# Can Broadband Internet Infrastructure Narrow the Income Inequality? An Analysis of the Effects of Broadband China Strategic Program

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**Abstract**
This study investigates the impact of enhanced internet infrastructure on intra-city income inequality within a developing context, amid the rollout of the Broadband China program from 2014 to 2016. Using a staggered difference-in-differences methodology, our analysis demonstrates that the significant increase in internet penetration induced by the program leads to a notable reduction in the income Gini coefficient of 0.037 (control mean: 0.458, standard deviation: 0.061). This decrease in income inequality is primarily driven by substantial income gains among low-income and middle-income households. We highlight that improved internet infrastructure fosters social equity by creating new employment opportunities for low-skilled workers, most of whom are from low- and middle-income households, particularly in the service sector. These findings underscore the critical role of technology in promoting inclusive economic growth and provide valuable guidance for policymakers aiming to leverage internet infrastructure investments to enhance social equity in developing countries.

Key words: Broadband Internet, Gini index, income inequality, low-skilled worker, low-income households
JEL Codes: D63; J38; L86; O53; R23; R28

**Introduction**
There has been extensive discussion on the benefits and harms of the ubiquitous internet. One strand of literature highlights that the advent of the internet has ushered in a new era of economic development and social transformation. It plays a crucial role in shaping economic development and institutions at the national level (Czernich, Falck, Kretschmer, & Woessmann, 2011; Gruber, Hätönen, & Koutroumpis, 2014; La Ferrara, 2016). At the micro level, the internet has brought considerable benefits to companies, households, and individuals, such as improved business performance and employee productivity (Mack & Faggian, 2013), and increased household income (Ariansyah, 2018; Atasoy, 2013). However, another strand of literature highlights potential welfare losses, such as political polarization (Levy, 2021) and the exacerbated inequalities (Goldfarb & Tucker, 2019).

As the internet transforms the ways in which people work, many researchers have focused on its impact on the labor market. Current studies present controversial results regarding the internet's effects on labor outcomes. Some research highlights the "skill bias" created by broadband internet adoption, where it complements skilled workers while substituting low-skilled workers, thereby widening the wage gap (Akerman, Gaarder, & Mogstad, 2015). However, as Acemoglu (2002) points out, for skilled workers, if replacing them with new technology is more profitable for the market, such technologies will attempt to replace skilled workers as well. In other words, technological development does not necessarily always impact one particular skill group, rather, its impact on the labor market depends on its relative profitability in replacing different skill groups. In fact, a recent study by Jin, Ma, and Zhang (2023), shows that the internet enhances employment quality for the low-skilled workers in China.

The extant literature shows that the impact of the Internet on the labor market is complex and varies across different contexts, potentially leading to either an increase or decrease in income inequality, and ultimately, asset inequality. On the one hand, ongoing discussions about the relationship between Internet expansion and labor income highlight how technological advancements can exacerbate wage disparities among workers (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019; Kogan, Papanikolaou, Schmidt, & Seegmiller, 2023; Kogan, Papanikolaou, Schmidt, & Song, 2020). On the other hand, a number of empirical studies show that the internet facilitates poverty alleviation by lowering barriers to information. In particular, e-commerce, together with the rise of the Internet effectively link the rural residents to the market, thereby narrowing the rural-urban income gap (Kenny, 2002; Qin & Fang, 2022). Although there is a substantial body of literature examining the Internet's effects from multiple perspectives, research specifically addressing its impact on intra-region inequality is still sparse. One close study in recent years found that between 2010 and 2016, higher Internet penetration rates were associated with increased consumption inequality in Chinese counties (Zhang, Li, & Xiao, 2020). However, the impact of the internet on income inequality is less examined, and it remains unclear whether it can ultimately alter the pattern of inequality in China or how it might do so.

This study aims to fill the existing research gap by providing the first empirical evidence on the impact of improved internet infrastructure on income distribution inequality in a developing context. We utilize data from the China Family Panel Studies (CFPS) and the China City Statistical Yearbook during the staggered implementation of the Broadband China Strategic Program from 2014 to 2016. This program serves as a natural experiment, marked by strong government support for upgrading regional internet infrastructure. Our findings indicate that enhanced internet infrastructure led to a statistically significant reduction in intra-city income inequality, as measured by a 0.037-point decrease in the Gini index (with a control mean of 0.458 and a standard deviation of 0.061). Moreover, we find that improved internet infrastructure boosts both household net income and labor income. The simultaneous increase in household income and reduction in city-level income inequality is due to income gains being concentrated among low- and middle-income households, while high-income families experience significantly smaller income increases. Consequently, the income gap is effectively narrowed. Additionally, we discover that the expansion of broadband internet access reduces income inequality through its effects on the labor market structure. Specifically, improved internet infrastructure supports the growth of the platform economy, creating new opportunities for low-skilled workers in sectors such as logistics and retail.

This study contributes to the existing literature in several ways. First, it addresses a critical gap in understanding the relationship between internet access and inequality. This paper uses Broadband China Strategic Program as a natural experiment to overcome endogeneity issues and provides novel evidence of its potential to reduce income disparities within cities. Second, by focusing on the Broadband China Strategic Program, this study offers valuable insights for policymakers seeking to leverage technological investments to promote inclusive growth. Our findings suggest that cities' efforts, such as targeted investments in broadband infrastructure, and the extra support from upper-level governments can effectively improve internet penetration rates, thereby reducing income inequality. This evidence supports the idea that digital inclusion policies can play a crucial role in ensuring that the benefits of technological progress are shared more equitably across society. Last, our analysis sheds light on the potential mechanisms through which better internet infrastructure can influence income distribution. By facilitating the growth of the digital economy and creating new employment opportunities for low-skilled workers, who are often from a low-income household, the upgraded internet infrastructure can empower historically disadvantaged groups and contribute to a more inclusive labor market.

**Institutional background**

Broadband Internet stands as one of the pivotal information and communication technologies, propelling a telecommunications market scale of approximately 100 billion in China. China initiated its access to broadband internet in 1994 and improved the coverage continuously, but the issues of insufficient network coverage and slow network speed still exist by the 2010s. Hence, in 2013, the Chinese State Council initiated the "Broadband China Strategic Program" (Broadband China hereinafter) to achieve China's future broadband internet development goals, given the increasingly important roles of ICT infrastructures in national development. Specifically, the program greatly emphasized expanding and optimizing broadband network coverage and scale, facilitating Internet access and enhancing user experiences. In detail, it aims to improve Internet penetration in various forms, including fixed Broadband and higher-speed third-generation Internet in urban and rural areas, and also to reduce the costs of Internet users[1].

[1] https://www.gov.cn/zwgk/2013-08/17/content_2468348.htm

Following the announcement of the Broadband China Strategic Program by the State Council, the initiative was subsequently assigned to the Ministry of Industry and Information Technology (MIIT), which developed detailed implementation plans. MIIT established an incentivization framework through the creation of "Broadband Demonstration Cities," which are expected to excel in ICT development and serve as regional leaders in this domain. Upon receiving the designation of Broadband China Demonstration City, these cities are tasked with achieving specific performance targets[2]. To facilitate this process, demonstration cities typically allocate dedicated funds for ICT development. Additionally, provincial governments offer various forms of support—both financial and technical—to assist these cities in effectively meeting their objectives[3]. The designation of these cities also attracts extra attention from both provincial and central governments. For example, demonstration cities are prioritized for new ICT technological support and project funding, in order to enhance their capacity to implement the program successfully and effectively. In other words, broadband demonstration cities received two types of treatments: the first is the effort for ICT upgrading from local government, and the second is the extra attention and benefits from upper level government agencies. The main policy implementation procedure is shown in Figure 1[4].

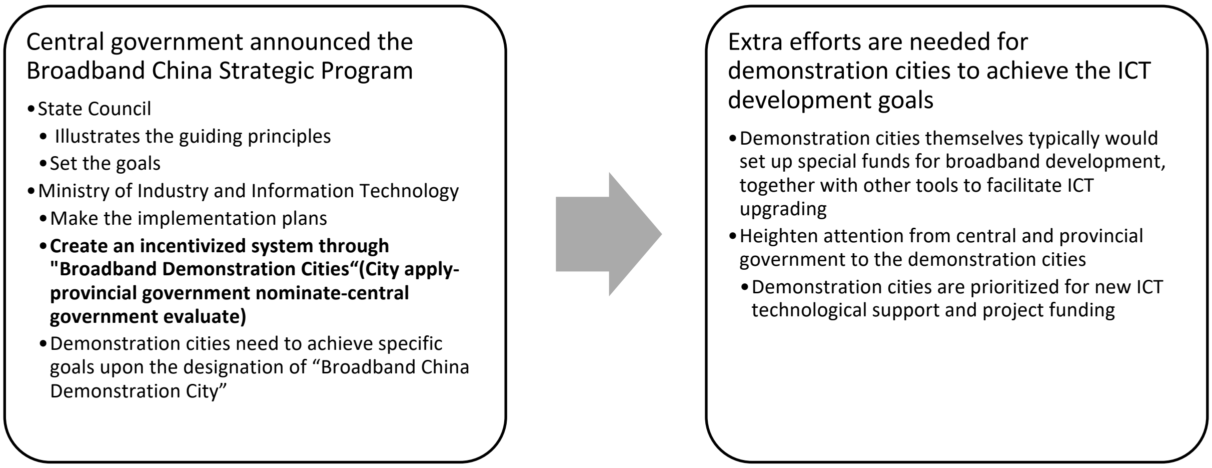



*Figure 1 Broadband China Strategic Program: A framework*

From 2014 to 2016, 113 cities and several other autonomous regions across China were designated as “Broadband Demonstration City”[5]. Specifically, in 2014, 36 cities, 2 autonomous regions, and 1 city cluster (composed of 3 cities) introduced the program and started strengthening the construction of fiber-optic and 3G networks to increase broadband network access speeds. In 2015, 37 cities and 2 districts of Chongqing municipality officially announced the introduction of the Broadband China program. In 2016, the Broadband China program was introduced to 36 cities, the other 2 districts of Chongqing municipality, and one autonomous prefecture. Demonstration cities receive financial and technology support from the local government in improving digital infrastructures and act as a role model for regular cities to learn about their development patterns. Descriptive evidence has shown that in demonstration cities the broadband infrastructure is improved and penetration rates are increased by the way of piloting in batches (Luo et al., 2022). By 2015, it reached 270 million households, with 65 percent of urban and 30 percent of rural residents, and the broadband access capacity achieved 20 Mbps in urban regions and 4 Mbps in rural regions. Using internet penetration rate as a proxy for the level of internet development, we find that there is an increasing trend in internet penetration rates since 2010, as shown in Figure 1[6]. We also show that, at

[2] https://www.gov.cn/gzdt/2014-01/16/content_2568722.htm

[3] For example, Qinghai Province set a 20 million funding specialized for broadband development following the announcement of BB. https://www.gov.cn/xinwen/2014-09/04/content_2745101.htm

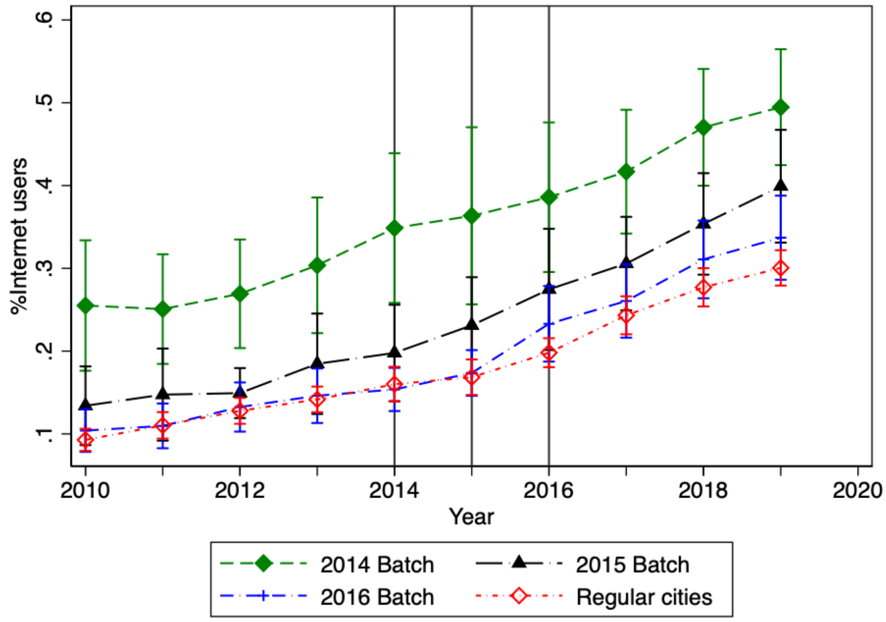
[4] Cities which can apply are prefecture-level and above cities, districts and counties under municipalities directly under the central government, counties directly administered by provinces, and city clusters that have been officially approved by the central or provincial government.

