepreneurship in the Digital Ecosystem published by the China Labor and Social Security Research Institute, the digital ecosystem has engendered new industries, business models, and paradigms, created numerous jobs, and transformed from the periphery to the centerpiece of the economy. For example, digital content, sharing economy, and e-commerce have become major employers of freelancers and informal workers[5]. The digital economy and digital finance also facilitate business venturing for individuals and entrepreneurs, increases financial availability, reduces credit thresholds, and boosts business incomes. Hence, we put forth the following hypothesis:

Hypothesis 1: Growing levels of digitalization support the increase of individual incomes.

3.1.2 Stylized fact 2: There is a greater degree of positive correlation between digital access and individual income

Using the method described above, we rank the two primary dimensions of digitalization in ascending order by numerical value into 100 equal shares to obtain the mean values of digital access, digital skills and usage, and mean household income. The findings point to a significant positive correlation between the two primary dimension indices and household income. In comparison, digital access and individual income have the highest fitted slope, implying that digital access has a more positive effect on individual income than digital skills or usage. China's massive digital infrastructure has boosted overall digital access for all of its residents, providing digital dividends to vulnerable groups as well as income growth potential for poor regions and households. In comparison, digital skills and usage have a smaller impact on individual income, showing that they are not yet a sufficient requirement for overall individual income growth.

For this stylized fact, existing research literature has established that internet access is an essential form of digitalization, serving as the key for households to reap digital benefits. A higher degree of digital access may encourage widespread individual participation in the digital economy, resulting in a positive income growth effect. As digital infrastructure improves and becomes more accessible, research has switched to the practical benefits of internet usage (van Deursen and Helsper, 2015). Those with strong digital skills and digital participation can generate effective economic output, demonstrating that appropriate digital skills and usage are a necessary but insufficient condition for individual income growth. According to research, when the opportunities for internet access and usage are equal, users with higher socioeconomic status and higher levels of education are more likely to reap the economic benefits of internet, whereas those less privileged and less educated use the internet more frequently for entertainment. Therefore, we propose the following hypothesis:

Hypothesis 2: Rising level of digital access serves as a key avenue for raising individual incomes.

3.1.3 Stylized fact 3: U-shaped relationship between digitalization and income distribution

We divide the CIDI into 15 equal shares in ascending order by numerical value to determine the Gini coefficient of household per capita income for each group, and then build a scatter chart with fitted line, as shown in Figure 1 (b). As illustrated by the chart, there is a U-shaped relationship between the CIDI and income distribution, implying that as individual digitalization increases, household marginal income may initially rise before falling, resulting in an initial improvement in the household income gap before widening.

[5] According to the *Statistical Report of China's Internet Development Status* provided by the China Internet Network Information Center (CNNIC), China's internet users have increased consistently in 2021. Instant messaging, online video, and short video penetration rates have reached 97.5%, 94.5%, and 90.5%, respectively, with 1,007 million, 975 million, and 934 million users. According to its Q1 2022 financial statement, Bilibili had 3.8 million monthly active uploaders in Q1 2022.

For this stylized fact, existing research conclusions on the digital economy and urban-rural income disparities all point to one phenomenon: the digital economy could have a non-linear relationship with the income gap effect (Cheng and Zhang, 2019; Chen and Wu, 2021). The digital economy may simultaneously exert a "convergence effect" and a "magnifying effect" on income gaps. As far as the "convergence effect" is concerned, rural ICT infrastructure has compensated for the lack of public, financial and industrial services in the countryside, undergirding the foundation for critical rural digital applications for smart agriculture, rural e-commerce, and digital life services. In this process, e-commerce provides additional assistance to poverty reduction and income growth, creating opportunities for innovations, businesses, and flexible and inclusive employment for farmers with modest digital skills (Qiu and Qiao, 2021). In terms of the magnifying effect, the digital economy is likely to widen the existing income gap since low-income individuals lack material, human and social capital compared with high-income individuals, and particularly in light of their differences in digital skills and usage due to disparate human capital (van Deursen and van Dijk, 2014; Liu, 2017). As revealed in the *Research Report on the Employment Development of Digital Economy in China (2021)* published by the China Academy of Information and Communication Technology (CAICT), the tertiary sector employs the most digital talent and also pays the highest, followed by the secondary industry and lastly, the primary industry. This structural differentiation may give rise to widening income gaps. Hence, we put forth the following hypothesis:

Hypothesis 3: Digitalization exerts dual effects on income distribution, including a "magnifying effect" and a "convergence effect".

3.2 Discussion of Mechanisms

We developed the following theoretical model, drawing on the configuration of the individual income function by Zheng (2019) and Li et al. (2020), as well as discussions of the individual income effect of digitalization in the existing research literature:

$$Y_j = A_j f\{L_j(h, \delta), K_j(P, H, S)\} \tag{1}$$

It is assumed that resident j's income function is determined by the labor factor and the capital factor. Specifically, the labor factor $L_j(h, \delta)$ encompasses working hours h and labor participation rate δ, and the capital factor $K_j(P, H, S)$ is an asset portfolio consisting of material capital P, human capital H, and social capital S.

