sustainability

Article

Can Digital Economy Drive Income Level Growth in the Context of Sustainable Development? Fresh Evidence from "Broadband China"

Dandan Kong [1,2,*], Jing Li [1] and Zehu Jin [1]

[1] School of Economics, Anhui University, Hefei 230601, China; 14028@ahu.edu.cn (J.L.); 12015@ahu.edu.cn (Z.J.)
[2] Department of Economics and Management, Bozhou University, Bozhou 236800, China
* Correspondence: kongtina@163.com

Abstract: In the context of the rapid development of digital economy and the promotion of sustainable development, this paper focuses on the impact of digital economy on income levels. Based on the panel data of 195 prefecture-level cities, the "Broadband China" pilot has been regarded as a natural experiment for the measurement of the digital economy. In this paper, a time-varying DID model was established to evaluate the influential effect of "Broadband China" on income growth. It was found that the coming into service of "Broadband China" has increased the overall income level of the Chinese labor force. Further research found that "Broadband China" has done more to raise the income levels of the high-skilled labor force, thus widening the income gap between the high-, medium-, and low-skilled labor force. "Broadband China" can affect the income growth via two mechanisms, namely, "increasing the entrepreneurship rate" and "leading to an increase in the overall number of professional and skilled labor force in China". In this case, the entrepreneurship rate of the high-skilled labor force may be higher than that of the medium- and low-skilled labor force due to human capital accumulation. The rapid increase in the high-skilled labor force in technical industries will lead to the situation where their income growth effect is higher than that of the medium- and low-skilled labor force. Based on the above research results, this paper puts forward policy suggestions from three aspects: further accelerating the process of digital economy; improving the institutional environment of the broadband network and standardizing the order of the construction of the broadband network; and further stimulating the entrepreneurial motivation of labor force, paying attention to the problem of skill bias and optimizing the employment structure, balancing efficiency and equity, and contributing to the ultimate sustainable development of developing countries.

Keywords: digital economy; sustainability; Broadband China; income level; high-skilled labor force; medium- and low-skilled labor force

Citation: Kong, D.; Li, J.; Jin, Z. Can Digital Economy Drive Income Level Growth in the Context of Sustainable Development? Fresh Evidence from "Broadband China". *Sustainability* **2023**, *15*, 13170. https://doi.org/10.3390/su151713170

Academic Editor: Thomas A. Clark

Received: 24 July 2023
Revised: 27 August 2023
Accepted: 30 August 2023
Published: 1 September 2023

1. Introduction

Sustainable growth refers to the idea that a country can sustain economic development without causing major economic, social, and environmental problems for future generations [1]. Today, the concept of sustainable development has become a global consensus and a guiding principle for the social and economic aspects of all countries. In recent years, global economic growth has been weak, and the outbreak of COVID-19 in 2020 and the Russian–Ukrainian war in 2022 have exacerbated the pressure on global economic recovery. Currently, although the global pandemic has been effectively alleviated, the Russian–Ukrainian war between Russia and Ukraine is tense, and the trend of economic downturn is obvious; thus, there are severe challenges in terms of employment, income growth, and sustainable development. There shall be new growth points in the economic recovery and the growth of labor income. Inequality in income distribution remains one of the most critical issues in economic development, sparking much debate among academics, economists, and policymakers [2]. As a popular topic on livelihood, labor income has long drawn the attention from researchers and policymakers [3,4]. Rising income inequality is not only a social and political issue but also an economic one [5]. Dealing with income growth and income distribution issues in a reasonable manner, moving towards common prosperity, and achieving sustainable development have become a classic issue that plagues the vast majority of countries and regions.

China, the world's largest developing country, has always placed high value on common prosperity. It has long been steadily liberating and developing productive forces, proactively preventing polarization while creating wealth. In this context, the mission for the new era has set to be salary and benefit increase, the income gap shrinking, and the achievement of common prosperity for all by improving the income levels for the medium- and low-skilled labor force, ultimately achieving sustainable development goals. The establishment of an effective digital economy infrastructure is necessary to enhance the international competitiveness of middle-income countries. From a national perspective, investing in the digital economy can be conducive to supporting sustainable development and accelerating regional integration processes [6]. With the growth of IT technology, the influences of digital economy on the labor income level have become one of the factors that are more discussed in the industry over the last few years. With the leaping forward of the current information and communication technology (ICT), the Internet development and effect represented by the digital economy has received great attention from the existing literature [7,8]. Developing the digital economy, promoting economic and social transformation, and fostering new momentum for economic growth have gradually become the global consensus [9]. According to the Report on Digital China Development 2022 released by the Cyberspace Administration of China, in 2022, the size of China's digital economy reached CNY 50.2 trillion, ranking second in the world, compared with a year earlier, representing a nominal growth of 10.3% and accounting 41.5% of GDP [10].

To promote the development of network infrastructure, China launched "Broadband China" as a pilot policy in 2014. A new round of informatization is being driven by broadband networks, and countries are increasingly focusing on the development of broadband networks as a vital strategy for countries to achieve the highest points of global economic, technological, and industrial competition. China has long placed significant importance on the construction of traditional infrastructure such as water, electricity, gas, and roads, and there is still a large space for the development of network infrastructure. Xue et al. reveled that compared with developed countries, China's network status was lagging due to incomplete network coverage, insufficient data transmission capacity, and unbalanced urban and rural development [11]. To address these issues, in 2013, the "Broadband China" Strategy and Implementation Plan was issued and promoted to a national strategy, followed by the issuance of the Management Measures for Creating "Broadband China" Demonstration Cities (Urban Agglomerations) by relevant departments. A total of 3 batches of 120 cities (urban agglomerations) were enrolled as "Broadband China" pilots from 2014 to 2016. It took three years to build the "Broadband China" pilot areas. The 120 cities enrolled had enhancements in various aspects and took the lead position in China at the end of the corresponding period, such as more than 85% of urban households having broadband access of 20 Mbps or more; broadband access for more than 90% of rural households of 4 Mbps or more; a fixed broadband home penetration rate of 55%; a popularity rate of 3G/LTE mobile telephones of 40%; a penetration rate of broadband users with 4 Mbps or above of 80%; and a penetration rate of broadband users with 8 Mbps or above of 35%. All these will boost the local online entrepreneurship, establishment of e-commerce platforms, online technology training, and other activities. By the end of 2022, China newly built 4.772 million kilometers of optical cable routes, with the total length of optical cable routes across the country reaching 59.58 million kilometers. Among them, the lengths of long-distance optical cable routes, local network relay optical cable routes, and access network optical cable routes were 1.095 million, 21.46 million, and 37.02 million kilometers, respectively [12]. By the end of 2022, China reached 1.071 billion Internet broadband access ports, a net increase of 53.2 million by the end of last year, with a total of 1.271 billion. Among them, the number of fiber access (FTTH/O) ports reached 1.025 billion, with a net increase of 65.34 million compared to the end of the previous year, and the proportion increased from 94.3% to 95.7%. By the end of 2022, the number of 10G PON ports with the capability of gigabit network services reached 15.23 million, with a net increase of 7.371 million during the conclusion of last year [13].

Govindan studied the interrelationship between digital connectivity and income inequality at the global and national levels, showing that the impact of ICTs on inequality was closely linked to the unique economic and technological characteristics of the Internet [14]. At the beginning of the 21st century, Dimaggio et al. [15] and Cheng et al. [16], based on CPS data, analyzed the effects of the Internet on workers' incomes. The results showed that the Internet had a positive contribution. Does the digital economy characterized by informatization have the potential drive to influence the labor income distribution in China, and how does it affect the income levels for high-, medium-, and low-skilled workers? What are theories and mechanisms behind it? These are questions worth further discussion.

In the context of the rapid development of digital economy and the promotion of sustainable development, we built a time-varying DID model to evaluate the impact of "Broadband China" on labor force income growth based on panel data from 195 prefecture-level cities, considering the "Broadband China" pilot as a natural experiment to measure the digital economy. It was found that the availability of "Broadband China" has increased the overall income level of the Chinese labor force. "Broadband China" may lead to the widening of income inequality while increasing the growth of the overall labor force income level." We also found that "Broadband China" can affect income growth through two mechanisms: "increasing the entrepreneurship rate" and "leading to an increase in the overall number of professional and skilled labor force in China". In this case, the entrepreneurship rate of the high-skilled labor force may be higher than that of medium- and low-skilled labor force due to the human capital accumulation. The rapid increase in high-skilled labor force in technical industries will lead to a situation where their income growth effect is higher than that of the medium- and low-skilled labor force. Based on the above research results, we propose relevant policy recommendations to promote developing countries to gradually move towards common prosperity and ultimately realize sustainable development.

The remaining parts of the paper are as follows. Section 2 presents a literature review. Section 3 is an introduction to the Materials and Methods. Section 4 reports the empirical conclusions and related analysis. The final section is a discussion of conclusions and implications.

2. Literature Review

The first type of literature relevant to this paper assessed the positive factors affecting labor income levels. It was found in most literature relevant to the research questions in the paper that labor income levels were positively influenced by trade protection, capital stock, urban scale, and years of education. For example, Dutta argued that the impact of trade protection on industry wage premiums was positive and statistically significant, and that, despite of a modest scope, workers employed in high-tariff industries received higher wages than clearly the same workers employed in low-tariff industries [17]. Lu and Cai showed that when the capital stock increased by 1%, the Gini coefficient would decrease by 26%, but the impact of capital on income disparities was positive in combination with openness or control variables for development levels [18]. Truong pointed out that the externalities of urbanization were reflected in the size of the urban population, which positively affected labor incomes in the region [19]. Through a literature review, Leuven and Oosterbeek found that on average, in different countries and periods, the wage of a moderately matched group increased by 8.9% for each additional year of education, while that of an over-educated group increased by 4.3%. The wage reduction of the under-educated group was 3.6% for each year of less schooling [20].