[5] We define “city" based on the Code for the Administrative Division of People's Republic of China. In this study, “city” refers to prefecture level administrative region.

[6] This figure is motivated by the descriptive evidence in Jin et al. (2023), but uses a different measure for internet

an aggregate level, introducing the Broadband China program in the treated cities leads to a significant increase in the share of internet users by around 4%, compared to the control cities, with no pre-trend found in internet penetration rates[7].

*Figure 2 Internet penetration rates: Broadband cities v.s. Regular cities*




*Note: Data are sourced from the China City Statistical Yearbook. The internet penetration rate is defined as the proportion of broadband internet users relative to the city's registered population. Confidence level is set at 95%.*

**Data and measurement**

**City data**

We integrate city-level data from two major sources: China City Statistical Yearbook and the formal policy document about the Broadband China program. We retrieve data from the policy document on the initial dates of the cities becoming Broadband China demonstration cities and establish a city list with the "first treated" timing. Then, we use the rich information from China City Statistical Yearbook to get statistics on the cities' socioeconomic conditions, including GDP, population, government investment in education and science, etc. To measure how complete the city's digital infrastructure is, we use internet penetration rate as a proxy, which is defined by the share of internet users among the average population of the city across a year. We construct an unbalanced panel dataset of 300 cities across China, with 110 cities in the treatment groups and the rest 190 cities in the control group from 2010 to 2019. Table A2 shows the summary statistics of all cities.

**Gini index and household level data**

To construct within-city inequality Gini index, we use the household dataset from CFPS. CFPS was launched by Peking University in 2010, and it is a nationally representative, biennial longitudinal general social survey project designed to document changes in Chinese society, economy, population, education, and health (Xie & Hu, 2014). We use five waves of CFPS adult database conducted in 2010, 2012, 2014-2015, 2016-2017, and 2018-2019. In our study, we are interested in the within-city inequality of the distribution of income,

penetration rate.

[7] We document cities' internet penetration rates in response to the program by the following model, using all city observations from the China City Statistical Yearbook: $y_{ct} = \alpha + \beta_1 BB_{ct} + \beta_2 y_{ct-1} + \gamma_c + \lambda_t + \varepsilon_{ct}$. See Appendix Table A3 and Figure A2.

asset, expense, and consumption. Inequality is measured by the Gini index[8] (Gini, 1921; Jenkins, 2024). The detailed description of variable construction is in Table A1 in Appendix. Table 1 presents the summary statistics of the CFPS city sample and household sample used in this study[9].

*Table 1 Summary statistics*

| | N | Mean | SD | Max | Min |
|---|---|---|---|---|---|
| ***Panel A: CFPS city Gini*** | | | | | |
| Gini: net income per capita | 577 | .444 | 0.068 | 0.641 | 0.243 |
| Gini: asset per capita | 577 | .515 | 0.077 | 0.793 | 0.293 |
| ***Panel B: CFPS household statistics*** | | | | | |
| Net family income per capita (yuan) | 61118 | 13582.260 | 14981.01 | 85000 | 0 |
| Total operational income per capita (yuan) | 61118 | 1006.713 | 2243.343 | 13714.29 | 0 |
| Labor income per capita (yuan) | 61118 | 9035.995 | 12287.08 | 70000 | 0 |
| Other income per capita (yuan) | 61118 | 3333.940 | 7315.032 | 40200 | 0 |
| Asset per capita (yuan) | 57970 | 143000 | 276000 | 1818240 | 0 |
| Urban area | 61118 | 0.478 | 0.500 | 1 | 0 |
| Family size | 61118 | 3.795 | 1.820 | 26 | 1 |

*Note: This table presents summary statistics for the key variables of interest in this study. The Gini indices are calculated using the China Family Panel Studies (CFPS) household database for the years 2010 to 2018. To mitigate the influence of outliers, direct measures of household income and assets in the CFPS database are winsorized at the 0th and 99th percentiles. Figure A1 compares the Gini index derived from the CFPS household data with the official Gini coefficients for disposable income reported by the National Bureau of Statistics for the corresponding survey years. While the Gini index for net income per capita from the CFPS database is higher than that for disposable income per capita reported by the National Bureau of Statistics, it exhibits a similar trend to the official records. This supports the validity of using the CFPS-based Gini index in this study.*

**Empirical strategy**

We estimate the intention-to-treat effects of better internet infrastructure brought by the Broadband China Strategic Program on intra-city income inequality through equation (1)[10]:

$$y_{ct} = \alpha + \beta_1 BB_{ct} + \boldsymbol{X_{ct}}'\beta_2 + \gamma_c + \lambda_t + \varepsilon_{ct} \text{ (1)}$$

[8] Gini index calculation in Jenkins 2024: $Gini = 1 + \frac{1}{N} - \frac{2}{m \times N^2} \sum_{i=1}^{N} (N - i + 1) y_i$ where N is the total number of observations, m is the mean of the outcome of interest (e.g., income). $y_i$ is the i-th observation of the outcome of interest sorted in the ascending order.

[9] Household controls are in Table A2.

[10] For household level analysis, we estimate the following two equations to obtain the intention-to-treat effects and dynamic effects of better internet infrastructure on household outcomes:

$$y_{hct} = \alpha + \beta_1 BB_{ct} + \boldsymbol{X_{hct}}'\beta_2 + \gamma_h + \lambda_t + \varepsilon_{hct} \text{ (1)}$$

$$y_{hct} = \alpha + \sum_n \beta_n BB_{ct}^n + \gamma_h + \omega_t + \boldsymbol{X}'_{hct}\theta + \varepsilon_{hct} \text{ (2)}$$

where $y_{hct}$ is the outcome of household h in city c in survey t, $BB_{ct}$ is a binary variable that indicates whether the Broadband program entered city c where the household resides in survey t or not, $\gamma_c$ and $\lambda_t$ are county and year fixed effects. $X'$ is a set of city-level controls that account for the potential impacts of time-varying county features.

where $y_{ct}$ is Gini index of city c in year t[11]; $BB_{ct}$ is a binary variable that indicates whether city c has been designated as a demonstration city in survey t or not, $\gamma_c$ and $\lambda_t$ are county and survey fixed effects. $X'$ is a set of city-level controls that account for the potential impacts of time-varying county features[12]. $\varepsilon_{ct}$ is error term. $\beta_1$ measures the intention-to-treat effects.

We also estimate the following dynamic TWFE linear regression specification to measure the effect of designated as demonstration cities at different lengths of exposure to the treatment. $BB_{ct}^n$ is a binary variable that indicates whether year t is n (n=-J, ..., J with leads for n<0 and lags for n>0) periods away from the BB introduction. n=0 represents the time when the BB is introduced to the city.

$$y_{ct} = \alpha + \sum_n \beta_n BB_{ct}^n + \gamma_c + \omega_t + \boldsymbol{X'}_{ct}\theta + \varepsilon_{ct} \text{ , (2)}$$

As a common step of testing parallel trend assumption, by estimating the above event study specification (2), we test whether pre-trend exists in the outcomes of interest between the treated and control cities. In other words, in the absence of the BB introduction, the treatment and control groups should evolve similarly in the outcomes[13]. In addition to canonical two-way fixed effects (TWFE) estimators, we also report a robust estimator by Callaway and Sant'Anna (2021) (CSDID hereinafter) to calculate both the treatment effects at an aggregate level and dynamic effects. CSDID estimate allows heterogeneous treatment effects across time and cities. For TWFE estimator, we cluster standard errors at city level. For CSDID estimator, we bootstrap standard error for 999 times to also address the concern of a relatively small amount of observations in our city-level analysis.

## Results

### Effects on inequality

We begin by presenting the estimates of the Broadband China's impact on intra-city inequality. As shown in Table 2, the implementation of the program in the treated cities leads to a significant reduction in income inequality, evidenced by a decrease in the Gini index of approximately 0.037. Figure 3 indicates no pre-existing trend before the policy implementation. Furthermore, Figure 3 reveals that the most significant reduction in income inequality occurs in the survey wave immediately following the program's implementation in the treated cities.

*Table 2 Effects of Broadband China on Gini index*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | TWFE | | CSDID | |
| ***Panel A: Income Gini as outcome*** | | | | |
| ATT | -0.028*** | -0.029*** | -0.029*** | -0.037*** |
| | (0.009) | (0.009) | (0.010) | (0.011) |
| Observations | 577 | 571 | 575 | 569 |
| City FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| City control | NO | YES | NO | YES |
| Control mean | | 0.458 | | |
| Standard deviation | | 0.061 | | |
| ***Panel B: Asset Gini as outcome*** | | | | |
| ATT | -0.017* | -0.019* | -0.016 | -0.010 |
| | (0.010) | (0.010) | (0.011) | (0.012) |
| Observations | 577 | 571 | 575 | 569 |
| City FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |

[11] We focus on income Gini index and asset Gini index.

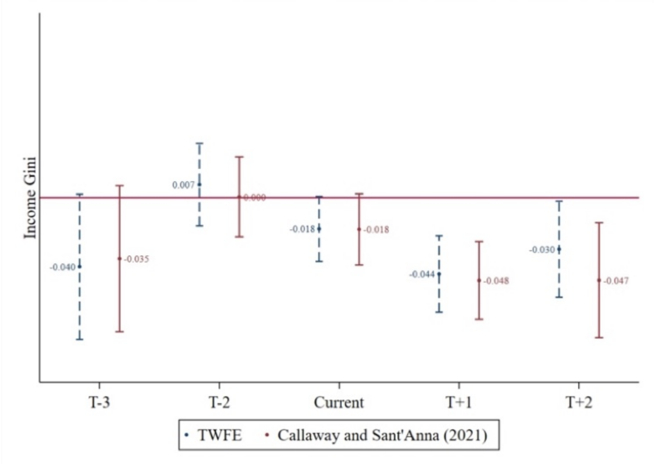
[12] The city controls incorporated in the regression analysis are natural growth rates and population density.