From a theoretical standpoint, the role of data in the digital economy has emerged as a crucial factor of production. This has led to a range of developments in microeconomic theories. Nevertheless, current research is still in the early stages regarding the concept of data and data assets, the extent and types of data capitalization, and the approach to pricing data assets (Xu et al., 2022). Before the establishment of a comprehensive data asset accounting method, it is our belief that the digital economy impacts individual income by influencing the labor and capital factors. More specifically, the digital economy has a "labor-enabling effect" and a "capital-multiplication effect".

3.2.1 Labor-enabling effect

The digital economy has transformed labor supply in the following two ways: First, remote work has become a new trend, increasing working hours and efficiency. During the COVID-19 pandemic, the digital economy has created flexible jobs for a large number of people who would otherwise be affected by pandemic-related lockdowns. Second, the digital economy has transformed traditional job patterns and concepts, boosting the employment rate. The digital economy may reduce asymmetry of job information and increase social capital to raise employment (Qi and Chu, 2021), making it more likely for individuals to start a business or be self-employed The digital economy creates flexible jobs and promotes informal employment. While raising the labor participation rate, it helps increase income sources for the flexibly employed. In this paper, we use D to denote the levels of individual digitalization, and D helps increase income by lengthening working hours h and raising labor participation rate δ and income, creating an "enabling effect", as manifested in $D \rightarrow h$, $\delta \rightarrow Y$. In the subsequent empirical test, we will use an intermediate effect model to test this mechanism.

3.2.2 Capital-multiplication effect

According to Hernando de Soto (2007), in his research on the transformation of assets into capital, he highlights the importance of the poor converting their labor force, housing, land, resources, and other physical assets into capital in the marketplace to escape poverty[6]. Qiu et al. (2016) stressed that utilizing internet technology to transform assets into income-yielding capital plays a crucial role in enhancing the "multiplication effect" of internet capital. In the digital era, the traditional disadvantages of gender, age, and education level no longer hold back individuals in the world of e-commerce and sharing economy. Instead, these factors can be turned into valuable capital to benefit from the digital economy.

In this manner, the digital economy modifies the portfolio of individual material, human, and social capital to turn them into a portfolio of capital assets and thereby increase incomes indirectly. First of all, idle assets can be converted into valuable material capital thanks to the digital economy. For example, Huolala is a platform freight firm where clients can hire a driver and van to deliver goods, while Ziroom lets users book flats and rooms online. These platforms allow owners of cars and homes to profitably share idle assets. Second, digital technologies speed up the dissemination of knowledge via online platforms and online education to share resources of formal education and skills training and lower the marginal cost of education by transcending the constraints of location and traditional educational system. In addition to enhancing practical skills, the proliferation of mobile devices may increase the composition of human capital and labor market competitiveness. Third, digital adoption goes beyond the conventional forms of social circles based on kinship, location, and economic ties to expand social networks based on family background, needs and ideals. Social capital and incomes of individuals will rise as social networks are used to acquire information. In summary, a rise in the level of digitalization could potentially generate indirect income growth via the multiplication effect of traditional capital factors. Such multiplication effect for various forms of capital is, however, dependent on differences in the existing capital factors.

The "multiplication effect" of digitalization on various facets of a capital portfolio is one way that a growing degree of digitalization may affect individual income by modifying the conditional expectation for the capital portfolio composed of individual material, human, and social capital. We may write this mechanism as $(P, H, S|D) \rightarrow Y$. We will test this mechanism using the adjustment effect model in the next empirical test.

Based on the above analysis, the impact of digitalization D on the individual income function can be expressed as follows:

$$Y_j = A_j f\Big(L_j\big(h(D), \delta(D)\big), E\big(K_j(P, H, S|D)\big)\Big) \tag{2}$$

The following equation can be obtained through a partial derivation of the individual income function:

$$\frac{\partial Y_j}{\partial D_j} = A_j \left[\frac{\partial Y_j}{\partial L_j} \frac{\partial L_j}{\partial D_j} + \frac{\partial Y_j}{\partial (K_j|D_j)} \frac{\partial (K_j|D_j)}{\partial D_j} \right]$$

$$= A_j \frac{\partial Y_j}{\partial L_j} \underbrace{\left(\frac{\partial L_j}{\partial h_j} \frac{\partial h_j}{\partial D_j} + \frac{\partial L_j}{\partial \delta_j} \frac{\partial \delta_j}{\partial D_j} \right)}_{\text{Digitalization's labor-enabling effect}} + A_j \frac{\partial Y_j}{\partial (K_j|D_j)} \underbrace{\left(\frac{\partial (P_j|D_j)}{\partial D_j} + \frac{\partial (H_j|D_j)}{\partial D_j} + \frac{\partial (S_j|D_j)}{\partial D_j} \right)}_{\text{Digitalization's capital-multiplication effect}} \tag{3}$$

[6] In his discussion, Soto (2007) did not clearly distinguish between assets and capital. Based on the differentiation made by Qiu et al. (2016), we refer to assets converted into capital in the internet market as "capital", and non-capitalized assets as "assets".