The second strand of literature relevant to this paper assessed the negative factors affecting the labor income levels. It was found in most literature relevant to the research questions in the paper that labor income levels were negatively influenced by the import competition, population aging and technical progress bias, information technology and computer age, and environmental regulations. For example, Javier noted that in most industries, the intensification of import competition tended to reduce employment and had a negative effect on workers' wages, albeit to a relatively small extent [21]. Yang et al. argued that population aging and technological progress bias had a negative impact on labor income levels [22]. Loukas and Brent pointed out that efficiencies in the capital-producing sector were often attributed to advances in the information technology and computing age, which prompted companies to shift from a reliance on labor to capital to the extent that labor's share of income declined [23]. Qing and Qi showed that in cities where the output value of polluting industries was relatively high, environmental regulations had a more obvious inhibitory effect on wage growth [24].

In other studies, it was found that educational attainment, trade openness, trade sanctions, and tariffs had important effects on labor income inequality. Park and Ma et al. showed that the more educated the labor force was, the more equal the distribution of labor income would be, and the wider the gap in labor education was, the more unequal the distribution of income would be. In addition, the impact of the Internet on groups with different education levels was different, that is to say, the higher the education level, the more benefit there would be [25,26]. Abdul's evidence supported a nonlinear relationship between China's trade openness and inequality. Using five alternative openness measures from 1952 to 2009, he concluded that although income inequality increased with the opening of trade, it declined after a tipping point. These results suggest that further trade openness may reduce inequality in the long run [27]. Afesorgbor et al. held that the imposition of trade sanctions had a deleterious effect on income inequality, and the longer the trade sanctions spanned longer durations, the greater the adverse effected on income inequality would be [28]. Murakami found that lower effective tariffs on end products would lead to higher industry wages and skill premiums [29]. In the aspect of countermeasures to reduce the labor force income gap, Rolim et al. and Antonelli et al. showed that the labor income inequality could be effectively mitigated through a combination of systems that protect workers, stimulated technological innovation, and transformed labor-intensive technologies that ultimately promote productivity growth [30,31]. Also, redistribution policies have achieved remarkably in raising the growth rate of medium- and low-income households and narrowing the income distribution gap [32]. By analyzing the above-mentioned literature, in this paper, the "Broadband China" pilot was used as a natural experiment to measure the digital economy, and a time-varying DID model was constructed to assess the impact of "Broadband China" on income growth. The influences of the digital economy on the income of labor with different skills and the mechanisms behind it are further discussed in the paper.

The possible marginal contributions of the paper are mainly reflected in two areas. Firstly, it is more reasonable than the traditional evaluation method of policy effect. This paper points out that the "Broadband China" pilot project is a natural experiment for measuring the digital economy. The impact of the digital economy on labor income levels was assessed with the creation of a DID model that is time varying. The conclusion is more reliable as it has passed the endogeneity test of the instrumental variable method, alleviated the endogenous issues raised by the non-randomness of pilot city selection for the "Broadband China" strategy, and underwent a robustness test. Secondly, this study broadens the perspective of the existing literature. With respect to the digital economy and sustainable development context, we consider the phenomenon of shared wealth, which includes both efficiency and equity, and verified the theoretical mechanism of digital economy affecting income growth by two paths: "increasing entrepreneurship rate" and "leading to an increase in the overall number of professional and skilled labor force in

China", providing micro-level evidence that the digital economy promotes income growth and widens the income gap between high-, middle-, and low-skilled labor.

3. Materials and Methods

3.1. Theoretical Analysis

The development of the Internet reduces the market entry cost, promotes trade among cities, and raises productivity and labor incomes [33]. Madan and Litan et al. reveled that the Internet was favorable for the growth of total factor productivity (TFP), per capita income level, and social economic development [34,35]. There is a positive relationship between the Internet and high personal pay, which will affect the pay structure and income distribution of society as a whole. ICT may have a negative impact on the income distribution. Brown and Campbell concluded that, by investing in ICTs to shift demand from low-skilled workers to a more qualified knowledge-based workforce, there would be an increased demand from businesses for highly skilled workers, and income disparities would be ultimately widened [36]. Xiao et al. argued that production technology upgrades resulting from the digital transformation of enterprises would drive investment in highly skilled labor, thus facilitating the upgrading of corporate human capital structures and increasing the income share of high-skilled labor. On the other hand, the digital transformation of enterprises may also directly replace some routine and repetitive low-skilled jobs. In other words, it would optimize the human capital structure by squeezing out part of low-skilled labor, thus affecting the labor income share [37].

Liu reveled that big data played a significant role in the digital economy, as it could activate the entrepreneurial enthusiasm of the labor market, leading to a significant growth in survival and opportunities for entrepreneurship [38]. Zhang et al., Zhao et al., and Liu et al. showed that the digital economy and finance could further expand the service scope and coverage of finance, and unfetter it from the binding force to benefit the family entrepreneurship, and with the constant support of national policies, the digital economy would continue to improve the macro market environment for mass entrepreneurship and innovation by providing financing channels, expanding information sources and enhancing the entrepreneurship demonstration effects [39–41]. The digital economy helped people get access to resources and information, lowered the start-up cost, and motivated the entrepreneurship passion and efficiency, so as to significantly boost the entrepreneurship rate and income level. Peng et al. found that the development of digital economy increased the non-agricultural employment and income for rural residents, and higher per capita income raised a non-agricultural entrepreneurial intention [42]. In addition, Yang et al. revealed that by promoting entrepreneurship, the digital economy greatly boosted incomes for urban and rural Chinese residents, and the growth in disposable income per capita for urban residents was more pronounced than for rural residents [43]. And the average education level of China's urban labor force was higher than the average education level of China's rural labor force. Therefore, we argue that the contribution of entrepreneurship to the income growth of the high-skilled labor force is higher than the income growth effect on middle- and low-skilled labor force.

The implementation of the "Broadband China" strategy fastened the deep integration of the digital economy into economic society, generating many technology-intensive industries. It triggered the skill bias effect and the demand for skilled talent and drove the overall income level of the labor force upward. The labor force with relatively higher incomes and education in high-skilled industries tended to earn more through the Internet than their peers [44]. Wang et al. argued that the artificial intelligence technology not only caused the change of labor positions, but also differentiated the production efficiency of different technical sectors, leading to a 0.75% annual increase in the labor income gap between the high-skilled and low-skilled labor [45]. Pissarides, Acemoglu, and Sun et al. reveled that an important theory explanation was the technical progress of skill bias. The income gap between the high- and low-skilled labor force was formed because of the income growth of the former exceeding that of the later. It was attributed to the desperate need of developing countries for technological progress brought by high-skilled talent, and the growing demand of the market for high-skilled labor force caused by the technological bias of the Internet popularization [46–48]. Autor et al. and Maarten et al. pointed out that the reason why the market demand for the labor force with higher education was growing, and driven by the Internet popularization, was that many tedious manual chores had been replaced by computers, reducing jobs of routine works in the market; therefore, personnels with better comprehensive capability or adaptability could benefit more in the iteration of science and technology [49,50].

According to the above analysis, the following research hypotheses are presented:

Hypothesis 1 (H1). *The implementation of the "Broadband China" strategy is conductive to the increase in the overall labor income level in China, as well as the constant income growth in the labor force market.*

Hypothesis 2 (H2). *The implementation of the Broadband China strategy has generated more income for the highly skilled workforce, thus widening the income gap between the high-skilled and the medium- and low-skilled labor force.*

Hypothesis 3 (H3). *By increasing the entrepreneurship rate and leading to an increase in the overall number of professional and skilled labor force in China, the "Broadband China" strategy could push for a constant income growth for the labor force market. Compared with medium- and low-skilled labor force, the high-skilled labor force may be more efficient in entrepreneurship, and the high-skilled labor force in technical industries has a greater growth rate, which leads to a greater income growth effect.*

3.2. Typical Facts

The labor force is divided into the high skilled and the medium and low skilled based on education level. According to Lu, the labor forces with college degrees and above are regarded as high skilled, and those with less than college degrees are the medium and low skilled [51]. The 34 cities that implemented the "Broadband China" strategy for the first time in 2014 were taken as the treatment group, and the other 104 cities that never implemented such a strategy were categorized as the control group. The average income data of the overall labor force, high-skilled labor force, and medium- and low-skilled labor force in the above treatment and control groups during the eight survey periods from 2011 to 2018 were regarded as typical fact samples. Please see Figures 1–4 for details. As shown in Figure 1, the overall income level of the labor force in the group of treatment and the control indicated an upward trend, and the overall labor income growth of the treatment group was significantly higher than that of the control group after 2014. As shown in Figure 2, the income level of the medium- and low-skilled labor force in the group of treatment and the control indicated an upward trend, and the income growth of medium- and low-skilled labor force in the treatment group was higher than that of the control group after 2014. As shown in Figure 3, the income level of high-skilled labor force in the group of treatment and the control indicated an upward trend, and the income growth of the high-skilled labor force in the treatment group was higher than that of the control group after 2014. As shown in Figure 4, eight surveys from 2011 to 2018 showed a steady rise in the average income of the overall, high-skilled, and medium- and low-skilled labor force in 34 cities where the "Broadband China" strategy was implemented for the first time in 2014. The income levels of the overall, high-skilled, and medium- and low-skilled labor force in 34 cities of the treatment group showed rapid growth since the implementation of the "Broadband China" strategy in 2014. Due to the timeliness, all three levels dropped a bit after they hit the maximum value in 2015, then gradually came back to normal growth after 2016. In addition, the income gap between the high-skilled and low- and medium-skilled labor force widened even more after 2014. This was possibly because amid the "Broadband China" strategy, the high-skilled labor force can quickly adapt to the income marginal effect brought by the technical progress as they have abundant experiences in higher education and adaptive professional skills. However, the general lack of such experiences and skills makes it difficult for the medium- and low-skilled labor force to break the technical barriers, and even harder to catch up to the speed of the income growth of the high-skilled labor force. Under the effect of the "Broadband China" strategy, their income gap will be further widened. A prima facie can be established from the above, that is, the "Broadband China" strategy has generally increased the labor income level but widened the income gap between the high-skilled and medium- and low-skilled labor force even more.