[13] Following Callaway and Sant'Anna (2021), we use a universal base year for pre-treatment periods to illustrate whether pre-trend exists or not.

| | | | | |
|---|---|---|---|---|
| City control | NO | YES | NO | YES |
| Control mean | | 0.519 | | |
| Standard deviation | | 0.077 | | |

*Note: Robust standard errors are in parentheses. Standard errors for TWFE estimators are clustered at city level. Standard errors for CSDID estimators are bootstrapped with 999 repetitions. *** p<0.01, ** p<0.05, * p<0.1.*

*Figure 3 Dynamic effects of Broadband China on income inequality*



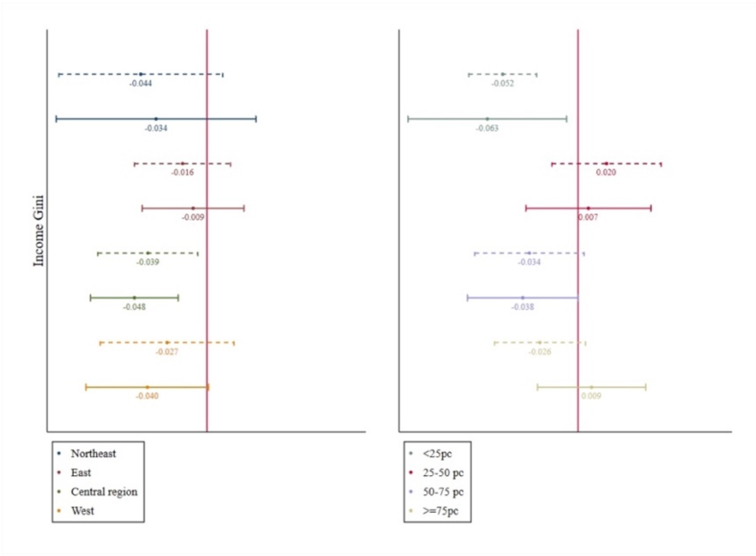

*Note: Confidence level is set at 95%. Standard errors for TWFE estimators are clustered at city level. Standard errors for CSDID estimators are bootstrapped with 999 repetitions.*

To further investigate the heterogeneous treatment effects of the Broadband China Strategic Program, we conduct a regional analysis by categorizing our sample into four geographical regions—Northeast, East, Central, and West—following the classification of the National Bureau of Statistics. Given the program's requirement for applicant cities to possess strong foundational conditions for broadband development, we hypothesize that the program's effects might differ based on pre-existing ICT infrastructure. To test this hypothesis, we divide our city sample into four groups based on their baseline internet penetration rates evenly: the first group is composed of cities whose baseline internet penetration is below the 25 percentile, then 25-50 percentile, 50-75 percentile, and above 75 percentile.

Figure 4 illustrates the results, revealing a reduction in the income Gini coefficient in the central region and among cities with baseline internet penetration rates below the 25th percentile. Notably, there is no evidence of pre-trends (see Figures A3). We can draw two key observations from these findings. First, the overall impact of the program on income inequality is predominantly influenced by developments in Central China. This pronounced effect may be attributed to the region's historical lag in infrastructure and economic development compared to coastal areas(Zheng, Shepherd, & Batuo, 2021), making improvements in internet access particularly significant.

Second, among cities with initial ICT conditions below the 25th percentile for baseline internet penetration, those designated as demonstration cities that received targeted support for broadband development experienced a more substantial decline in income inequality than their non-treated counterparts with similar baseline conditions. This finding partially mitigates concerns that the benefits of enhanced internet infrastructure may be concentrated in treated cities that previously had better conditions.

*Figure 4 Heterogeneous treatment effects of Broadband China on income inequality*




*Note: Confidence level is set at 95%. Dashed lines are for TWFE estimates and solid lines are CSDID estimates.*

**Effects on household income**

We then use CFPS household-level data to assess whether the Broadband China program affects household income[14]. As shown in Table 3, at an aggregate level, the introduction of the program significantly increases net income, labor income, and other income[15] for households in the treated cities compared to their control counterparts. Figure 5 shows no significant pre-existing trend, although one survey wave before the policy intervention, the other income for households in the treated group was slightly lower than that of the control group. These results suggest that the program significantly improves income level for households in the demonstration cities, with treatment effects on these outcomes increasing over time in the post-implementation periods[16]. Notably, the increase in labor income is delayed, becoming statistically significant two survey waves after the program's implementation.

*Table 3 Effects of Broadband China on household income*

| | (1)<br>Net family income per capita | (2)<br>Total operational income per capita | (3)<br>Labor income per capita | (4)<br>Other income per capita |
|---|---|---|---|---|
| ***Panel A: TWFE estimates*** | | | | |
| ATT | 2,887.680** | 83.565 | 1,212.376*** | 1,571.617* |
| | (1,229.093) | (89.546) | (379.607) | (881.518) |
| Observations | 58,381 | 58,381 | 58,381 | 58,381 |
| Household FE | YES | YES | YES | YES |
| Survey FE | YES | YES | YES | YES |
| Household control | YES | YES | YES | YES |
| ***Panel B: CSDID estimates*** | | | | |
| ATT | 2,893.598*** | 46.901 | 1,351.599*** | 1,396.195*** |
| | (239.122) | (33.330) | (195.692) | (112.827) |
| Observations | 53,362 | 53,362 | 53,362 | 53,362 |
| Household FE | YES | YES | YES | YES |
| Survey FE | YES | YES | YES | YES |

[14] The sampled households do not migrate across cities, which rules out the concern that between-city migration might lead to biased estimates. Household level controls are indicator variables for household living conditions, including urban area indicator, major water, and fuel source.

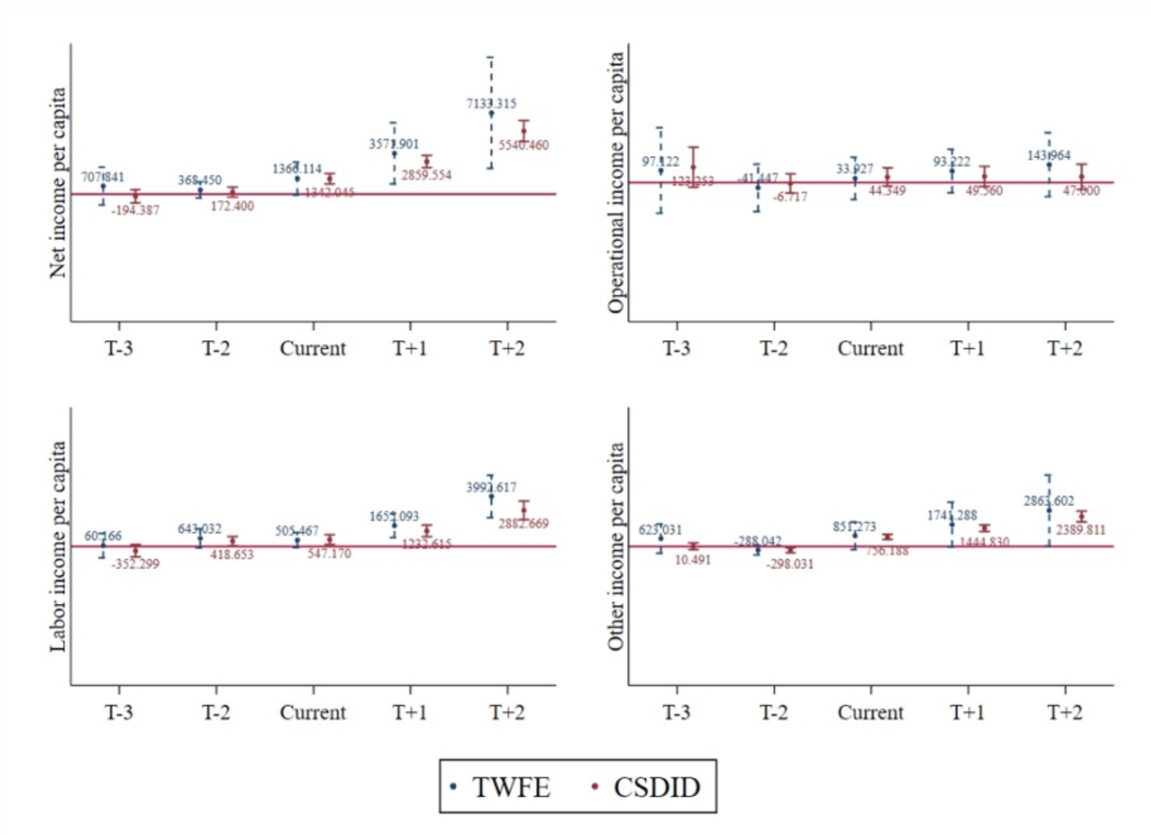
[15] "Other income" includes financial income, such as dividends, and income from other sources defined by CFPS.

[16] This increase over time could be a result of stronger exposure to broadband internet and better internet quality over time.

| | | | | |
|---|---|---|---|---|
| Household control | YES | YES | YES | YES |
| Control mean | 10669.2 | 1163.521 | 7280.87 | 2123.156 |
| Std. Dev. | 11955.24 | 2347.159 | 10076.77 | 5324.031 |

*Note: Household net income is a variable aggregated by CFPS and is available directly from the household data base. It is the sum of operational income, labor income and other income (income from financial activities and other activities), minus the operational costs. Operational cost is not available in each survey wave, thus, we report the total amount of operational income for this specific income type. The only difference between total income and net income is for operational income. Standard errors for TWFE estimators are clustered at city level. Standard errors for CSDID estimators are bootstrapped with 999 repetitions. *** p<0.01, ** p<0.05, * p<0.1.*

*Figure 5 Dynamic effects of Broadband China on household income*




*Note: The confidence level is set at 95%. For the figure in the upper right corner, the y-axis range is set from -1000 to 1000, while the ranges for the other three figures extend from -10,000 to 10,000. Dashed lines are for TWFE estimates and solid lines are CSDID estimates.*

**Heterogeneity by baseline income level**

Why does the introduction of the BB program simultaneously reduce income inequality while increase household income? To address this question, we further examine the heterogeneity of the treatment effects on household income based on baseline average income levels of households in our sample. We categorize households into three groups according to the percentile of their average income prior to the policy implementation within the city. Specifically, we first rank each household in an ascending order according to their average net income per capita before the policy introduction. Then, we divide the households into subgroups evenly: We define the low income group as households whose average net income is below the 33 percentile of the income distribution. Middle income group includes households whose average net income is in the 33-66 percentile. High income group refers to households whose average net income is above 66 percentile.

We estimate the baseline specification separately for each group. The regression results, presented in Table

4, reveal that significant net income increases are observed among all the three groups. The net income increase for the low- and middle-income groups is primarily driven by the increase in labor income and other income. However, the net income increase for the high-income group is mainly driven by the increase in other income. Additionally, the increase in net income for the low- and middle-income groups is significantly larger than the increase for the high-income families[17]. This suggests that the reduction in income inequality may be attributed to the catch-up effect among low- and middle-income families. Consistent with the increasing treatment effects on income over time for the full sample, we also observe a rise of treatment effects on net income, labor income and other income for all the three types of households over time (see Figure A4 and A5).