Factors such as social and financial status play a great role in determining an individual's access to and utilization of information technologies. These factors also contribute to disparities in the level of digitalization and impact an individual's income through the labor-enabling effect and capital-multiplication effect. In the subsequent section, we will examine relevant hypotheses using the CHDES database.

4. Empirical Analysis

4.1 Empirical Model Specification and Data

We specify the following empirical model to investigate the relationship between the individual level of digitalization and individual income:

$$lnPersonal\_income_{ij}=r_0+r_1CIDI_{ij}+r_2X_{ij}+\varphi_j+\mu_{ij} \quad (4)$$

where, $Personal\_income_{ij}$ is the resident annual income for household i in city c, and is logarithmically transformed to mitigate deviation. $CIDI_{ij}$ is the individual digitalization index. X_{ij} denotes control variables at the individual and household levels, φ_j is the fixed effect of the location of the household, and μ_{ij} is stochastic disturbance term. Our model has introduced control variables at the and household levels. At the individual level, we have controlled for gender, age, quadratic term of age, length of education, political background, marital status, health level, and employment status. At the household level, we have controlled for family size and dependency burden (proportion of family members aged 16 and below or above 60 years). Moreover, we have introduced the fixed effect of county/district into the model to control for the joint effects of regional characteristics on the individual level of digitalization and individual income. Since our analysis is focused on the relationship between the level of digitalization and individual income, we have clustered standard errors within the county/district level to avoid the impact of correlation between households in a county or district on the estimated results.

In this paper, we primarily rely on data at three levels: (i) Variables such as individual income, online individual operating income, and per capita household income are directly from the Individual Digital Economy Survey questionnaire, adopting logarithmic transformations to mitigate deviation; (ii) the CIDI index created above is employed to denote the level of digitalization; (iii) other variables are from the household digital economy survey questionnaire. Table 3 provides a statistical description of relevant variables.

Table 3: Statistical Description of Variables

Variable		Sample size	Mean	Standard deviation	Min.	Max.
Explained variable	Individual income (10,000 yuan)	1,675	4.7809	4.9079	0.0000	25.0000
	Individual online operating income (10,000 yuan)	1,675	0.0185	0.1179	0.0000	1.0000
	Per capita household income (10,000 yuan)	1,675	5.8994	5.4635	0.4000	30.0000
Individual level	Gender (male=1)	1,675	0.4478	0.4974	0.0000	1.0000
	Age	1,675	38.0710	12.4421	14.0000	87.0000
	Education years	1,675	12.5845	3.1215	0.0000	18.0000
	Political status (Party member=1)	1,675	0.0519	0.2220	0.0000	1.0000
	Marital status (Married=1)	1,675	0.7093	0.4542	0.0000	1.0000
	Health status	1,675	3.7427	0.4962	1.0000	4.0000
	Employment status (Employed=1)	1,675	0.5988	0.4903	0.0000	1.0000
Household level	Family size	1,675	2.9713	1.1744	1.0000	9.0000
	Family dependency burden	1,675	0.1901	0.2521	0.0000	1.0000

Source: CHDES database.

4.2 Empirical Results

4.2.1 Baseline regression results

In columns (1) through (4) of Table 4, we take into account the CIDI's impact on individual income, and gradually control for individual and household characteristics, as well as the fixed effect of county/district. The results indicate that the CIDI's estimated coefficient values are all positive and significant, suggesting that an improvement in the level of digitalization helps raise individual income. In terms of economic significance, when the CIDI increases by one standard deviation (0.13), individual income will rise by 5.93 percentage points. This finding has verified Hypothesis 1. In columns (5) and (6), we consider the household income effects of digital access and digital skills and usage as two primary indicators, controlling for individual and household characteristics, as well as the fixed effect of county/district, through regression. Results suggest that the two indicators both have significantly positive effects on the estimated values of the impact coefficient for individual income, and digital access has a more significant effect on the improvement of individual income compared with digital skills and usage. In terms of economic significance, when the digital access index increases by one standard deviation (0.13), individual income will rise by 4.99 percentage points. When the digital skills and usage index increases by one standard deviation (0.24), individual income will rise by 3.85 percentage points. This explains that digital access has become an important way to raise individual income, which is consistent with Hypothesis 2.

Table 4: CIDI and Individual Income: Baseline Model

	(1)	(2)	(3)	(4)	(5)	(6)
	ln*Personal_income*					
CIDI	0.9491*** (0.1725)	0.4873*** (0.1608)	0.5188*** (0.1592)	0.4622*** (0.1750)		
Digtal_connect					0.3988** (0.1953)	
Digtal_skill_uses						0.1615** (0.0795)
Control variable of individuals	No	Yes	Yes	Yes	Yes	Yes
Control variable of households	No	No	Yes	Yes	Yes	Yes
Fixed effect of county/districts	No	No	No	Yes	Yes	Yes
Observations	1,675	1,675	1,675	1,675	1,675	1,675
R^2	0.0168	0.0870	0.0969	0.1934	0.1927	0.1915

Note: Numbers in parentheses are clustered robust standard errors, and ***p<0.01, **p<0.05, and * p<0.1. The same below.
Source: CHDES database.