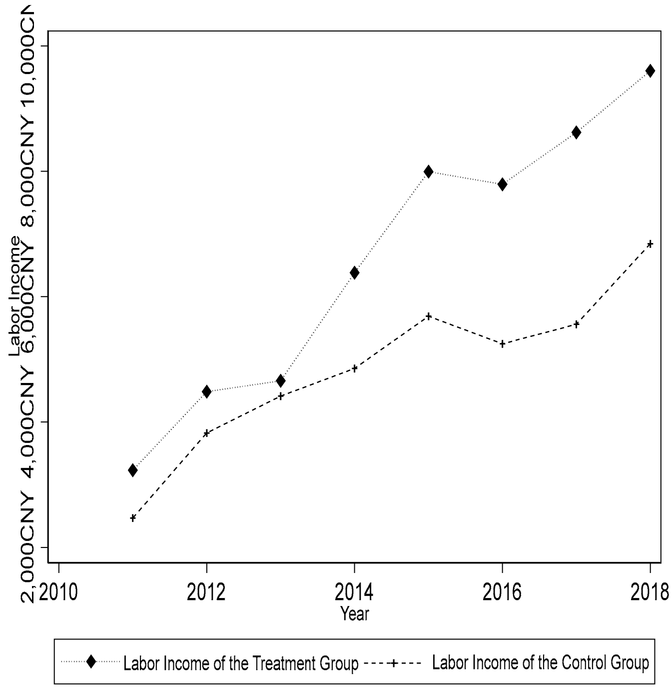

Figure 1. Labor Income of the treatment group and the control group.

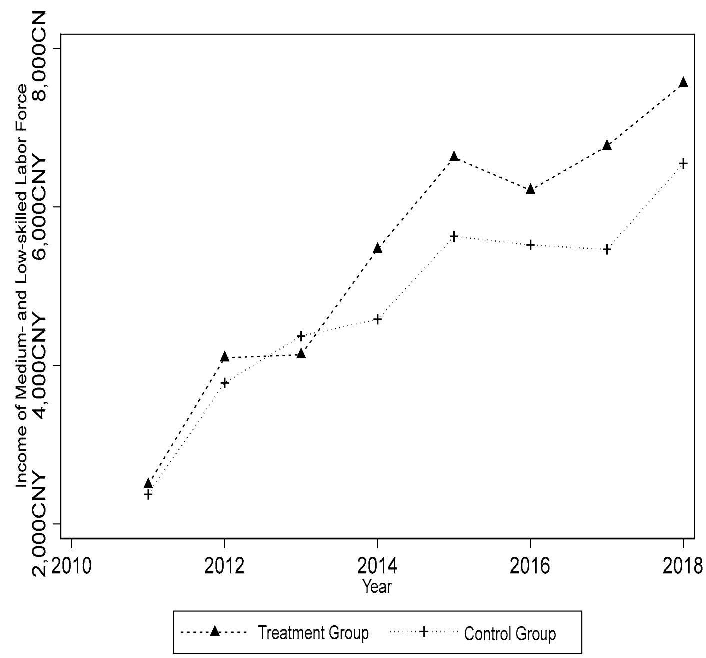

Figure 2. Income of the medium- and low-skilled labor force in the treatment group and the control group.

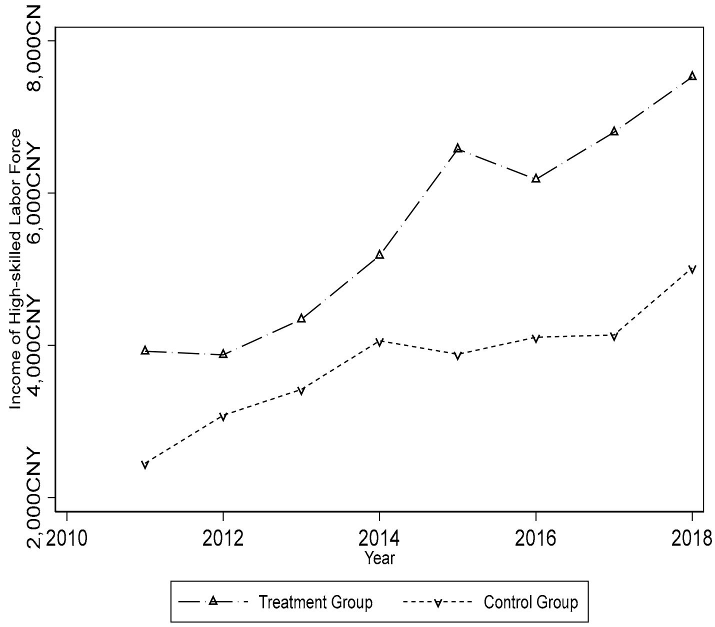

Figure 3. Income of the high-skilled labor force in the treatment group and the control group.

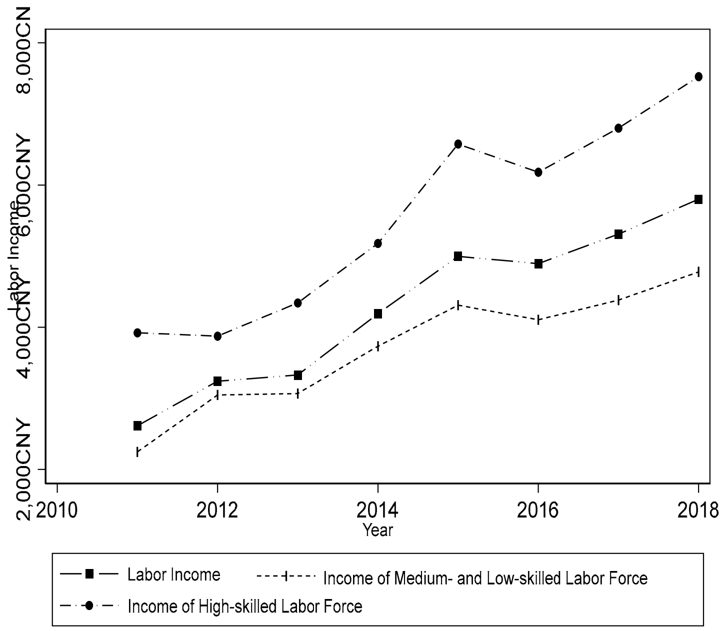

Figure 4. Labor income of the treatment group.

3.3. Methods Selection

3.3.1. Dynamic Model

We used not only the standard time-varying DID model but also the event analysis method to evaluate Broadband China's dynamic impact. The premise of a time-varying DID model is that the treatment group and the control group have parallel trend characteristics before the strategy implementation, that is, both groups' trends of labor income level remained consistent before the implementation of the broadband strategy. In the paper, we built the test model (1) for labor income level (logarithm) and the event dummy variable D_{ik} based on the practice of Beck et al. [52]. The estimated equation is as follows:

$$ln(wage_{it}) = a_0 + \sum_{k=-6}^{5} \beta_k D_{ik} + \gamma X_{it} + \mu_t + \theta_i + \varepsilon_{it} \quad (1)$$

In Equation (1), a_0 is the intercept term, and D_{ik} represents the event dummy variable. We set the year prior to the policy change as the omitted group, with k of the event dummy variable D_{ik} representing the relative time before and after the implementation of the strategy. In addition, in our regressions, the regression coefficient β represents the policy effect before and after the occurrence of " $\pm k$" for the "Broadband China" policy. In the above formula, the subscripts i and t represent the city and year, respectively. $ln(wage_{it})$ is the explained variable; the control variable X_{it} in the paper includes the unemployment rate of skilled workers of city i in year t, fiscal and science and technology expenditures, upgrading of industrial structure, and scale of science education. γ is the regression coefficient of the control variables. In this paper, μ_t, the time fixed effect, and θ_i, the city fixed effect, were controlled to address missing variable bias, and ε_{it} is a stochastic disturbance term (ε_{it} satisfies the assumption of unbiasedness; the assumption that the random disturbance term is independent of the explanatory variables, the assumption of no multicollinearity, the assumption of zero mean, the assumption of homoskedasticity and no serial correlation, and the assumption of normality). The event analysis method can intuitively show the dynamic adjustment of labor income levels with the implementation of the "Broadband China" policy. If the regression coefficient β does not pass the significance test, it indicates that prior to the implementation of the policy, there is no significant difference in labor income between the treatment group and the control group. If a passes the significance test, after the implementation of the "Broadband China" pilot policy, there is a significant difference in labor income between the treatment group and the control group.

3.3.2. Base Regression Model

In the determination of the causal relationship between the digital economy and labor income growth in a labor market, we considered the "Broadband China" pilot policy implemented since 2014 as an exogenous policy shock. This exogenous event serves as a natural experiment to evaluate how the digital economy affects the growth of labor incomes by implementing a double-difference approach. Since the "Broadband China" demonstration cities are established in a stepwise manner, the traditional DID is only applicable to assess the effect of the policy at a single point in time. In this paper, a time-varying DID model was built on the basis of approach of Card and Krueger [53]. The group dummy was set to 1 for pilot cities and 0 for non-pilot cities, and the year dummy was set to 1 for the year of policy implementation and subsequent years, and 0 for the remaining years. Therefore, we constructed A time-varying DID model as below:

$$ln(wage_{it}) = a_0 + \delta D_{it} + \gamma X_{it} + \mu_t + \theta_i + \varepsilon_{it} \tag{2}$$

In the above formula, a_0 is the intercept term, and the subscripts i and t represent the city and year, respectively. $ln(wage_{it})$ is the explained variable, and the core explanatory variable D_{it} represents a dummy variable of the interaction term between group and policy time to identify cities where broadband is launched in year t. The regression coefficient δ of D_{it} reflects the effect of the "Broadband China" pilot policy. Other symbols X_{it}, γ, μ_t, θ_i, and ε_{it} are interpreted in the same way as Formula (1).