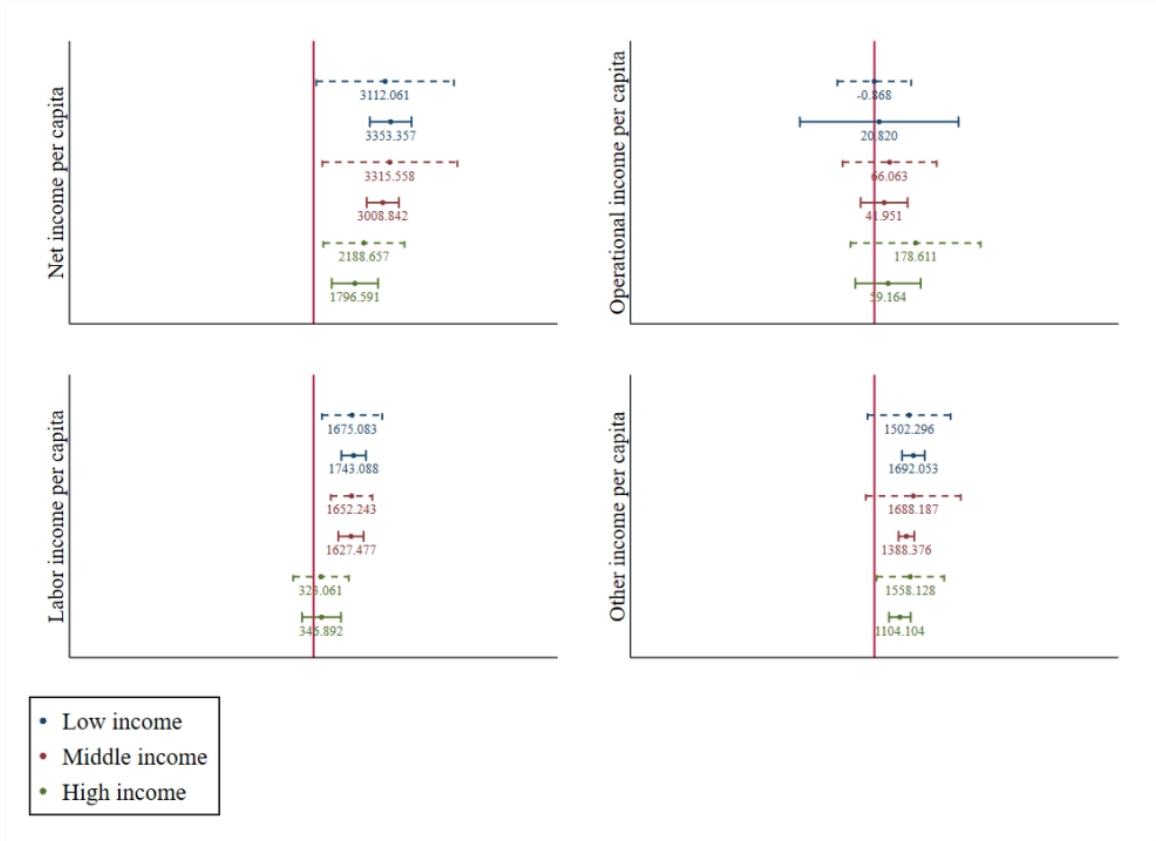
*Table 4 Effects of Broadband China on household income by income groups*

| | (1)<br>Low income | (2)<br>Middle income | (3)<br>High income |
|---|---|---|---|
| ***Panel A: Net income as outcome*** | | | |
| ATT | 3,353.357*** | 3,008.842*** | 1,796.591*** |
| | (462.259) | (357.367) | (513.691) |
| Observations | 16,669 | 17,899 | 18,051 |
| Control mean | 5529.418 | 8932.42 | 15830.17 |
| Std dev | 7144.607 | 8747.809 | 14063.54 |
| ***Panel B: Operational income as outcome*** | | | |
| ATT | 20.820 | 41.951 | 59.164 |
| | (175.895) | (52.014) | (72.471) |
| Observations | 16,669 | 17,899 | 18,051 |
| Control mean | 910.973 | 1206.259 | 1437.342 |
| Std dev | 1711.652 | 2213.641 | 2908.317 |
| ***Panel C: Labor income as outcome*** | | | |
| ATT | 1,743.088*** | 1,627.477*** | 346.892 |
| | (273.656) | (280.964) | (432.301) |
| Observations | 16,669 | 17,899 | 18,051 |
| Control mean | 3530.72 | 6170.204 | 10306.49 |
| Std dev | 6223.477 | 7517.376 | 11503.71 |
| ***Panel D: Other income as outcome*** | | | |
| ATT | 1,692.053*** | 1,388.377*** | 1,104.104*** |
| | (250.093) | (174.330) | (241.848) |
| Observations | 16,669 | 17,899 | 18,051 |
| Control mean | 1131.182 | 1552.353 | 3632.041 |
| Std dev | 2865.332 | 3822.466 | 7535.33 |

Note: Robust standard errors are in parentheses. Standard errors for TWFE estimators are clustered at city level. Standard errors for CSDID estimators are bootstrapped with 999 repetitions. *** p<0.01, ** p<0.05, * p<0.1.

[17] P-values from Wald-square test for the difference in BB's effects on net income between the low- and high-income group, and between the middle- and high-income group are 0.021 and 0.049, respectively.

*Figure 6 Heterogeneous treatment effects by household income level*

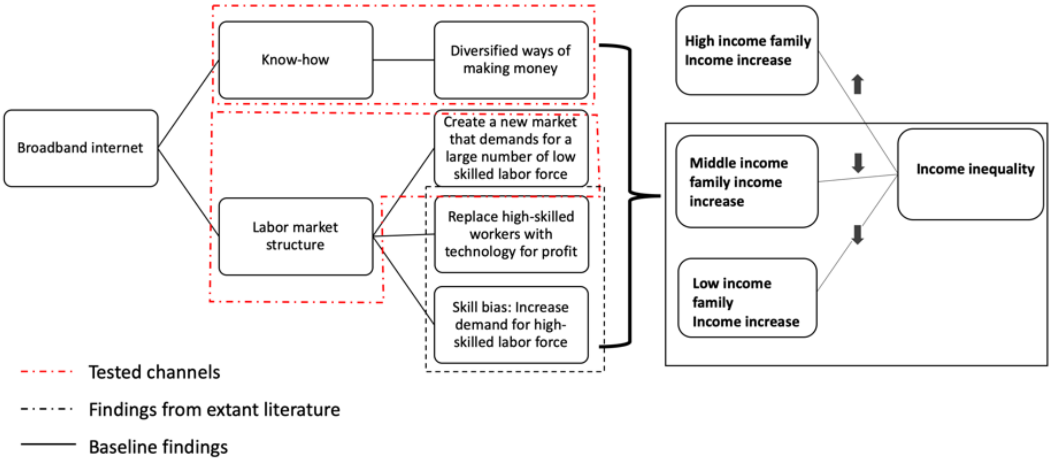



*Note: The confidence level is set at 95%. In the figure located in the upper right corner, the y-axis range is from -1000 to 1000, whereas the ranges for the other three figures extend from -10,000 to 10,000. Dashed lines are for TWFE estimates and solid lines are CSDID estimates.*

**Mechanism**

This section explores the mechanisms through which the Broadband China program influences income inequality. We first propose a conceptual framework based on the current literature and our baseline findings, as is shown in Figure 6. Drawing upon existing literature, we focus on two primary channels: the provision of free public goods in the form of information and shifts in labor market structure. Prior research primarily examines the direct effects of broadband internet on individual outcomes like income and employment, and our findings suggest that the Broadband China program's impact on reducing income inequality stems largely from increased net income, particularly in labor income, among low- and middle-income families. Therefore, it is crucial to analyze its individual-level effects in relation to specific features of the families at different income percentiles.

*Figure 4 Conceptual framework: How Broadband Internet affects income inequality*




We begin by examining how broadband internet impacts families across different income percentiles through the mechanisms of information dissemination. By lowering information costs, the internet makes previously expensive knowledge more accessible to users. For instance, the rise of self-media on social platforms, facilitates the dissemination and popularization of specialized knowledge, enabling individuals to discover new income-generating opportunities. Our analysis reveals a significant increase for all income types of families in other income—encompassing financial income (e.g., interest and dividends) and miscellaneous income—following the Broadband program's implementation. However, the overall impact of this information channel on income inequality remains ambiguous, as high-income households also report increased other income, a primary driver of their net income growth. This finding only indicates that families across the income spectrum can now leverage readily available information to acquire new skills and capitalize on emerging opportunities[18].

Next, we examine the impact of broadband internet on labor market structure. Given the finding in Jin et al. (2023) that the Broadband China program had no significant effect on high-skilled workers' labor market outcomes, we focus on how improved internet access creates new opportunities for low-skilled labor. The rise of the platform economy, fueled by broadband expansion, has generated numerous service sector jobs, particularly in logistics, ride-hailing services, and online shopping platforms[19]. For example, between 2012 and 2018, the total volume of express deliveries surged nearly eightfold, driven by the growth of online shopping and food delivery services. These positions typically have low entry barriers and are classified as low-skilled jobs[20]. Anecdotal evidence also suggests a shift in the low-skilled labor landscape, with workers transitioning from primary and secondary industries to these new, higher-paying opportunities in the third industry[21]. Supporting this observation, we find that workers from low- and middle-income households generally have fewer years of education[22]. Additionally, the proportion of labor income derived from the service sector has increased over the research period for low- and middle-income families in demonstration cities (see Figure A4). This suggests that improved internet access, through its influence on the platform economy, has created new pathways for low-skilled workers to access higher-paying jobs, potentially

[18] We plot the trend in the number of jobs from 2012 to 2018 (the second to the fifth survey wave), and we find a similar evolving pattern in the number of jobs for the different types of households in the treatment and control groups. See Figure A6.

[19] According to the Statistical Report on Internet Development in China by the China Internet Network Information Center (CINIC), internet business transaction applications (e.g., online shopping and food delivery) and public service applications (e.g., online car-hailing) have been developing at a very fast pace since 2010.

[20] According to CINIC report, the number of online shopping users has been on the rise for nearly a decade. As of December 2018, the number of online shopping users reached 610 million, accounting for 73.6\% of the total number of Internet users. The food delivery industry started in 2010. By the end of 2018, the number of food delivery users reached 406 million, which is around four times of the 2015.

[21] https://k.sina.cn/article_1649252577_624d98e101901bsp1.html?from=tech

[22] Workers from high-income family have an average of 8.13 years of education, while these from low- and middle-income families have an average of 6.19 years of education (p-value of t-test of equality < 0.01).

contributing to the observed reduction in income inequality.

To provide more robust evidence on the influencing channel through which better ICT infrastructure reduces intra-city income inequality, we empirically test if the implementation of BB program increases the number of employees in the third industry, which also incorporate logistics and retail industry. Table 5 reports the result. The outcomes of interest are the log transformation of the number of workers in the third industry, logistics, retail, hoteling and catering, residential and other services, which are also indicated by the column title. The results show that the implementation of the BB program significantly increased employees in the third industry by around 10 percent. Particularly, for the logistics industry, it increases by around 16%. We then incorporate the two variables into the baseline regression as control, as is shown in Table 6. The first column of Table 6 reports the baseline results, and Column (2) to Column (4) add the log value of number of employees in the third industry, the logistic industry, and both variables as controls. As shown from the last 3 columns in Panel B (more robust CSDID estimates), adding the number of third industry employees leads to insignificant effects of the Broadband China program on income inequality and a substantial drop in the coefficient magnitude. This provides supportive evidence for the labor market structure change channel.