4.2.2 Endogeneity test

Baseline regression has the problem of endogeneity stemming from omitted variables and reverse causality. On one hand, unobservable individual characteristics such as the acceptance of new things and individual personalities may influence the individual level of digitalization and the individual level of income, giving rise to a deviation of omitted variables. On the other hand, the income effect of the individual level of digitalization is often subject to endogeneity bias stemming from reverse causality. This can be mitigated by introducing control variable and instrumental variables (IV). First, control variable: In this paper, we have controlled in the questionnaire for the time when an individual acquired his first smart device (*First_equipment*) to reduce the endogeneity impact stemming from unobservable individual characteristics. As column (1) of Table 5 reveals, the regression results are consistent with the baseline results after the inclusion of the above variable, thus proving the robustness of results. Second, the instrumental variable method: On the basis of referencing the existing research literature, we use online shopping dependence (*onlineshopping_dependence*) and the logarithmic value of household spherical distance to provincial capital (*lndistance*) as the CIDI's instrumental variables. The implications of online shopping dependence are twofold: On one hand, an online shopper must have internet access and possess the skills to complete a deal, and digital literacy is essential for people to engage in online shopping. On the other hand, dependence on online shopping is indicative of personal shopping preferences and habits[7]. Some consumers prefer online shopping because it allows them buy cost-effective items from name brands and compare technical specifications (Beauchamp and Ponder, 2010), whereas others prefer brick-and-mortar stores because it allows them to enjoy the shopping experience, interact with others and express their social emotions (Schmid and Axhausen, 2019). Such dependence on online consumption has little to do with personal income, and therefore satisfies exogenous requirements.

Referencing Zhang et al. (2019), we adopt the spherical distance between household residence and a provincial capital city computed using the geological information system (GIS) as the second instrumental variable. Generally speaking, a provincial capital city is not only a local economic center, but also a digital economy hub. The closer an individual is to the provincial capital, the higher his digital literacy would be. Nevertheless, our survey indicates that compared with cities and central and eastern regions, China's countryside and western region are latecomers in terms of informatization and digitalization, benefiting from a late-mover advantage and catch-up effect, as manifested in even more advanced technology and equipment[8]. The geographical distance variable is usually not directly correlated with individual income, thereby satisfying the exogeneity condition.

Columns (2) and (3) of Table 5 report regression results of the two-stage least square (2SLS) method. Judging by the first-stage results of column (2), both instrumental variables may significantly increase the individual level of digitalization, thereby verifying that the instrumental variables satisfy the correlation hypothesis. Column (3) presents the second-stage regression results. After a regression analysis is performed using the instrumental variables, the results are consistent with the baseline regression results in the above section, i.e. the individual level of digitalization may significantly raise individual income. The Cragg-Donald Wald F value of the first-stage instrument variable is 157.00, and the Kleibergen-Paap rk Wald F value is 130.70, which are both greater than 10 and thus exclude the problem of weak instrumental variable. In a nutshell, the conclusion that the individual level of digitalization has a positive income effect is fairly robust.

Table 5: CIDI and Individual Income: Endogeneity Test

	(1)	(2)	(3)
	Inclusion of explanatory variables	IV	
	ln*Personal_income*	*CIDI*	ln*Personal_income*
CIDI	0.3845** (0.1843)		1.1636*** (0.4396)
First_equipment	-0.0145*** (0.0055)		

[7] We appreciate the inspirations from anonymous review experts.

[8] According to data from the CHDES, the level of digital service supply in China is much higher in the countryside than in urban areas, and higher in the western region than in the central and eastern regions. When comparing urban and rural areas, the downlink speed, uplink speed, and network latency in the countryside are 76.476 Mbps, 23.613 Mbps, and 42.628 ms (network latencies refer to the time it takes for end-to-end data transmission, and higher values indicate serious network latencies), which are generally superior to those in urban districts at 74.352 Mbps, 24.042 Mbps, and 45.583 ms, as well as those in counties at 72.176 Mbps, 21.520 Mbps and 49.214 ms. Downlink speed, uplink speed and network latency in the western region are 81.443 Mbps, 23.103 Mbps, and 46.361 ms, which are significantly better than those in the eastern region at 71.595 Mbps, 24.019 Mbps, and 46.742 ms, as well as those in the central and northwestern regions at 70.458 Mbps, 21.108 Mbps, and 42.919 ms.