3.3.3. Instrumental Variables Method

The time-varying DID model is used to assess the impact of the "Broadband China" pilot policy on labor income levels, ideally by randomly setting up a "Broadband China" demonstration city. However, it is undeniable that the choice of "Broadband China" pilot cities is not entirely random but is influenced by the level of economic development and the improvement of the social security system. If these factors also affect the increase in labor income level, it will lead to policy endogeneity problems, which will cause biased estimation results. In this paper, the research of Liu et al. was referred to, and the instrumental variable of urban altitude fluctuation was used to avoid the interference of the above factors as much as possible [54]. The correlation condition of the instrumental variable is satisfied by the urban altitude fluctuation, which directly affects the Internet popularity rate.

The greater the urban altitude fluctuation, the higher the cost of network infrastructure construction will be, and the worse the signal, the lower the feasibility will be. Therefore, the correlation demand of the instrumental variable is satisfied by the urban altitude fluctuation. Meanwhile, the urban altitude fluctuation, as an instrumental variable, satisfies the exogenous condition. Geographic locations and topographic features are exogenous variables that are independent of the economic system and have little correlation with socio-economic factors, thus not affecting the level of labors' income level. However, geographical conditions cannot be directly used for the panel data analysis because they are time-independent variables during the study period. Therefore, in this paper, the processing scheme of Nunn and Qian was referred to, and the result obtained by multiplying and logarithmizing the urban altitude fluctuation with the Internet popularity rate of different years of the studied cities was taken as a new instrumental variable that changes with time [55]. We use the instrumental variable method to conduct a further experiment for the results of the "Broadband China" pilot policy to promote labor income levels. So, this paper refers to the study of Angrist and Krueger to construct the following instrumental variables model [56]:

$$ln(wage_{it}) = a_0 + \delta D_{it} + \gamma X_{it} + \mu_t + \theta_i + \varepsilon_{it} \tag{3}$$

$$cov(Z_{it}, D_{it}) \neq 0 \tag{4}$$

$$cov(Z_{it}, \varepsilon_{it}) = 0 \tag{5}$$

In Equation (3), the same as the base regression model (2), all symbols are interpreted with the same meaning as the symbols in the base regression model (2). In Equations (4) and (5), a valid instrumental variable (Z_{it}) should satisfy both conditions, i.e., the instrumental variable is correlated with the core explanatory variable, $cov(Z_{it}, D_{it}) \neq 0$, which satisfies the criteria for the instrumental variables, and at the same time, the instrumental variable is uncorrelated with stochastic disturbance terms, $cov(Z_{it}, \varepsilon_{it}) = 0$, which satisfies the exogeneity condition of the instrumental variable. Finally, the correlation and exogeneity of the instrumental variables were tested by two-stage least squares method.

3.3.4. Variable Selection, Data Source, and Processing

Variable Selection

The explained variable $ln(wage_{it})$ is the logarithm of the monthly labor income in city i of year t. The core explanatory variable D_{it} represents a dummy variable of the interaction term between group and policy time to identify cities where broadband is launched in year t. A total of 91 cities in the treatment group and 104 cities in the control group received treatment due to the availability of data. For cities involved in "Broadband China", the current year and subsequent years of the launch were marked as 1, and 0 for the rest of the years (regarded as a treatment group, 91 cities in total). Cities that have never been involved were marked as 0 (regarded as a control group, 104 cities in total). The control variable X_{it} in the paper includes the unemployment rate of skilled workers of city i in year t, fiscal and science and technology expenditures, upgrading of industrial structure, and scale of science education.

Control variables that may have an influence on the labor income are also required for a more comprehensive analysis on the influential impact of the "Broadband China" strategy on income. There are four control variables in the papers, as follows: (1) Financial expenditure on science and technology are the most direct indicators of government support for science and technology innovation [57]. Taking into account differences in local economic development and fiscal conditions, "*tec*" refers to the level of fiscal and scientific expenditure as a proportion of total local fiscal expenditure. (2) The pattern of economic growth tends to shift gradually from the dominance of the primary sector to the dominance of the secondary and tertiary sectors, reflecting the process of "servicization of the economy", which is represented by the proportion of the tertiary sector to the secondary sector, representing an upgrading of the industrial structure. (3) The proportion of college students at schools reflects the national education level, which is the main drive for the science and technology progress. "*edu*" marks the scale of science education, represented by the proportion of college students in schools in the total population in regions. (4) "$unemployment_{it}$" marks the unemployment rate of the labor force in city i in year t, represented by the proportion of the unemployment population in the total economically active population. The unemployment rate is calculated with micro individual data from CMDS. The unemployment population refers to the groups of people that are unemployed due to personal or employer reasons, but with abilities and intentions to work (excluding seasonal shutdowns). The total economically active population is the summation of the employment and unemployment population.

Data Source and Processing

We constructed a panel sample of prefecture-level cities (including municipalities directly under the central government) by combining a variety of data sources such as the China Migrants Dynamic Surveillance Survey (CMDS) database, the Cathay Pacific, the CEEC database, and the China Urban Statistical Yearbook, after a series of screenings. The CMDS data are the result of an annual large-scale national sample survey of migrants conducted by the China National Health Commission (CNHSC) since 2009. The annual large-scale nationwide sample survey of the floating population was obtained from the database, which was only updated until 2018; therefore, the time frame of the data studied in this paper was from 2011 to 2018. The China Mobile Population Dynamic Monitoring Survey (CMDS) database survey targets 31 provinces (autonomous regions and municipalities) and the Xinjiang Production and Construction Corps, where the mobile population is more concentrated in the inflow area, with a sample size of nearly 200,000 households per year, with the survey content including, but not being limited to, basic demographic information of the mobile population and its family members, the scope and tendency of mobility, employment, income, and expenditure, and so on. The explained variable $wage_{it}$ of monthly labor income and the unemployment rate in the control variable were calculated from the totaled microscopic individual data of CMDS (2011–2018). The macro data of other control variables were sourced from CSMAR, the CEInet Statistics Database, and the China City Statistical Yearbook. The original samples were processed as follows when sorting micro CMDS data: (1) Only samples of prefecture-level municipalities and municipalities are reserved. (2) Given the labor income studied in the paper, only employed individuals aged between 16 and 60 were kept. A total of 934,933 samples of micro individuals were kept out of 1,383,277 original samples of individual migrants from CMDS 2011–2018 after screening, as mentioned above. After the aggregation and average and removing missing and invalid values of city variables, the panel sample size of cities obtained in the paper was 1560, totaling 195 cities, including 91 in the treatment group and 104 in the control group. The urban labor income was the logarithm of the average sum of monthly individual income variables provided by CMDS. The core explanatory variable represents a dummy variable of the interaction term between group and policy time, marked as (D). The coefficient being significant and greater than 0 indicates that the broadband strategy has a positive facilitating effect on the labor income; otherwise, it is negative. The descriptive statistics of the above variables are presented in Table 1.

Table 1. Variable description and descriptive statistical results.

Variables	Variable Description	Sample Size	Mean	SE	Max	Min
$wage_{it}$	Monthly income of the labor force of city *i* in year *t*	1560	3389.343	965.230	8637.5	695.556
$wage_{ith}$	Monthly income of the high-skilled labor force of city *i* in year *t*	1560	3776.970	1397.034	16,100	750
$wage_{itl}$	Monthly income of the medium- and low-skilled labor force of city *i* in year *t*	1560	3320.728	942.983	10,580	680
tec	Financial expenditure on science and technology	1560	1.851	1.656	16.273	0.068
upgrading	Upgrading of industrial structure	1560	0.960	0.502	4.348	0.114
edu	Scale of science education	1560	2.270	2.690	13.112	0.001
$unemployment_{it}$	Unemployment rate	1560	0.035	0.043	0.471	0.012
$unemployment_{ith}$	Unemployment rate of high-skilled labor force	1560	0.026	0.007	0.467	0.001
$unemployment_{itl}$	Unemployment rate of medium- and low-skilled labor force	1560	0.045	0.011	0.533	0.017

4. Results

4.1. Event Analysis Method

As shown in Figure 5, there was no systematic and significant difference in the income of the sample labor force between the pilot and non-pilot areas before the implementation of the "Broadband China" pilot strategy. After the implementation of the "Broadband China" strategy, the difference in labor income between the treatment group and the control group cities widened and passed the significance level test. Therefore, the parallel trend test held. In addition, the year in which the strategy was implemented had no effect on labor income, but had a significant effect in the second year, and the effect of the strategy gradually increased with the increase in years. This indicates that the effect of the "Broadband China" pilot strategy has a certain lag and sustainability.