Table 5 Can Broadband China program influence the number of employees in the third industry?

| | (1)<br>**Third industry** | (2)<br>**Logistics** | (3)<br>**Retail** | (4)<br>**H&C** | (5)<br>**Residential** |
|---|---|---|---|---|---|
| ***Panel A: TWFE*** | | | | | |
| ATT | 0.111*** | 0.151** | 0.117 | 0.107 | 0.136 |
| | (0.033) | (0.070) | (0.080) | (0.118) | (0.167) |
| constant | 12.364*** | 9.591*** | 9.735*** | 8.381*** | 6.966*** |
| | (0.007) | (0.016) | (0.018) | (0.026) | (0.038) |
| Observations | 576 | 576 | 576 | 576 | 569 |
| R-squared | 0.979 | 0.945 | 0.926 | 0.905 | 0.820 |
| City FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| ***Panel B: CSDID*** | | | | | |
| ATT | 0.095** | 0.156** | 0.100 | 0.084 | 0.063 |
| | (0.046) | (0.073) | (0.103) | (0.148) | (0.194) |
| Observations | 574 | 574 | 574 | 574 | 567 |
| City FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |

*Note: The column titles represent the dependent variables in the regressions. The outcomes of interest include the logarithmic transformations of the number of employees in the third industry, logistics industry, retail industry, hotel and catering industry (H&C), and residential industry. Robust standard errors are in parentheses. Standard errors for TWFE estimators are clustered at city level. Standard errors for CSDID estimators are bootstrapped with 999 repetitions. *** p<0.01, ** p<0.05, * p<0.1.*

Table 6 Effects of Broadband China on income Gini with the number of third-industry workers as control

| Dep. Var.: Income Gini | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: TWFE*** | | | | |
| ATT | -0.029*** | -0.025*** | -0.028*** | -0.025*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Observations | 571 | 571 | 571 | 571 |
| City FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| City control | YES | YES | YES | YES |

| | | | | |
|---|---|---|---|---|
| Log employees in the third industry | NO | YES | NO | YES |
| Log employees in logistics | NO | NO | YES | YES |
| ***Panel B: CSDID*** | | | | |
| ATT | -0.037*** | -0.017 | -0.012 | -0.021 |
| | (0.011) | (0.015) | (0.013) | (0.015) |
| Observations | 569 | 569 | 569 | 569 |
| City FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| City control | YES | YES | YES | YES |
| Log employees in the third industry | NO | YES | NO | YES |
| Log employees in logistics | NO | NO | YES | YES |

*Note: The dependent variable is income Gini coefficient. Robust standard errors are in parentheses. Standard errors for TWFE estimators are clustered at city level. Standard errors for CSDID estimators are bootstrapped with 999 repetitions. *** p<0.01, ** p<0.05, * p<0.1.*

**Robustness checks**

**Self-selection of demonstration cities**

The major concern of estimating equation (2) to identify $\beta_1$ is that there are certain selection standards of cities to be BB demonstration cities. In other words, the treatment assignment is non-random. The official selection criteria, as outlined in the policy document, prioritize cities with a strong foundation for digitalization[23], suggesting potential self-selection into the treatment group. While the policy emphasizes a robust ICT foundation as a prerequisite, a qualitative assessment reveals that not all treated cities possessed exemplary ICT conditions at baseline. For instance, Wuzhong, a demonstration city in the 2014 cohort, had an internet penetration rate significantly lower than the cohort average, accompanied by lower GDP per capita and population density. This suggests that while all applicant cities undergo evaluation, the probability of selection varies, and the designation as a demonstration city reflects a city's commitment to ICT advancement and broadband prioritization, potentially accompanied by increased support from higher-level governments.

Empirically, the satisfaction of parallel trends assumptions alone does not address the self-selection issue. To mitigate this concern, we first examine the determinants of treatment assignment. Baseline differences between demonstration and control cities (Table A7) reveal that demonstration cities tend to be more affluent, with greater investments in education and science, and higher baseline internet penetration rates, aligning with the BB policy document. However, regressing treatment timing on baseline city characteristics (Table A8) shows no statistically significant relationship, indicating that while treatment assignment is non-random, treatment timing is. This allows for a valid comparison between early- and later-treated groups, though in the last paragraph, we already illustrated the advantage of using the never-treated units as control as not every treated city had a good baseline ICT condition. Panel A in Table 7 shows that using not-yet-treated cities as control yields similar results[24]: The implementation of BB leads to a significant reduction in income Gini by 0.031, and its dynamic effects (shown in Figure A7) on income Gini implies no pre-trend.

As a supplement and to further address the concern of non-random selection of the demonstration cities, we account for the government's selection criteria for the demonstration cities. We use the city's baseline internet penetration rate as a proxy for its baseline ICT condition, and then we incorporate the interaction between baseline internet penetration and time dummies to control its effects. Accordingly, we estimate equation (3) as follows.

$$y_{ct} = \alpha + \beta_1 BB_{ct} + \phi Internet_{baseline}\lambda_t + X_{ct}'\beta_2 + \gamma_c + \lambda_t + \varepsilon_{ct} \quad (3)$$

[23] https://www.gov.cn/gzdt/2014-01/16/content_2568722.htm

[24] For convenience, here we directly report the more robust CSDID estimates.

where $Internet_{baseline}$ is the city's baseline internet penetration. The other notations have the same meaning as the ones in the baseline equation. $\phi$ captures the effects of baseline internet penetration over time. Table x reports the results. Consistent with the baseline findings, the estimation controlling for city's baseline internet conditions give similar results: the implementation of BB leads to a reduction of 0.028 of income Gini in the treated cities, compared to their control counterparts.

**Alternative interpretation**

During the rollout of the Broadband (BB) initiative, China concurrently implemented other policies aimed at improving ICT infrastructure, potentially influencing our analysis of the BB program's impact on income inequality. We focus on two notable policies: the Universal Telecom Service Program (UTS) and the Smart City Program (SCP). The UTS, implemented from 2016 to 2018, aimed to bridge the digital divide between rural and urban areas. This government-funded program facilitated over 40 billion yuan in investments by China's major telecom operators, enabling the construction of fiber optic networks and 4G base stations in 130,000 administrative villages, including 43,000 impoverished villages. Niu, Jin, Wang, and Zhou (2022) demonstrate that the UTS contributes to digital financial inclusion, suggesting its potential to mitigate intra-city inequality by enhancing connectivity and creating economic opportunities in underserved areas. Similarly, the SCP, piloted in over 100 cities between 2012 and 2015, seeks to leverage advanced technologies to improve urban management and quality of life. Focusing on areas like transportation, energy management, public safety, and environmental monitoring, the SCP has been shown to benefit pilot cities by upgrading industrial structures and fostering innovation (Wu, Xie, & Lyu, 2023), with potential implications for income distribution.

To isolate the BB initiative's effects from these concurrent policies, we incorporated an interaction term combining treatment status in each policy context with post-treatment year indicators into our baseline regression. This approach allows us to control the potential confounding effects of the UTS and SCP, ensuring a more precise estimation of the BB program's impact on income inequality. Table 9 demonstrates that incorporating these policies into our analysis does not significantly alter the magnitude or statistical significance of the BB program's effects on income inequality. This finding underscores the robustness of our results, suggesting that the observed reduction in income inequality is specifically attributable to the BB initiative and not confounded by the UTS or SCP. The BB initiative emerges as a key driver of change in addressing income disparities, highlighting the importance of continued investment in broadband infrastructure to promote economic equity.

**Table 7 Robustness checks**

| | (1) | (2) |
|---|---|---|
| ***Panel A : Not-yet treated cities as control*** | | |
| | Income Gini | Asset Gini |
| ATT | -0.035** | -0.011 |
| | (0.010) | (0.012) |
| Observations | 569 | 569 |
| City FE | YES | YES |
| Year FE | YES | YES |
| ***Panel B: Control baseline internet penetration*** | | |
| ATT | -0.025** | -0.006 |
| | (0.011) | (0.013) |
| Observations | 569 | 569 |
| City FE | YES | YES |
| Year FE | YES | YES |
| City control | YES | YES |
| Baseline internet penetration × Time | YES | YES |
| ***Panel C: Control for relevant policies*** | | |
| | Income Gini | Asset Gini |

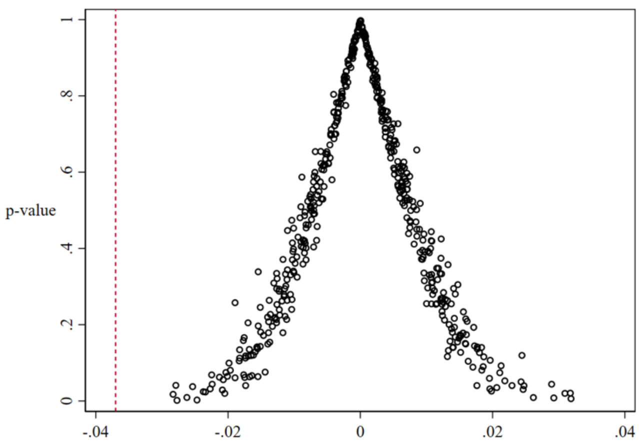
| | | |
|---|---|---|
| ATT | -0.038*** | -0.006 |
| | (0.011) | (0.011) |
| Observations | 564 | 564 |
| City FE | YES | YES |
| Year FE | YES | YES |
| City control | YES | YES |
| UTS | YES | YES |
| SCP | YES | YES |

*Note: Column title indicates the dependent variable in the regression. Robust standard errors are in parentheses. Standard errors for CSDID estimators are bootstrapped with 999 repetitions. *** p<0.01, ** p<0.05, * p<0.1.*

**Placebo test**

Another concern is that the coefficient $\beta_1$ in our baseline specification captures not only the effects of Broadband China entrance but also the effects of other time-varying city-level factors. Following Ferrara, Chong, and Duryea (2012) and Jin et al. (2023), we conducted a placebo test based on randomly generated treated cities as the hypothetical experiment group with random assignment of BB entrance timing, and we repeated this procedure 500 times to generate the distribution of the estimated $\beta_1$, which is expected to capture the difference in outcomes of interest between the hypothetical treatment and control groups after the fictitious entrance timing of BB. If it is not significantly different from 0, it implies that our baseline results are indeed a causal interpretation. Figure 9 shows the distribution of $\beta_1$ using hypothetical treated units and BB entrance timing for the effects on income inequality. These estimates are normally distributed around 0, with most p-values greater than 0.1. They also lie far from the red vertical line, which indicates the true effect of the policy shock on income inequality. We also conducted placebo for the household level analysis, including the overall income increase and income increase of each specific household type by baseline income percentile. The results in Figure A8-A9 show consistent findings.