Table 5 Continued

	(1)	(2)	(3)
	Inclusion of explanatory variables	IV	
	ln*Personal_income*	*CIDI*	ln*Personal_income*
Onlineshopping_dependence		0.0146*** (0.0009)	
lndistance		0.0069* (0.0036)	
Control variable for individuals	Yes	Yes	Yes
Control variables for households	Yes	Yes	Yes
Fixed effect of county/districts	Yes	Yes	Yes
Observations	1,605	1,675	1,675
R^2	0.2012	0.3196	0.1859

4.2.3 Robustness test

First, perform the CIDI's robustness test. In the prior part, we utilized the stratified analysis method to calculate the importance of each factor based on the relative size of the numerical values, which may be subjective. We assigned weights to the two dimensions of digital access and digital skills and usage based on the essentiality, hierarchy, and importance of each factor to the level of digitalization, which may have an impact on the robustness of empirical results[9]. To eliminate this potential impact, we first traversed through 100 weight combinations of digital access and digital skills and usage between 0 and 1, and then performed another regression analysis of individual income to arrive at the new CIDI[10]. According to the findings, the CIDI coefficient is considerably positive at the 5% level, ruling out the impact of weight assignment in developing the CIDI on the robustness of regression results. Second, substitute the explained variable. In this section, we substituted individual income with household per capita income (*family_income_pc*) in a robustness regression analysis, controlling for representative individual and household characteristics, as well as the fixed effect of county/districts[11], and the results are shown in column (1) of Table 6. We observed that the estimated values of the CIDI's coefficient are significantly positive: When the CIDI increases by one standard deviation, household per capita income rises by 8.89 percentage points, demonstrating the robustness of the results. Third, focus on labor samples. The digital economy has generated more informal jobs and removed age, gender, and geographical barriers to traditional employment. However, the income growth effect may be concentrated among the productive working population. In this research, we use a larger sample size to focus on labor samples, omitting men under the age of 16 and women over the age of 55, as well as those who do not want or have the conditions to seek work owing to schooling, further education, or illnesses. Finally, we collected 1,234 regression samples, as shown in column (2) of Table 6. The results reveal that all of the estimated coefficients of the level of digitalization are significantly positive: When the CIDI increases by one standard deviation, individual income rises by 9.15 percentage points, which is greater than the increases in the baseline regression and household per capita income regression in the preceding section, thereby confirming the robustness of the baseline regression results.

[9] We appreciate the valuable insights provided by anonymous review experts.

[10] See the appendices on the *China Industrial Economics* website (http://ciejournal.ajcass.org) for the estimated coefficients and significance levels.

[11] According to an analysis of survey data, it was discovered that 73.6% of respondents from representative households are the most educated individuals in their respective families. Considering the close relationship between digital literacy and education, the respondents in question can be seen as the most digitally literate individuals in their families. For the purposes of this paper, they are referred to as representative individuals of households.

Table 6: CIDI and Individual Income: Robustness Test

	(1)	(2)
	Substitution of the explained variable	Focus on labor samples
	ln*family_income_pc*	ln*Personal_income*
CIDI	0.6928*** (0.1309)	0.7130*** (0.2159)
Number of observations	1,675	1,234
R^2	0.3877	0.1906

Note: Regression results have introduced the control variable of individuals, the control variable of households, and the fixed effect of county/districts. The same below.

4.3 Heterogeneity Analysis

In addition to the income growth effect, we should also investigate the income distribution effect of the digital economy, paying attention to income gaps between regions, urban and rural areas, and sectors under the strategy of creating a new development paradigm. In this section, we will further discuss how the digital economy may influence income gaps between urban and rural areas and sectors.

4.3.1 E-commerce has reduced urban and rural income gaps but widened regional income gaps

According to the results in columns (1) and (2) of Panel A of Table 7, when the CIDI increases by one standard deviation, household income in China's eastern region rises by 7.20 percentage points, while the effect on household income growth in the central and western regions is insignificant. Given that individual income in China's eastern region is higher than in the central and western regions, the digital economy has somewhat widened regional income disparities. According to the regression results in columns (3) and (4), increasing the CIDI by one standard deviation improves individual income in the countryside and counties by 5.62 percentage points, whereas the effect on urban individual income is insignificant. Given that individual income is higher in cities than in the countryside and counties, the digital economy has helped to close the urban and rural income divide to some degree.

Table 7: Heterogeneity Analysis of the CIDI with Respect to Individual Income

	(1)	(2)	(3)	(4)
Panel A: Regional and urban-rural heterogeneity of the CIDI with respect to individual income				
	Western and central regions	Eastern region	Countryside and counties	Cities
CIDI	0.3813 (0.2947)	0.5615*** (0.1962)	0.4378* (0.2411)	0.3037 (0.2793)
Observations	868	807	1,050	625
R^2	0.2173	0.1721	0.2264	0.2132
Panel B: Regional and urban-rural heterogeneity of the CIDI with respect to individual online operating income				
	Western and central regions	Eastern region	Countryside and counties	Cities
CIDI	0.0305* (0.0162)	0.0698** (0.0308)	0.0550** (0.0233)	0.0331 (0.0279)
Observations	868	807	1,050	625
R^2	0.0752	0.1072	0.0922	0.1077
Panel C: Percentile regression of the CIDI with respect to individual income				
	0.25	0.5	0.75	0.95
CIDI	0.5960*** (0.2235)	0.5881*** (0.1947)	0.6603*** (0.1453)	1.0801*** (0.2137)
Observations	1,258	1,258	1,258	1,258