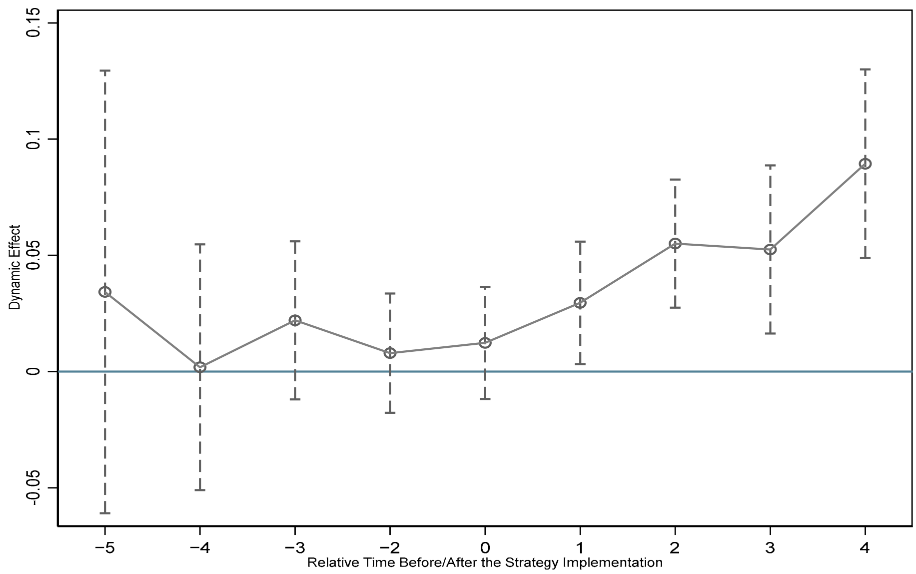

Figure 5. Results of the event analysis method.

4.2. Benchmark Regression

In the Benchmark regression, we estimated the equation by ordinary least squares, and the results are shown in Table 2. The "Broadband China" strategy had a significant positive impact on labor income in all four regressions. The city effect was fixed in the paper in column (1), and the regression coefficient 0.3631 was significantly positive at the 1% level. A series of control variables were added in the paper in column (2), namely, financial expenditure on science and technology, upgrading of industrial structure, scale of science education, and unemployment rate, which may have a significant impact on labor force income. The regression coefficient 0.1727 was significantly positive at the 1% level. The results of these two columns indicate that the "Broadband China" strategy had a positive promotion effect on labor force income. The digital economy represented by "Broadband China" has elevated the overall labor income in China. In columns (3) and (4), year fixed effects and four control variables were gradually added in this paper. Coefficients of core explanatory variables declined but were significant at the level of 5%. The basic conclusion of the previous regression did not change by this. To sum up, it was made clear that there was an increase in the level of labor income in cities implementing the "Broadband China" strategy. The application and progress of network technology continually reduce the cost of information acquisition and transaction, as well as safeguarding the continuous flow of information. On this basis, trade activities between different regions become closer, and the comprehensive productivity of various factors is improved, leading to an increase in the labor income level. This result verifies H1 in the paper.

Table 2. Benchmark regression results.

Variables	**Explained Variables: *ln(wage$_{it}$)***			
	(1)	**(2)**	**(3)**	**(4)**
D	0.3631 *** (0.0187)	0.1727 *** (0.0186)	0.0248 ** (0.0136)	0.0231 ** (0.0135)
tec		0.0382 *** (0.0079)		0.0127 ** (0.0053)
upgrading		0.4753 *** (0.0293)		0.0092 ** (0.0258)
edu		0.0604 *** (0.0140)		0.0028 ** (0.0093)
$unemployment_{it}$		−0.0001 *** (0.0000)		−0.0001 *** (0.0000)
Year fixed effect	No	No	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
R^2	0.2163	0.4146	0.7441	0.7502
N	1560	1560	1560	1560

Note: Standard errors are in parentheses, and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively. The same applies below.

4.3. Endogeneity Issues

In the analysis according to Section 3.3.3, we performed a two-stage least squares estimation of the equations, and the results are shown in Table 3. We can see clearly in column (1) of Table 3 that after the endogenous bias was weakened, the instrumental variable was significantly correlated with D at the level of 1%, indicating that conditions related to instrumental variables were met. The result of the test in column (2) satisfied the exogenous test of instrumental variables, and the *KP-F* statistic was 45.925, indicating that no weak instrumental variables had arisen. In other words, the benchmark conclusion obtained in this paper still held after using instrumental variables to reduce endogenous issues.

Table 3. Addressing endogeneity.

Variables	**Phase I of 2SLS**	**Phase II of 2SLS**
	(1)	**(2)**
D		0.4920 *** (0.0981)
Z	0.2118 *** (0.0265)	
Control variables	Yes	Yes
KP-F statistic		45.925

Note: The instrumental variable Z in this paper was obtained by multiplying and taking the logarithm of the urban altitude fluctuation and the Internet penetration rate of the studied city in different years. Column (1) is the correlation test between D and Z, and column (2) is the exogenous test of Z. The *KP-F* statistic was 45.925.

4.4. Robustness Test

4.4.1. Propensity Score Matching

Refraining from the selection bias of changing trends between the treatment group and the control group, we adopted PSM-DID method to further test the baseline regression results. Cities selected from the control group had similar conditions to those in the treatment group. In the paper, the four control variables are the same as in the baseline regression, are chosen for matching, and the treatment group is matched based on a one-to-two nearest neighbor matching method. The standard errors of the covariates before and after the matching decrease significantly, and the absolute values of the standard errors after the matching are all less than 10%. p-values after the matching are not significant, indicating that the control and treatment groups are balanced. As shown in Figure 6, most of the samples are within the common value range after the matching, indicating that the sample loss is relatively small when using the propensity score matching.

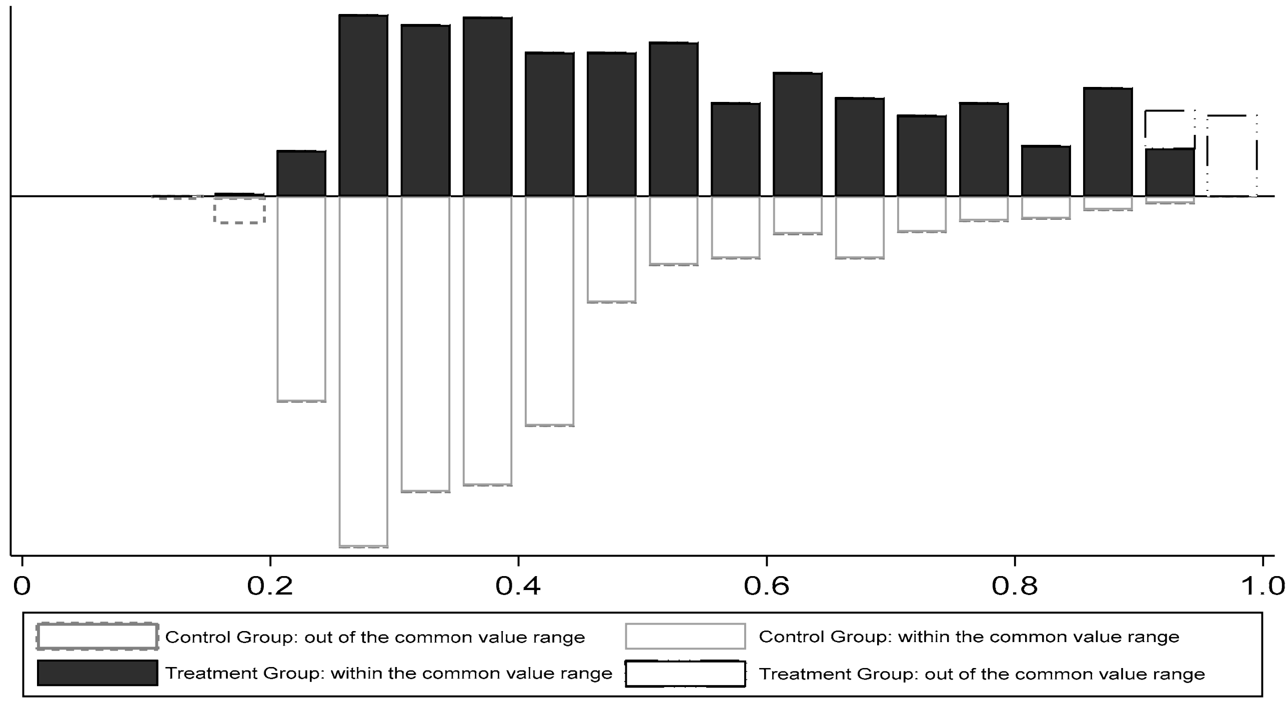

Figure 6. Overlap region of the propensity score matching.

4.4.2. Placebo Test

In this paper, the establishment time of the "Broadband China" pilot areas was simulated to explore its role in the labor income. If the coefficient is not significant, it shows that "Broadband China" has some effect on labor income growth. Specifically, by advancing the establishment time of the "Broadband China" pilot areas by 1 year, 2 years, and 3 years, we explored whether the artificially set D had a significant impact on the labor income. Columns (1), (2), and (3) of Table 4 are the regression results for advancing the establishment time by 1 year, 2 years, and 3 years, respectively. The results show that D did not have a significant influence on the labor income, which supports the benchmark regression results of the paper.

Table 4. Robustness checks.