Figure 5 Placebo test: income Gini




*Note: The red vertical line is the estimated coefficient from baseline specification. This figure reports the estimated CSDID coefficients from fictitious treatment timings and treatment status with 500 repetitions.*

**Conclusions**

Leveraging the implementation of the Broadband China Program, we find that better internet infrastructure helps to reduce income inequality, as measured by the Gini coefficient, by approximately 0.037 points. Meanwhile, this reduction is mainly concentrated in central China and is attributed to greater income gains among low- and middle-income households. Our findings suggest that expanding broadband internet access can effectively reduce income inequality by supporting economic stimulation policies targeting central regions, where its marginal impact is greater due to the relatively less developed economies compared to other regions. Specifically, policies in central China focus on enhancing connections among different cities within the region, and the internet plays a key role in facilitating these connections[25]. Our finding aligns with the theoretical framework proposed by Acemoglu (2002), where the impact of technology on inequality is contingent on its relative profitability in replacing different skill groups. In the context of China's digitalization, the rise of the platform economy has created thousands of job openings in sectors that require minimal education and offer higher wages compared to traditional low-skilled jobs, such as agriculture and construction.

Our results have important implications for policymakers. First and foremost, this study shows that improvements in broadband infrastructure supported by the government can effectively reduce income inequality. This evidence supports the idea that digital inclusion policies can play a crucial role in ensuring that the benefits of technological progress are shared more equitably across society. Consequently, policymakers could prioritize investments in internet infrastructure, particularly in rural and underdeveloped regions. Second, to expand the low-skilled beneficiaries of the better Internet, both policymakers and platform companies can take advantage of the opportunities created by the digital economy and provide relevant trainings to these prospective workers. These initiatives could teach prospective workers how to use apps to connect with restaurants and customers as delivery staff, as well as how to become online influencers and gain income through e-commerce platforms like TikTok. Last but not least, a competitive digital market is essential for ensuring that the benefits of digitalization are shared broadly. Therefore, policies that promote competition and protect gig workers should be encouraged[26].

While this study provides valuable insights into the impact of broadband internet access on intra-city income inequality in China, there still are several caveats. Firstly, this study focuses on intra-city inequality, but it is equally important to understand how digitalization affects income disparities between cities. Future research could explore the spatial distribution of the benefits of broadband expansion. Second, the findings of this study may not be generalizable to other developing contexts. China's rapid economic growth and unique digital landscape may differ significantly from other developing countries, such as India or African nations. Therefore, it is essential to conduct further research in diverse contexts to understand the nuanced impact of broadband expansion on income inequality across different regions and economies. Finally, future research could explore the long-term effects of broadband expansion on income inequality. Our research time window spans from 2010 to 2018 with the policy implementation period from 2014 to 2016. This suggests that we can only observe a relatively short period of time of the program's effects on income inequality, but the long-term dynamics of income inequality may differ.

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[25] For example, in 2016, Chinese government requires Wuhan, one of cities in central region to open platform function, which is based on the development of the internet: https://baike.baidu.com/item/%E4%B8%AD%E9%83%A8%E5%9C%B0%E5%8C%BA/7549145?fr=ge_ala

[26] Policy for the development of platform business in China: https://www.ndrc.gov.cn/xxgk/zcfb/tz/202201/t20220119_1312326.html

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**Appendix**

**Tables**

Table A1 Variable description

| Variable type | Variable name | Definition | Description |
|---|---|---|---|
| **Outcome variable** | | | |
| | gini_net_income | Within city income Gini | Continuous variable. Calculation: $Gini = 1 + \frac{1}{N} - \frac{2}{m \times N^2} \sum_{i=1}^{N} (N - i + 1) y_i$ $y_i$ is household net income per capita. |
| | gini_total_asset | Within city asset Gini | Continuous variable. Same calculation method as above. $y_i$ is household total asset per capita. |
| | net_income | Household net income per capita | Continuous variable. Net household income is the sum of all income sources minus household operating costs. |
| | oper_income | Household operational income per capita | Continuous variable. Household business income refers to the total income generated by household agricultural production or non-agricultural production (without deducting household business costs). |
| | labor_income | Household labor income per capita | Continuous variable. Total income from family labor. |
| | other_income | Household other income per capita | Continuous variable. The sum of household financial activities income, direct transfer income and other income. |
| **Explanatory variable** | treat | Treatment group | Binary variable. This variable takes the value of 1 if the respondent lives in a Broadband China Demonstration City, otherwise it takes the value of 0. |
| | enter | Implementation time of Broadband China | The values are 0, 2014, 2015, and 2016. If the city has not implemented the strategy, the value is 0. |

| | | | |
|---|---|---|---|
| | post | Post-treatment time | Binary variable. If the survey year is greater than or equal to the time when the Broadband China Strategy was implemented in the city, the value is 1, otherwise it is 0. |
| **Control variable** | | | |
| | natural_growth | Natural population growth rate | Continuous variable. The data comes from the City Statistical Yearbook. |
| | density | Population density | Continuous variable. The total registered population is divided by the city's administrative area (people/square kilometer). The data comes from the city statistical yearbook. |
| | edu | Education level | Continuous variable. In the city-level analysis, this variable is calculated using the CFPS individual database and is the average education level of all persons within the city. |
| | urban | Urban area | Binary variable. When the household lives in an urban area, the value is 1, otherwise it is 0. |
| | water | Drinking water sources | Categorical variable. The value is an integer from 1 to 7, representing the water source as river/lake water, well water, tap water, mineral water/purified water/filtered water, rainwater, kiln water and other water sources. |
| | fuel | Fuel Source | Categorical variable. The value is an integer from 1 to 7, representing the fuel source as firewood, coal, natural gas/liquefied gas, solar energy, biogas, electricity, and other sources. |

Table A2 Summary statistics: Household controls

| | N | Mean | Max | Min |
|---|---|---|---|---|
| **Water sources** | | | | |
| River/Lake water | 61111 | .006 | .074 | 1 |
| Well | 61111 | .274 | .446 | 1 |
| Tap water | 61111 | .667 | .471 | 1 |
| Mineral/Purified/Filtered water | 61111 | .01 | .101 | 1 |
| Rainwater | 61111 | .004 | .067 | 1 |
| Cellar water | 61111 | .016 | .124 | 1 |
| Other water sources | 61111 | .02 | .141 | 1 |
| **Fuel sources** | 61111 | .003 | .05 | 1 |
| Firewood/Straw | 61104 | .317 | .465 | 1 |
| Coal | 61104 | .063 | .243 | 1 |
| Gas/Liquid | 61104 | .335 | .472 | 1 |
| Natural gas/Pipe-line gas | 61104 | .094 | .292 | 1 |
| Solar energy/Methane | 61104 | .008 | .087 | 1 |
| Electricity | 61104 | .18 | .385 | 1 |
| Other fuel sources | 61104 | .003 | .056 | 1 |

Table A2 City summary: All cities

| | N | Mean | SD | Max | Min |
|---|---|---|---|---|---|
| Internet penetration rate | 2878 | .213 | .18 | 1.89 | .003 |
| Log GDP | 2612 | 27.988 | .94 | 31.273 | 25.368 |
| Population density (person/squar | 2914 | 422.159 | 305.13 | 1440.26 | 0 |
| Log total household savings | 2907 | 25.358 | 1.015 | 28.948 | 15.478 |
| Log total income from post-communication | 2894 | 19.728 | 1.298 | 25.64 | 11.156 |
| Log total income of the employed | 2900 | 14.314 | 1.003 | 18.699 | 11.865 |
| Log education expenditure | 2910 | 22.237 | .84 | 25.456 | 8.216 |
| log science | 2910 | 19.471 | 1.399 | 24.74 | 15.462 |

Table A3 Effects of Broadband China on internet penetration: All cities

| Dep. Var.: Internet penetration rate | (1) | (2) |
| --- | --- | --- |
| ATT | 0.029*** | 0.035** |
| | (0.011) | (0.015) |
| Observations | 2,852 | 2,529 |
| City FE | YES | YES |
| Year FE | YES | YES |
| Lag internet penetration | NO | YES |
| Control mean | 0.181 | |
| SD. | 0.144 | |

Note: Robust standard errors are presented in parentheses. Bootstrapped standard errors are reported based on 999 repetitions. City controls include the logarithm of GDP, the logarithm of total household savings, the logarithm of average income of the employed, the logarithm of income from post-communication businesses, the logarithm of expenditure on education and science, and population density, all of which capture time-variant socio-economic conditions within the city. *** p<0.01, ** p<0.05, * p<0.1.

Table A5 Application qualifications

| City applicants should have a good foundation for broadband development, and ought to meet at least 4 requirements from the following: |
|---|
| (i) 85% of urban households have access to broadband of 20Mbps and above;<br>(ii) 90% of rural households have access to broadband of 4Mbps and above;<br>(iii) 55% of households have access to fixed broadband;<br>(iv) 40% of the population has access to 3G/LTE mobile phones;<br>(v) 80% of broadband users have access to 4Mbps and above;<br>(vi) 35% of broadband users have access to 8Mbps and above. |

Table A4 Baseline difference in city features by treatment status

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Internet penetration rate | 0.141 | 0.214 | 0.073*** | 0.319 |
| | (0.105) | (0.202) | (0.019) | |
| Log GDP | 27.728 | 28.358 | 0.631*** | 0.513 |
| | (0.710) | (1.002) | (0.113) | |
| Population density (person/square kilometers) | 375.002 | 500.906 | 125.904*** | 0.292 |
| | (272.240) | (335.098) | (42.842) | |
| Log total household savings | 24.977 | 25.635 | 0.657*** | 0.467 |
| | (0.986) | (1.006) | (0.126) | |
| Log total income from post-communication businesses | 19.180 | 19.818 | 0.638*** | 0.394 |
| | (0.978) | (1.289) | (0.139) | |
| Log total income of the employed | 14.010 | 14.708 | 0.698*** | 0.537 |
| | (0.708) | (1.091) | (0.122) | |
| Log education expenditure | 21.971 | 22.419 | 0.448*** | 0.306 |
| | (1.189) | (0.854) | (0.117) | |
| Log science expenditure | 19.124 | 20.029 | 0.905*** | 0.545 |
| | (0.954) | (1.359) | (0.154) | |
| Observations | 181 | 109 | 290 | |

Note: Base year is one year prior to the implementation of Broadband China program (2013). Robust standard errors in parentheses. We report the bootstrapped standard errors with 100 repetitions. *** p<0.01, ** p<0.05, * p<0.1.

Table A8 Determinants of treatment timing

| Dep. Var.: Year of implementation | (1) |
|---|---|
| Log GDP | -0.184 |
| | (0.268) |
| Population density (person/square kilometers) | 0.000 |
| | (0.000) |
| Log total household savings | 0.195 |
| | (0.324) |
| Log total income from post-communication businesses | -0.012 |
| | (0.114) |
| Log total income of the employed | -0.134 |
| | (0.350) |
| Log education expenditure | 0.074 |
| | (0.244) |
| Log science expenditure | -0.220* |
| | (0.129) |
| Observations | 108 |
| R-squared | 0.209 |

Note: Base year is one year prior to the implementation of Broadband China program (2013). Though the coefficient of science expenditure is significant, it is at a 10% significance level (i.e., marginally significant). Robust standard errors in parentheses. We report the bootstrapped standard errors with 100 repetitions. *** p<0.01, ** p<0.05, * p<0.1.