Table 7 Continued

	(1)	(2)	(3)	(4)
Pseudo R^2	0.1799	0.1280	0.1292	0.2006
Panel D: Sectoral heterogeneity of the CIDI with respect to individual income				
	Working Samples	Primary industry	Secondary industry	Tertiary industry
CIDI	0.7163*** (0.2274)	0.0412 (0.6268)	1.1402 (0.8385)	0.8469*** (0.3036)
Observations	1,258	266	199	793
R^2	0.1714	0.3659	0.4786	0.1990

One explanation is the permeability of digital technologies. China's countryside is fast catching up with metropolises in terms of increasing people's online operating income through e-commerce, which serves as a new source of income for rural residents. The urban-rural digital divide has shrunk as a result of the successful fight against poverty, as well as the improvement and even "late-mover advantage" of rural digital infrastructure. In this paper, we substituted the dependent variable in equation (4) with online individual operating income and logarithmically transformed it to reduce deviation. Online individual operating income includes earnings from the online marketing of non-farm products or services, the operation of online shops, and the delivery of remote services via the internet, as well as earnings from the online marketing of agricultural products, the operation of online accounts, advertising, and donations from users and fans. According to the results in columns (1) and (2) of Panel B of Table 7, when the CIDI rises by one standard deviation, the online operating income of residents in China's western and central regions increases by 0.39 percentage points, while the online operating income of residents in the eastern region increases by 0.90 percentage point. One probable explanation is that prosperous regions are more adept at integrating resources such as infrastructure, logistics, talent, and businesses, resulting in a better business climate for e-commerce. According to the results in columns (3) and (4), when the CIDI increases by one standard deviation, residents in the countryside and county seats will see their online operating income increase significantly by 0.71 percentage points, whereas this effect is insignificant for urban residents, demonstrating that the countryside has more opportunities to raise incomes through e-commerce and close the urban-rural income gap.

4.3.2 Growing sectoral income disparities due to industrial digitalization

In the preceding section, our OLS regression only yielded the impact of digitalization on the expected incomes of residents, and cannot further investigate the impact on income distribution. Panel C of Table 7 lists the regression results of the individual income effect of digitalization at the 25^{th}, 50^{th}, 75^{th} and 95^{th} quantiles[12]. Judging by the results, the individual income effect of digitalization increases with a rise in quantile, i.e. high-income individuals benefit more from digitalization. Based on a comparison of the regression results in columns (1) through (4), when the CIDI increases by one standard deviation, difference in the increase of individual incomes at the 95% quantile and the 25% quantile is 6.21 percentage points, indicating a significantly positive difference in the marginal contributions of digitalization to residents with different levels of income, potentially widening income gaps.

A possible reason is that rapid development in the internet and telecom industries, e-commerce retail, software, and science and technology related to the digital economy has not only led to an increasing share of China's tertiary industry, but also facilitated the flow of digital talent to the tertiary

[12] In order to explore the intrinsic mechanism by which individual income gaps are widened, we present the quantile regression results of our work samples. The quantile regression of total sample data exhibits the same characteristics, i.e. high-income individuals benefit more from an increase in the level of digitalization, demonstrating the robustness of this conclusion.

industry, causing a shift in the employment structure. Given that wage compensation is the highest in the tertiary industry[13], this structural change has also triggered a shift in income gaps across sectors. In our data, the primary industry encompasses agriculture, forestry, animal husbandry, and fishery, the secondary industry refers to manufacturing, construction, and others, and the tertiary industry includes retail and wholesale, transportation, warehousing and postal service, hotel and catering, residential services, repair, and other services. The intrinsic mechanism by which digitalization widens income gaps can be proven if an increase in the individual level of digitalization may significantly raise individual incomes in the tertiary industry.

Panel D of Table 7 reports the individual income effect of digitalization for manufacturing digitalization in the primary and secondary industries and service digitalization in the tertiary industry. According to the regression results in columns (2) through (4), when the CIDI increases by one standard deviation, individual income in the tertiary industry will rise by 10.87 percentage points, whereas this effect is insignificant for employees in the primary and secondary industries. A possible explanation is that high-income residents are better positioned to benefit from the opportunities of digital skills and usage to improve their incomes.

In summary, the above regression results indicate that the level of digitalization has both convergence and magnifying effects on individual incomes, thus supporting Hypothesis 3.

5. Mechanism Analysis: Labor-Enabling and Capital Multiplication Effects

The preceding section examined the overall income effect of the individual level of digitalization. A more in-depth discussion of the differential effects of digitalization on various sorts of individual income could give an initial assessment for the mechanism analysis of the CIDI's income effect. In this article, we present a regression analysis of the CIDI's effects on three non-transfer incomes: individual wage income, property income, and operating income. According to the size and significance of the regression coefficients, the CIDI has the greatest impact on wage income growth, followed by a positive effect on property income, while its influence on total-sample operating income is minor[14]. This finding provides key inspirations for discussions about the income effects of individual levels of digitalization: Wage income is predominantly derived from labor income, whereas property and operating incomes are derived from returns on individual capital factors. Based on the individual income function developed in Section 3, this section investigates how the individual level of digitalization contributes to factor income and thus influences individual income growth and income inequality via the labor-enabling effect and the capital multiplication effect, which increases individual income growth and income inequality as a mechanism.