Variables	One Year in Advance	Two Years in Advance	Three Years in Advance	Excluding Female Samples	Excluding 70 Cities
	(1)	(2)	(3)	(4)	(5)
D	0.0088	−0.0003	0.0076	0.0228 **	0.0201 **
	(0.0139)	(0.0155)	(0.0197)	(0.0527)	(0.0204)
tec	0.0129 *	0.0130 *	0.0131 *	0.0038 **	0.0347 **
	(0.0052)	(0.0052)	(0.0053)	(0.0205)	(0.0115)
upgrading	0.0012	0.0121	0.0119	0.0187 *	0.0058 *
	(0.0272)	(0.0272)	(0.0272)	(0.1061)	(0.0340)
edu	0.0020	0.0016	0.0017	0.0490 *	0.0145 *
	(0.0093)	(0.0093)	(0.0093)	(0.0361)	(0.0197)
$\text{unemployment}_{\text{it}}$	−0.0001 ***	−0.0001 ***	−0.0001 ***	−0.0002 ***	−0.0001 **
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Year/City fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.7497	0.7496	0.7497	0.6951	0.6874
N	1560	1560	1560	1560	1048

4.4.3. Confounding Policies

Two other policies had an impact on labor income during the "Broadband China" strategy pilot. One of them was the implementation of the "Selective Second Child Policy" and the "Universal Second Child Policy". In January 2014, the Selective Second Child Policy began to be piloted in Chinese provinces and cities, and that of the "Universal Second Child Policy" began on 1 January 2016. The implementation of this policy seriously affects the employment rate of women, both within and out of the childbearing age, because according to Chinese traditional customs, the responsibilities of giving birth to, nurturing, and taking care of children mostly fall on women. In this context, some women will become unemployed, which will have a further effect on the overall labor income. Therefore, after excluding female samples, we re-estimated model (1). Another policy is the national e-commerce model city policy. The National Development and Reform Commission of China and related agencies successively established 70 national e-commerce demonstration zones in 2011, 2014, and 2017. This policy has many similarities with the strategy studied in the paper. To avoid its impact on the benchmark results, this model excluded the aforementioned 70 cities and estimates the model (1) again. The above estimation results are still robust, as shown in columns (4) and (5) of Table 4.

4.5. Further Discussion and Mechanism Test

4.5.1. Influences of "Broadband China" on the Income of Labor Force with Different Skills

Over the past four decades, China has seen a high-speed growth in its economy. However, issues including income inequality have become increasingly prominent. Research shows that China is in the rank of countries who have the most unequal income distribution among the world, the increasingly widening income gap of which has aroused people's attention [58]. With reference to the model (1), in this paper, the labor force was divided into the high-skilled and medium- and low-skilled labor force. The explained variables $ln(wage_{ith})$ and $ln(wage_{itl})$ represent the logarithm of the monthly income levels of high-skilled and medium- and low-skilled labor force in city i in year t, respectively. The core explanatory variable D remains unchanged. The control variables $unemployment_{ith}$ and $unemployment_{itl}$ represent the unemployment rates of high-skilled and medium- and low-skilled labor forces in city i in year t, respectively, and other control variables remain unchanged. The annual fixed effect is μ_t, the city fixed effect is θ_i, and ε_{it} is the stochastic disturbance term. According to the regression results, the "Broadband China" strategy ensures a substantial positive impact on the labor income. In Table 5, columns (1) and (2) show the estimated results of the Broadband China strategy for medium- and low-skilled and highly skilled workforce income growth without control variables, respectively. Columns

(3) and (4) show the estimates after adding control variables and two fixed effects. The income growth of the medium- and low- skilled and high-skilled workforce was shown to be significantly impacted by the "Broadband China" strategy, as can be seen in the table above, with a greater increase in the income level of high-skilled labor force, thus further widening the income gap between the high-skilled and medium- and low-skilled labor force. This result verifies H2 in the paper.

Table 5. Further regression results.

Variables	$\ln(wage_{itl})$	$\ln(wage_{ith})$	$\ln(wage_{itl})$	$\ln(wage_{ith})$
	(1)	(2)	(3)	(4)
D	0.3518 ***	0.9012 ***	0.0234 **	0.0633 **
	(0.0192)	(0.0691)	(0.0137)	(0.0738)
tec			0.0111 **	0.0205 **
			(0.0053)	(0.0287)
upgrading			0.0033	0.0861
			(0.0261)	(0.1412)
edu			0.0005	0.0457
			(0.0094)	(0.0506)
$unemployment_{itl}$			−0.0141 ***	−0.0006 ***
$unemployment_{ith}$			(0.0012)	(0.0002)
Year/City fixed effects	Yes	Yes	Yes	Yes
R^2	0.1964	0.1107	0.7526	0.3813
N	1560	1560	1560	1560

4.5.2. Mechanism Test

The previous section discussed the carrying out of the "Broadband China" strategy and analyzed its theoretical mechanism. Based on this, the internal influence mechanism of the "Broadband China" strategy on the labor income is stated. Firstly, the digital economy has significantly increased China's labor income level by promoting entrepreneurial activities. In order to verify the mechanism, this paper calculated the entrepreneurship rate indicators of the medium- and low-skilled and high-skilled labor force aged 16 to 60 in 195 prefecture-level cities from 2011 to 2018 based on the previous data processing standards. The explained variable $Entreh_{itl}$ is the entrepreneurship rate of medium- and low-skilled labor force in city i in year t, which is also the proportion of the number of medium- and low-skilled entrepreneurs in that year in the employment status of all of the medium- and low-skilled labor force. The explained variable $Entreh_{ith}$ is the entrepreneurship rate of high-skilled labor force in city i in year t, which is the proportion of the number of high-skilled entrepreneurs in that year in the employment status of all of the high-skilled labor force. The core explanatory variable D remains unchanged. The control variables $unemployment_{itl}$ and $unemployment_{ith}$ represent the unemployment rates of medium- and low-skilled and high-skilled labor force in city i in year t, respectively. Other control variables remain unchanged. The year fixed effect is μ_t, the city fixed effect is θ_i, and ε_{it} is the stochastic disturbance term. We used the same regression method as that in the model (1), and the empirical results are shown in Table 6. The estimated coefficients of the core explanatory variables in columns (1) and (2) of Table 6 ensured a positive impact at the significance levels of 1% and 5%, respectively, indicating that the "Broadband China" strategy significantly increased the entrepreneurship rates of the medium- and low-skilled and high-skilled labor force, among which, the estimated coefficient for the increase in the entrepreneurship rate of medium- and low-skilled labor force was slightly higher than that of high-skilled labor force, whose income growth, however, was greater than that of medium- and low-skilled labor force. On the one hand, under the background of the "Broadband China" strategy, some high-skilled labor force was more willing to stay in high-paying technical industries, which have higher income than that brought by the entrepreneurship of medium- and low-skilled labor force. On the other hand, another part of the high-skilled labor force who chooses entrepreneurship has a higher human capital level than the medium- and low-skilled labor force. They are better at using professional skills to break through entrepreneurial technological barriers, thus having a higher entrepreneurial efficiency than that of the medium- and low-skilled labor force. According to relevant research, with the development of the digital economy, the effect of the digital divide is more obvious, shown in the phenomenon of “anti-urbanization”, reducing the effectiveness of the digital economy to help rural residents to start a business, with the income gap of urban and rural residents becoming larger [59]. Moreover, as the 2021 Monitoring and Survey Report on Migrant Workers shows, among all migrant workers, people with literacy in high school and below account for 87.5% [60]. Therefore, it is necessary to guide rural residents migrating across provinces and cities, who consist of a higher proportion of the medium- and low-skilled labor force, to start businesses in an active and efficient way.

Table 6. Mechanisms.

Variables	$\mathbf{Entreh_{itl}}$	$\mathbf{Entreh_{ith}}$	$\mathbf{Techni_{itl}}$	$\mathbf{Techni_{ith}}$
	(1)	**(2)**	**(3)**	**(4)**
D	0.0401 ***	0.0232 **	0.0029 ***	0.0157 ***
	(0.0129)	(0.0109)	(0.0011)	(0.0053)
Control variables	Control	Control	Control	Control
Year/City fixed effects	Yes	Yes	Yes	Yes
R^2	0.1576	0.1078	0.0410	0.0297
N	1560	1560	1560	1560

This article continues to analyze the impact of the digital economy on the proportion of professional and technical personnel. Based on the 2022 industrial classification for national economic activities, this paper classified technology industries, providing scientific and technical services, information transmission, software and information technology services, and professional equipment manufacturing. According to the previous data processing standards, the explained variable $Techni_{itl}$ is the proportion of professional and technical personnel in the medium- and low-skilled labor force in city i in year t, which is also the proportion of medium- and low-skilled professional and technical personnel in that year in the employment status of all of the medium- and low-skilled labor force. The explained variable $Techni_{ith}$ is the proportion of professional and technical personnel in the high-skilled labor force in city i in year t, which is also the proportion of high-skilled professional and technical personnel in that year in the employment status of all high-skilled labor force. The core explanatory variable D remains unchanged. $unemployment_{itl}$ and $unemployment_{ith}$ represent the unemployment rates of the medium- and low-skilled and high-skilled labor force in city i in year t, respectively. Other control variables remain unchanged. The year fixed effect is μ_t, the city fixed effect is θ_i, and ε_{it} is the stochastic disturbance term. We used the same regression method as that in the model (1). The regression results are shown in columns (3) and (4) of Table 6. The core interpretation variable’s estimated coefficient was significantly positive at the significance level of 1%, further indicating that the “Broadband China” strategy led to an increase in the proportion of professional and technical staff of the medium- and low-skilled and high-skilled labor force. Moreover, the implementation of the “Broadband China” strategy significantly increased the proportion of high-skilled labor force in the technology industry at a faster rate compared with the medium- and low-skilled labor force. The higher salary in the technology industry should be the main reason for the faster labor income growth of the high-skilled labor force compared with the medium- and low-skilled labor force. In summary, the “Broadband China” strategy has led to an increase in labor income levels through measures such as increasing the proportion of entrepreneurship and promoting the growth of the proportion of technical industry personnel. Due to the human capital accumulation, the entrepreneurial efficiency of the high-skilled labor force is higher than that of medium- and low-skilled labor force, and the growth rate of professional and technical personnel in the high-skilled labor force is greater than that in the medium- and low-skilled labor force. The above empirical results of the mechanism verify H3 in the paper.