**Figures**

Figure A1: Validate Gini coefficients calculated from CFPS: A comparison to official reports

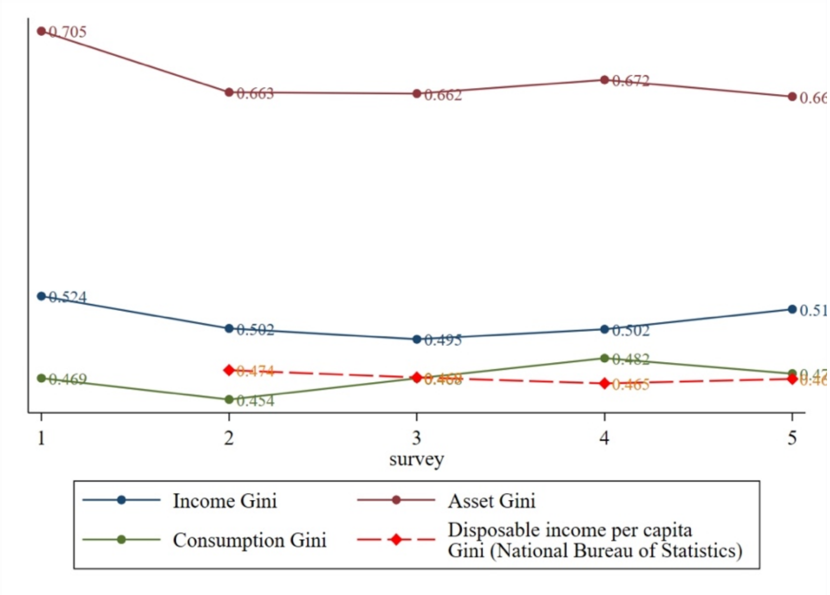
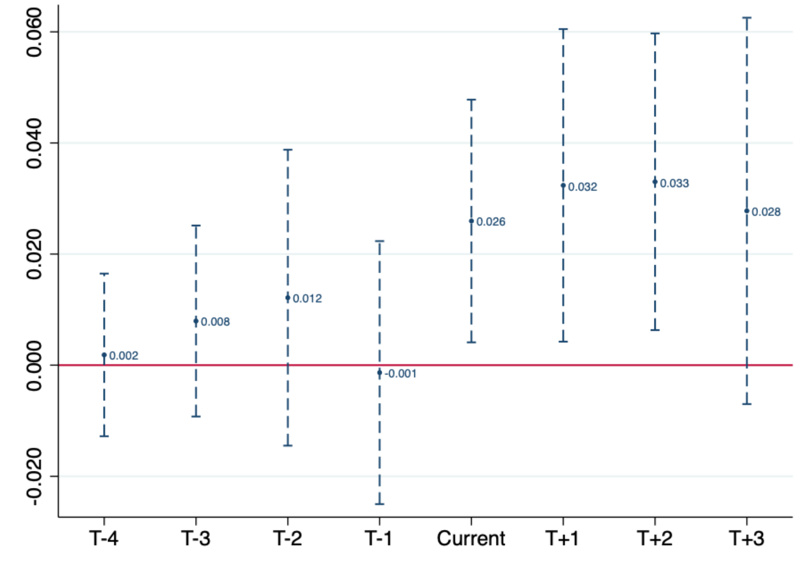
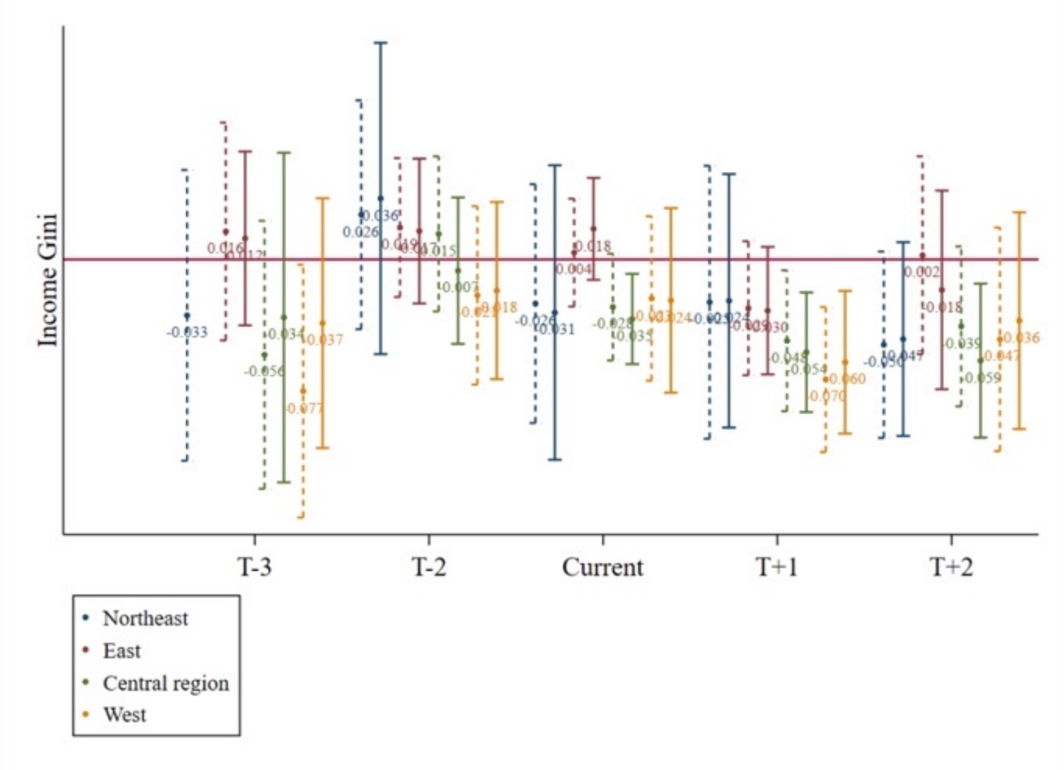


Figure A2: Dynamic effects of Broadband China on internet penetration

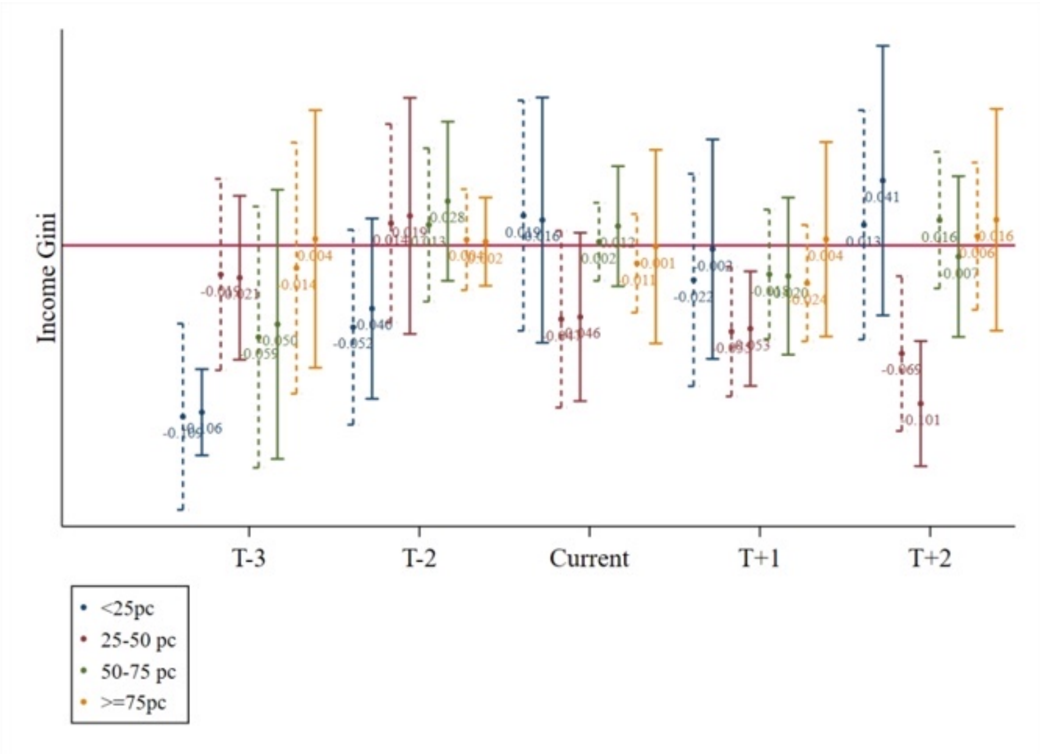



Note: Standard errors are bootstrapped with 999 repetitions. Confidence level is set at 90% confidence level.

Figure A3: Dynamic effects on income inequality by region and baseline internet penetration