5.1 Digitalization's Labor-Enabling Effect

This section focuses on verifying two pathways: Whether digitalization may lengthen the duration of online work and learning, as well as whether it may increase the likelihood of employment and so raise income. Using Jiang's (2022) reflections and suggestions on the mediating effect in his research on causality inference, as well as the common practice in frontier research literature, we selected variables with a clear causal relationship with the explained variable (individual income) to demonstrate causality between the treatment variable (*CIDI*) and mechanism variables (duration of online working and learning (*Workonline_hours*) and employment status (*Employed)*). Obviously, when people spend

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[13] Refer to the *CAICT's Research Report on the Employment Development in China's Digital Economy: New Forms, Business Models and Trends (2021)*, which suggests that the average salary of digital economy jobs in the tertiary, secondary and primary industries are 11,061.5 yuan/month, 8,408.9 yuan/month on the 7,462.9 yuan/month, respectively.

[14] See appendices on the *China Industrial Economics* website (http://ciejournal.ajcass.org) for the sizes and significance of the regression coefficients.

more time working online (to generate cash directly), learning (to improve human capital indirectly), or working, their chances of earning an income, particularly wage income, increase dramatically. This causality appears to require no testing. When investigating the mediating effect, our focus is to test the causality between the treatment variable and the mediator variables.

Table 8 shows the CIDI's influence on working hours and labor participation rates. Column (1) data show that the higher the degree of digitalization, the longer the length of online working and learning. However, there could be a reverse causal relationship between the two. To rule out the competing hypothesis that "more time spent online increases the level of digitalization, which in turn significantly increases working hours and indirectly raises individual income", this section tests the CIDI's effect on the duration of individual online entertainment (*Enteronline_hours*). If such an intrinsic relationship exists, it is evident that the CIDI has a significant impact on the length of online entertainment. However, the CIDI has no significant effect on the duration of individual online entertainment, implying that a higher individual level of digitalization contributes to longer working hours and, therefore, higher income.

Table 8: Test of the CIDI's Labor-Enabling Effect

	(1)	(2)	(3)	(4)	(5)
	Working hours		Labor participation rate		
	Workonline_hours	*Enteronline_hours*	*Employed*	Non-working age (Age<16 and age > 60)	Working age (Age≥16 and age≤60)
				Employed	*Employed*
CIDI	6.9907*** (0.5160)	0.7283 (0.4763)	0.3382*** (0.0406)	0.1119 (0.0712)	0.3745*** (0.0495)
Observations	1,675	1,675	1,675	441	1,234
R^2	0.2369	0.0616	0.8829	0.9343	0.8312

We also investigated the CIDI's impact on the labor participation rate. The results in column (3) of Table 8 show that higher levels of digitalization are connected with a higher likelihood of individual employment. Missing factors may cause this causal identification to deviate. This research uses a heterogeneous approach for different groups to establish whether the CIDI has a meaningful causal influence on the labor participation rate. Columns (4) and (5) restricted the samples to non-working age categories (those under 16 and over 60) and working-age groups (those aged 16 to 60). If there is no causal association and other omitted variables are at play, the effect should be constant across all age groups. According to the findings, the CIDI has only significantly enhanced the likelihood of employment for those of working age, while having no significant effect on those of non-working age. This has shown that increasing digitalization improves employment prospects and indirectly raises personal income. In other words, a rising level of digitalization can increase individual income by enabling the labor factor.

5.2 Digitalization's Capital Multiplication Effect

In this section, we will verify three mechanisms of impact, including whether digitalization may raise individual income by improving physical (*Physicalcapital*), human (*Humancapital*), and social capital (*Socialcapital*), respectively. Individual ownership of vehicles, spacious per capita housing area, and possession of property income from immovable properties such as housing and vehicles are used as proxy variables for material capital to reflect the possibility of rising digitalization converting idle assets into income-generating material capital. A high level of education (junior college/bachelor degree or higher) is used as a proxy variable for human capital to indicate the likelihood that improving digital literacy can boost income. We use interpersonal networking expenses and the ability to add WeChat friends as proxies for social capital to reflect the prospect that digitalization can increase income by expanding the digital social network. Table 9 presents the CIDI's diverse effects on individual income in terms of material, human, and social capital.