5. Conclusions and Implications

5.1. Conclusions

Based on panel data from 195 prefectural cities, the "Broadband China" pilot is considered a natural experiment to measure the digital economy. This paper established a time-varying DID model to assess the impact of "Broadband China" on the income growth. As the results show, the "Broadband China" strategy drives the overall growth in labor income levels. After endogenous testing of tool variable method and multiple robustness tests, this result is still true. Further research found that the "Broadband China" strategy has increased the income level of high-skilled labor force more, thus widening the income gap between the high-skilled and medium- and low-skilled labor force. From the perspective of mechanism analysis, the "Broadband China" strategy mainly drives the overall labor income growth by increasing the entrepreneurship rate and leading to an increase in the overall number of professional and skilled labor force in China. In this case, the entrepreneurship rate of highly skilled labor force may be higher than that of medium- and low-skilled labor force due to the human capital accumulation. The rapid increase in high-skilled labor force in technical industries will lead to the situation where their income growth effect is higher than that of the medium- and low-skilled labor force.

5.2. Policy Implications

The findings of this paper have the following policy implications:

(1) The relevant departments should further promote the process of network infrastructure construction and further intensify the implementation of the "Broadband China" strategy through rational planning of the process so that more laborers can enjoy the dividends brought by the digital economy. Developed countries have long used the information technology revolution to promote the economic growth with superb technical advantages. Developing countries should seize the opportunities brought by the digital revolution to actively promote the economic development, guide more workers to improve their income levels with the aid of the digital economy, and eventually achieve sustainable development in developing countries. By rationally planning the process of the "Broadband China" strategy, we will make further steps to strengthen its implementation.

(2) Efforts shall be intensified to improve the institutional environment, accelerate the introduction of relevant laws and regulations, clarify the legal status of broadband networks as national public infrastructure, and strengthen the protection of broadband network facilities. We should protect personal information in accordance with the law, create a safe and trustworthy network environment, promote the development of broadband applications, and standardize the construction order. In accordance with the Urban and Rural Planning Law; the Land Management Law and the Urban Communications Engineering Planning Code; and other laws, regulations, and norms, broadband network construction will be incorporated into urban and rural planning and overall land use planning in various places. Attention shall also be paid to effectively implement the engineering design, construction, and acceptance specifications for broadband network facilities in residential neighborhoods and residential buildings. The broadband network shall be well connected with the planning and construction of highways, railroads, airports, and other transportation facilities.

(3) We will go a step further to encourage the entrepreneurial enthusiasm of the labor force, pay attention to skill bias, and optimize the employment structure. We should cultivate an innovative and risk-taking labor force and improve the human capital accumulation of the medium- and low-skilled labor force through multiple channels to enhance their entrepreneurial efficiency. At the same time, in the face of the individual skills gap in the context of digital development, the medium- and low-skilled

labor force should actively participate in the training of big-data-related skills and continuously improve their ability and quality through "learning by doing", as well as gradually extending their education. Relevant departments should increase the proportion of financial education investment, gradually popularize and introduce information technology into the basic education system, expand the scope of information database application, and take effective measures to further increase the income of medium- and low-skilled labor force. For high-skilled talent, a good working and R&D environment should be created, and fairness and efficiency should be paid equal attention.

5.3. Limitations and Future Research Directions

Two limitations of this paper are presented. On the one hand, due to objective reasons, the data in this study cannot be updated in a timely manner. The CMDS is the data of the large-scale annual nationwide mobile population sample survey conducted by the National Health and Health Commission since 2009, and the most recent data update was in 2018. Therefore, the time horizon of the panel data sample in this paper is from 2011 to 2018. This will lead to the fact that recently developed research results cannot be fully applied in the research process and should be gradually supplemented and optimized in the future. On the other hand, the technical means based on the information platforms and investigations are restricted, so the information collected is not perfect enough, and the data need to be further enriched. In the future, empirical research will be further strengthened. Based on more abundant and novel sample data, we will further verify and predict the influencing factors of labor income and the internal theoretical mechanism through exploratory research. Therefore, we will put forward the countermeasures to improve the labor income level and optimize the ways for narrowing the gap among the high-, medium-, and low-skilled labor force. Meanwhile, the multi-disciplinary members are absorbed into the research process, and the multi-disciplinary discussion and multi-angle analysis help to strengthen the ability of problem solving.

Author Contributions: Conceptualization, D.K.; data curation, D.K.; formal analysis, D.K. and J.L.; investigation, D.K. and J.L.; methodology, D.K. and J.L.; resources, D.K. and J.L.; software, D.K. and Z.J.; validation, D.K. and Z.J.; writing—original draft, D.K. and J.L.; writing—review and editing, D.K. and Z.J. All authors have read and agreed to the published version of the manuscript.

Funding: This article was funded by the Humanities and Social Sciences Research Project of Ministry of Education: Research on the Influences of Labor Force Polarization on Technological Innovation in China (No: 18YJC790037) and the Project of National Social Science Fund of China: Research on Boosting High-quality Economic Growth by Correcting Misallocation of Human Capital (No: 18BJL025).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the research data subjects.

Acknowledgments: The authors are grateful to the editor and anonymous reviewers for their insightful and helpful comments.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Eva, M.; Popescu, M.E.; Cristescu, A.; Vasilescu, M.D. Assessing minimum wage policy implications upon income inequalities. The case of romania. *Sustainability* **2019**, *11*, 2542. [CrossRef]
2. Le, T.-H.; Nguyen, C.P.; Su, T.D.; Tran-Nam, B. The Kuznets curve for export diversification and income inequality: Evidence from a global sample. *Econ. Anal. Policy* **2019**, *65*, 21–39. [CrossRef]
3. Cong, B.T.; Van, T.Q. The Impacts of Spatial Interaction on Agricultural Productivity and Average Income: A Case of Vietnam. *J. La Soc.* **2021**, *2*, 12–20. [CrossRef]
4. Ravallion, M. Income inequality in the developing world. *Science* **2014**, *344*, 851–855. [CrossRef]

5. Sungmun, C. Is the Current Trend of Income Inequality Sustainable? *Sustainability* **2019**, *11*, 5329. [CrossRef]
6. Balcerzak, P.A.; Pietrzak, B.M. Digital Economy in Visegrad Countries. Multiple-criteria Decision Analysis at Regional Level in The Years 2012 and 2015. *J. Compet.* **2017**, *9*, 5–18. [CrossRef]
7. Harb, G. The economic impact of the Internet penetration rate and telecom investments in Arab and Middle Eastern countries. *Econ. Anal. Policy* **2017**, *56*, 148–162. [CrossRef]
8. Ali, M.A.; Alam, K.; Taylor, B.; Rafiq, S. Does ICT maturity catalyse economic development? Evidence from a panel data estimation approach in OECD countries. *Econ. Anal. Policy* **2020**, *68*, 163–174. [CrossRef] [PubMed]
9. Li, H.; Yang, S.G. The Road to Common Prosperity: Can the Digital Countryside Construction Increase Household Income? *Sustainability* **2023**, *15*, 4020. [CrossRef]
10. CAOC. Digital China Development Report 2022. Available online: http://www.cac.gov.cn/2023-05/22/c_1686402318492248.htm?eqid=e964285800089bd400000004646d59f6 (accessed on 23 May 2023).
11. Xue, C.; Meng, Q.X.; He, X.J. Network Infrastructure and the Diffusion of Technological Knowledge: Evidence from a Quasi-natural Experiment. *J. Financ. Econ.* **2020**, *46*, 48–62. [CrossRef]
12. Central Government of the People's Republic of China. The State Council on the issuance of the "Broadband China" Strategy and Notice of Implementation Plan. Available online: https://www.gov.cn/zwgk/2013-08/17/content_2468348.htm (accessed on 17 August 2013).
13. Central Government of the People's Republic of China. Communications Industry Statistical Bulletin 2022. Available online: https://www.gov.cn/xinwen/2023-02/02/content_5739680.htm?eqid=f1980c9900002b9b000000056459bf36 (accessed on 2 February 2023).
14. Govindan, P. The Digital Divide and Increasing Returns: Contradictions of Informational Capitalism. *Inf. Soc.* **2007**, *21*, 41–51. [CrossRef]
15. Dimaggio, P.; Bonikowski, B. Make Money Surfing the Web? The Impact of Internet Use on the Earnings of U.S. Workers. *Am. Sociol. Rev.* **2008**, *73*, 227–250. [CrossRef]
16. Cheng, M.W.; Zhang, J.P. Internet Popularization and Urban-rural Income Gap: A Theoretical and Empirical Analysis. *Chin. Rural. Econ.* **2019**, *2*, 19–41. Available online: https://kns.cnki.net/kcms2/article/abstract?v=3uoqIhG8C44YLTlOAiTRKibYlV5Vjs7iLik5jEcCI09uHa3oBxtWoMrudmJ7cUEQLiUkGOH-UH4Ap9z4Vt8jE_rkIa8kc7PK&uniplatform=NZKPT&src=copy (accessed on 23 July 2023).
17. Dutta, P.V. Trade Protection and Industry Wages in India. *ILR Rev.* **2007**, *60*, 268–286. [CrossRef]
18. Lu, D.X.; Cai, W.G. Effective Factor Endowments, Trade Openness and Income Distribution in China. *Front. Econ. China* **2011**, *6*, 188–210. [CrossRef]
19. Truong, C.B. The nexus between spatial structure and labour income: Evidence from Vietnam. *Reg. Stud. Reg. Sci.* **2023**, *10*, 294–311. [CrossRef]
20. Leuven, E.; Oosterbeek, H. Overeducation and Mismatch in the Labor Market. *Handb. Econ. Educ.* **2011**, *4*, 283–326. [CrossRef]
21. Javier, S. The employment and wage effects of import competition in Switzerland. *Int. J. Manpow.* **1998**, *19*, 438–448. [CrossRef]
22. Yang, Y.; Jiang, W.H.; Zhang, W.F. Can Ageing of Population, Biased Technology Progress Reduce the Labor Income Share in China: Theoretical and Empirical Analysis Based on Provincial Panel of China. *Econ. Probl.* **2018**, *6*, 6–13. [CrossRef]
23. Loukas, K.; Brent, N.M. The Global Decline of the Labor Share. *Q. J. Econ.* **2014**, *129*, 61–103. [CrossRef]
24. Qing, M.; Qi, Y. Research on Income Distribution Effect of Environmental Regulation. Economics and management studies. *Res. Econ. Manag.* **2019**, *40*, 70–81. [CrossRef]
25. Park, K.H. Educational expansion and educational inequality on income distribution. *Econ. Educ. Rev.* **1996**, *15*, 51–58. [CrossRef]
26. Ma, S.Z.; Wu, P.; Pan, G.J. Internet Use, Consumer Service Industry Expansion and Labor Income Differentiation. *Econ. Dyn.* **2022**, *2*, 68–84. Available online: https://kns.cnki.net/kcms2/article/abstract?v=3uoqIhG8C44YLTlOAiTRKibYlV5Vjs7iJTKGjg9uTdeTsOI_ra5_Xa5LQr3cFVxvyEvySg2NQzYdB6Ky77USoKKSpxRggmEx&uniplatform=NZKPT&src=copy (accessed on 23 July 2023).
27. Abdul, J. Modeling income inequality and openness in the framework of Kuznets curve: New evidence from China. *Econ. Model.* **2012**, *29*, 309–315. [CrossRef]
28. Afesorgbor, S.K.; Mahadevan, R. The Impact of Economic Sanctions on Income Inequality of Target States. *World Dev.* **2016**, *83*, 1–11. [CrossRef]
29. Murakami, Y. Trade liberalization and wage inequality: Evidence from Chile. *J. Int. Trade Econ. Dev.* **2021**, *30*, 407–438. [CrossRef]
30. Rolim, L.N.; Baltar, C.T.; Lima, G.T. Income distribution, productivity growth, and workers' bargaining power in an agent-based macroeconomic model. *J. Evol. Econ.* **2023**, *33*, 473–516. [CrossRef]
31. Antonelli, C.; Tubiana, M. The rate and direction of technological change and wealth and income inequalities in advanced countries. *Technol. Forecast. Soc. Chang.* **2023**, *191*, 122508. [CrossRef]
32. Tang, G.J.; Yan, D.Y.; Feng, S.Z. A Path Towards Common Prosperity: The Effect of Redistribution Policies on Income Distribution. *Econ. Res. J.* **2023**, *58*, 23–39. Available online: https://kns.cnki.net/kcms2/article/abstract?v=3uoqIhG8C44YLTlOAiTRKibYlV5Vjs7ioT0BO4yQ4m_mOgeS2ml3UH49Bw-lXUbWf0WkJYP8sVOMgk4vJn11lVAoAsn0d73g&uniplatform=NZKPT&src=copy (accessed on 23 July 2023).
33. Qiu, L.J.; Zhong, S.B.; Sun, B.W. Blessing or curse? The effect of broadband Internet on China's inter-city income inequality. *Econ. Anal. Policy* **2021**, *72*, 626–650. [CrossRef]

34. Madon, S. The Internet and socio-economic development: Exploring the interaction. *Inf. Technol. People* **2000**, *13*, 85–101. [CrossRef]
35. Litan, R.E.; Rivlin, A.M. Projecting the Economic Impact of the Internet. *Am. Econ. Rev.* **2001**, *91*, 313–317. [CrossRef]
36. Brown, C.; Campbell, B.A. The Impact of Technological Change on Work and Wages. *Ind. Relat.* **2002**, *41*, 1–33. [CrossRef]
37. Xiao, T.S.; Sun, R.Q.; Yuan, C.; Sun, J. Digital transformation, human capital restructuring and labor income share in enterprises. *J. Manag. World* **2022**, *38*, 220–237.
38. Liu, C.H. The impact of digital economy on industrial structure upgrading and entrepreneurship growth. *Chin. J. Popul. Sci.* **2022**, *2*, 112–128. Available online: https://kns.cnki.net/kcms2/article/abstract?v=3uoqIhG8C44YLTlOAiTRKibYlV5Vjs7iJTKGjg9uTdeTsOI_ra5_XRx8dQl7G4l6EXvk6wYP1nH6bM6j4UI0DXD0Qqeri3Iv&uniplatform=NZKPT&src=copy (accessed on 23 July 2023).
39. Zhang, X.; Wan, G.H.; Zhang, J.J.; He, Z.Y. Digital Economy, Financial Inclusion, and Inclusive Growth. *Econ. Res. J.* **2019**, *8*, 71–86. Available online: https://kns.cnki.net/kcms2/article/abstract?v=3uoqIhG8C44YLTlOAiTRKibYlV5Vjs7iLik5jEcCI09uHa3oBxtWoHGwy9XepWzLFTF3B_FHQzTBVrZfn3j1RYNNBDsw-g9k&uniplatform=NZKPT&src=copy (accessed on 23 July 2023).
40. Zhao, T.; Zhang, Z.; Liang, S.K. Digital Economy, Entrepreneurial Activity and High Quality Development-Empirical Evidence from Chinese Cities. *J. Manag. World* **2020**, *36*, 65–76. [CrossRef]
41. Liu, G.; Zhang, L.R.; Liang, H.; Wang, Z.Y. A study on information sharing mechanism of Internet entrepreneurship—A two-stage model integrating online crowdfunding and social data. *J. Manag. World* **2021**, *37*, 107–125. [CrossRef]
42. Peng, K.Q.; Liu, X.L. Farmers' income growth, formal credit availability and off-farm entrepreneurship. *J. Manag. World* mboxtextbf2016, *7*, 88–97. [CrossRef]
43. Yang, W.M.; Su, L.; Wang, M.W. Digital Financial Inclusion and Income of Urban and Rural Residents: Based on the Intermediary Effect of Economic Growth and Entrepreneurial Behavior. *J. Shanghai Univ. Financ. Econ.* **2020**, *22*, 83–94. [CrossRef]
44. Hua, Y.; Zhang, H.Y. Internet Penetration and Income Inequality: Evidence from the Chinese Young Labor Market. *Appl. Econ.* **2022**, 1–15. [CrossRef]
45. Wang, L.H.; Hu, S.M.; Dong, Z.Q. Does Artificial Intelligence Technology Induce Labor Income Inequality—A Model Inference and Classification Assessment. *China Ind. Econ.* **2020**, *4*, 97–115. [CrossRef]
46. Pissarides, C.A. Learning by Trading and the Returns to Human Capital in Developing Countries. *World Bank Econ. Rev.* **1997**, *11*, 17–32. [CrossRef]
47. Acemoglu, D. Patterns of skill premia. *Rev. Econ. Stud.* **2003**, *70*, 199–230. [CrossRef]
48. Sun, Y.P.; Xu, Y.B. A study on the impact of Internet penetration on income distribution in China—An empirical analysis based on CFPS data. *Macroeconomics* **2021**, *7*, 161–175. [CrossRef]
49. Autor, D.H.; Levy, F.; Murnane, R.J. The Skill Content of Recent Technological Change: An Empirical Exploration. *Q. J. Econ.* **2003**, *118*, 1279–1333. [CrossRef]
50. Maarten, G.; Manning, A.; Salomons, A. Job Polarization in Europe. *Am. Econ. Rev.* **2009**, *99*, 58–63. [CrossRef]
51. Lu, J.L. Capital Accumulation and Skill Premium: Evidence from China. *China Econ. Q.* **2017**, *16*, 577–598. [CrossRef]
52. Beck, T.; Levine, R.; Levkov, A. Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States. *J. Finance* **2010**, *65*, 1637–1667. [CrossRef]
53. Card, D.; Krueger, A.B. Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania: Reply. *Am. Econ. Rev.* **2000**, *90*, 1397–1420. [CrossRef]
54. Liu, C.M.; Ma, Q.S. Study on the Impact of Network Infrastructure Construction on Total Factor Productivity Growth: A Quasi-Natural Experiment Based on the "Broadband China" Pilot Policy. *Chin. J. Popul. Sci.* **2020**, *3*, 75–128. Available online: https://kns.cnki.net/kcms2/article/abstract?v=3uoqIhG8C44YLTlOAiTRKibYlV5Vjs7i8oRR1PAr7RxjuAJk4dHXoqmsJ0NR0BTUPX6p0OhhYlR0XedZy38Hq8why09YBEyW&uniplatform=NZKPT&src=copy (accessed on 23 July 2023).
55. Nunn, N.; Qian, N. US Food Aid and Civil Conflict. *Am. Econ. Rev.* **2014**, *104*, 1630–1666. [CrossRef]
56. Angrist, J.D.; Krueger, A.B. Does compulsory school attendance affect schooling and earnings? *Q. J. Econ.* **1991**, *106*, 979–1014. [CrossRef]
57. Lee, C.-Y. The differential effects of public R&D support on firm R&D: Theory and evidence from multi-country data. *Technovation* **2011**, *31*, 256–269. [CrossRef]
58. Chang, G.H. The cause and cure of China's widening income disparity. *China Econ. Rev.* **2002**, *13*, 335–340. [CrossRef]
59. Chen, W.; Wu, Y. Digital Economy's Development, Digital Divide and the Income Gap Between Urban and Rural Residents. *South China J. Econ.* **2021**, *11*, 1–18. [CrossRef]
60. Central Government of the People's Republic of China. 2021 Migrant Worker Monitoring Survey Report. Available online: https://www.gov.cn/xinwen/2022-04/29/content_5688043.htm (accessed on 29 April 2022).