Table 9: Test of the CIDI's Labor-Enabling Effect and Capital Multiplication Effect

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	ln*Personal_income*					
	Material capital		Human capital		Social capital	
CIDI	0.4497** (0.1738)	0.4230** (0.2039)	0.4633*** (0.1746)	0.1313 (0.2643)	0.3516** (0.1752)	0.1658 (0.1901)
Physicalcapital(*highlevel=1*)	0.2250*** (0.0632)	0.1929 (0.1387)				
Physicalcapital×CIDI		0.0781 (0.3017)				
Humancapital(*highlevel=1*)			0.0681 (0.0733)	-0.1895 (0.1543)		
Humancapital×CIDI				0.6219** (0.2956)		
Socialcapital(*highlevel=1*)					0.4597*** (0.0549)	0.0388 (0.1718)
Socialcapital×CIDI						0.9867*** (0.3683)
Observations	1,675	1,675	1,675	1,675	1,675	1,675
R^2	0.2027	0.2027	0.1938	0.1955	0.2293	0.2317

Results in columns (1) and (2) of Table 9 suggest that the interaction term between the dummy variable of material capital and the CIDI is positive but insignificant. A possible reason is that on average, the level of digitalization has not been fully integrated with material capital and therefore has a modest effect on overall individual income. The positive interaction term explains that digitalization's individual income growth effect may increase with the improvement of material capital. The digital economy creates conditions for idle assets such as housing and cars to be turned into income-generating material capital to raise incomes. This conversion mechanism, however, is subject to the amount of traditional material capital. Residents with an abundance of material capital have a greater advantage when it comes to benefiting from the "capital multiplication effect", and are therefore more likely to gain more incomes.

As can be seen from the results of columns (3) and (4) of Table 9, the coefficient of the interaction term between the dummy variable of human capital and the CIDI is significantly positive, indicating that digitalization may have widened income gaps between high- and low-human-capital individuals. The digital economy's penetration, especially the extensive use of mobile devices in various settings, helps overcome the constraints of geographical location and the traditional educational system. However, low-human-capital individuals are more likely to use digital devices for entertainment rather than for work. In contrast, high-human-capital individuals may utilize their information advantage to pursue education for themselves and their children, creating a positive feedback loop in which human capital both increases and benefits from digitalization, thereby contributing to income growth.

According to the results in columns (5) and (6) of Table 9, the coefficient of interaction term between the dummy variable of social capital and the CIDI is significantly positive, suggesting that the extent to which digitalization may contribute to individual income is subject to the level of individual social capital. Information, evaluation and scoring established using the digital factor over the course of digitalization have lowered the “verification cost” (Goldfarb and Tucker, 2019), and newly established digital creditworthiness has weakened traditional social networks based on kinship, proximity and business relations. Nevertheless, high-social-capital individuals are more likely to convert their social skills and connections into digital trust and broaden their social networks for income growth.

Based on the above analysis, the individual level of digitalization may influence individual income through its labor-enabling effect and capital multiplication effect. It needs to be noted that the multiplication effect of digitalization for the traditional capital factors is also subject to the increasing differentiation of capital factors in the digital era. In promoting digitalization, policymakers need to pay more attention to this new type of “Matthew effect”.

6. Concluding Remarks and Policy Recommendations

In this paper, we developed the CIDI using the CHDES database to comprehensively measure the individual level of digitalization across the two dimensions of digital access and digital skills and usage, thereby expanding the measurement of digitalization in the research literature. In this research, we studied the microscopic mechanism via which digitalization may influence individual income, and we discovered that increasing the CIDI by one standard deviation (0.13) would result in a rise in individual income by 5.93 percentage points. After addressing the endogeneity problem, we confirmed that digitalization contributes to higher individual income. Further, we examined the digital economy’s heterogenous effects on individual income gaps: In terms of urban and rural differences, the countryside and counties may narrow income inequality through e-commerce and other channels; sector-wise, the influx of digital talent into high-paying industries has also widened income inequality. Finally, we incorporated digital literacy into the individual income function to investigate the methods by which digital literacy may influence individual income via the labor-enabling effect and capital multiplication effect. This study employs indicators, stylized facts, and empirical findings to enhance our comprehension of the potential for individual income to increase via digitalization, drawing on the development practices of the digital economy.

In this study, we propose the following policy recommendations: First, it is critical to develop digital infrastructure and supporting sectors in order to reduce the urban-rural income gap, which is essential to creating a new development paradigm according to the Report to the 20th CPC National Congress. Recent years have seen great progress of digital infrastructure and emergence of new digital economy business models in rural China, thanks to the CPC Central Committee’s and the State Council’s strong support to developing the “digital countryside”. However, digital infrastructure is still less available and affordable in the countryside than in urban areas. The eastern region continues to outperform the central and western regions in terms of resource integration and industrial development. New-generation digital technologies should be adopted to build digital infrastructure and speed up digitalization in less developed regions. Meanwhile, the government should strengthen ICT systems for logistics, finance, and other auxiliary sectors to ensure fair access to public services while modernizing rural governance. Second, the digital economy highlights the need of human capital. Education and human capital are crucial for the development of poor regions, as their absence is a major obstacle to progress. Given the lack of human capital in less developed regions, it is critical to beef up educational spending and policy preferences for low-income groups and rural areas in order to increase digital literacy and bring about the digital economy’s spillover effects, which will consolidate the results of poverty reduction and countryside revitalization. Meanwhile, it is critical to provide farmers with digital skills training, special services, and policy support to improve labor force endowment and digital technology compatibility, as well as to encourage people with digital skills to return to the countryside to foster rural digital human capital and achieve the digital economy’s enabling effect for income growth.

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