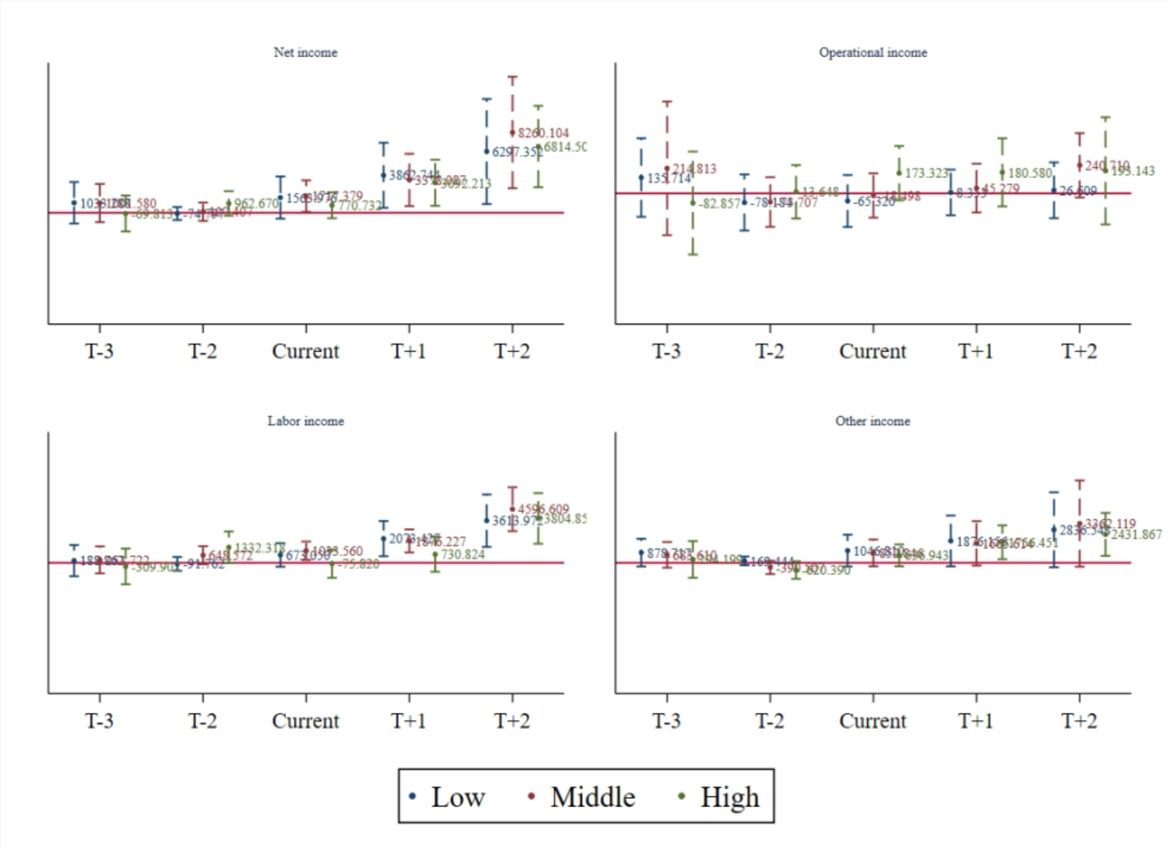

Panel A: By region




Panel B: By baseline internet penetration

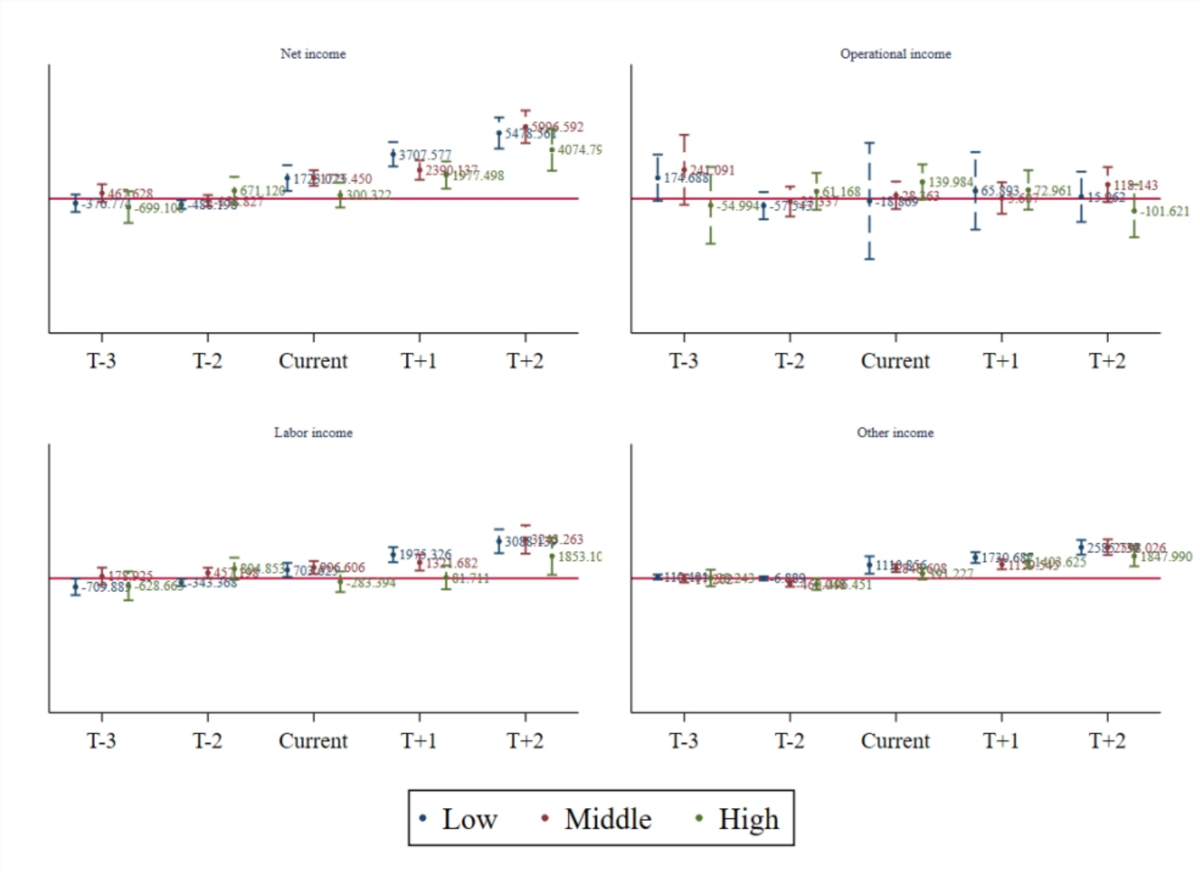
Note: Confidence level is 95%. *** p<0.01, ** p<0.05, * p<0.1. All coefficients are estimated based on regressions with city fixed effect, survey wave fixed effect, and city controls.

Figure A4: Dynamic effects of BB on household income
by household income type (TWFE estimates)



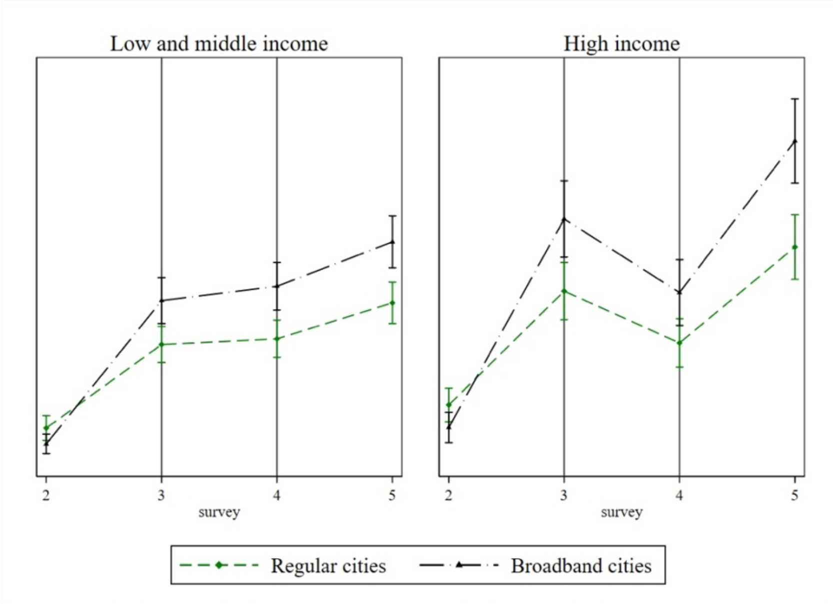

Note: Confidence level is set at 95% level. The range for the outcome operational income is from -1000 to 1000, while for the rest 3 outcomes is from -10000 to 10000.

Figure A5: Dynamic effects of BB on household income
by household income type (CSDID estimates)



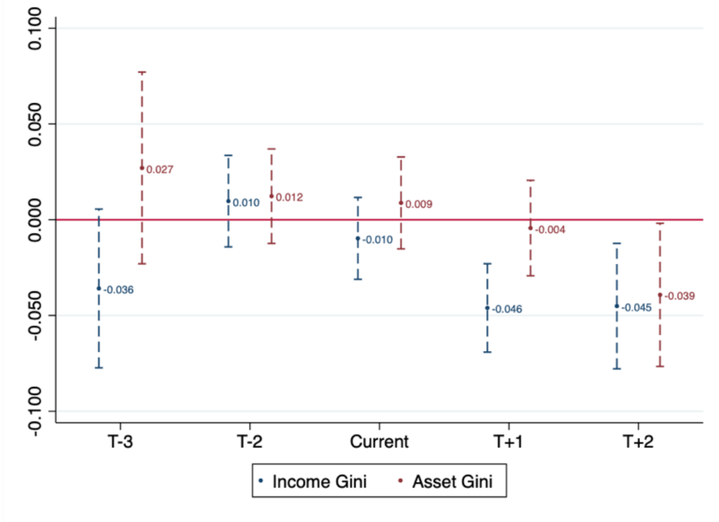

Note: Confidence level is set at 95% level. The range for the outcome operational income is from -1000 to 1000, while for the rest 3 outcomes is from -10000 to 10000.

Figure A6: Proportion of income from the third industry of total labor income

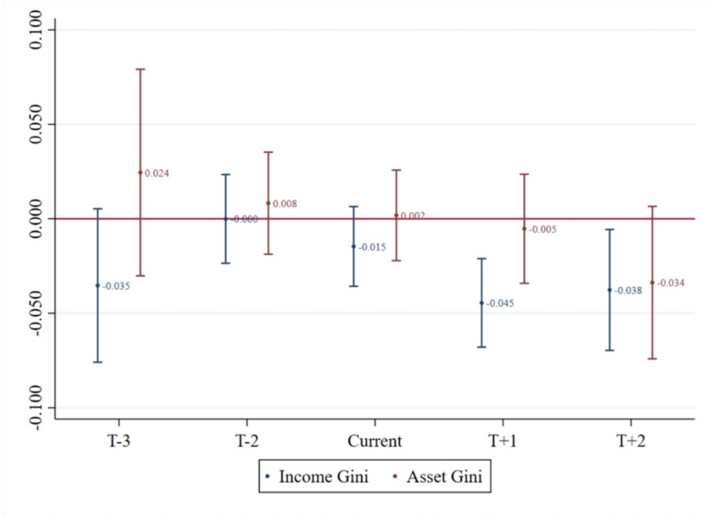



Note: This figure plots the trend in the proportion of income from the third industry of total labor income over the second to the fifth survey wave using raw data from CFPS individual data base. The first survey wave was excluded because there are too many missing observations.

Figure A7 Robustness check: Dynamic effects of Broadband China on Gini index



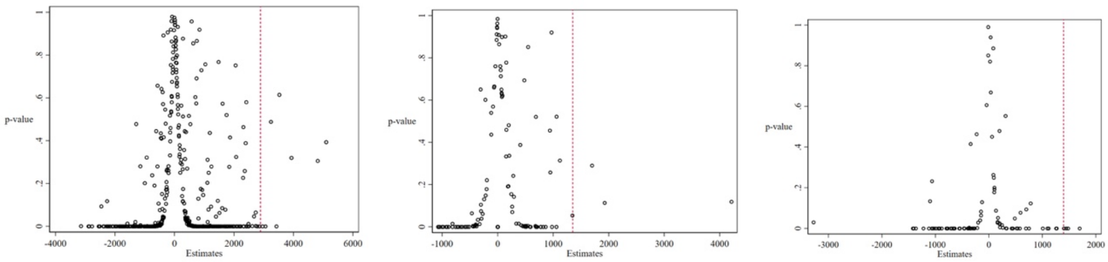

Panel A: Not-yet-treated as control group




Panel B: Add interaction between baseline internet penetration and time dummies

Note: Confidence level is set at 95%. This figure reports the dynamic effects of Broadband China on Gini index using CSDID approach. *Standard errors for CSDID estimators are bootstrapped with 999 repetitions.*

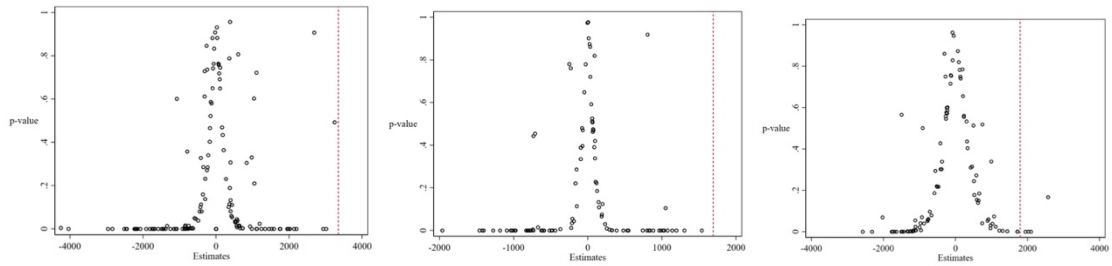
Figure A8 Placebo test: Household income.




Net income Labor income Other income

Note: The red vertical line is the estimated coefficient from baseline specification. This figure reports the estimated CSDID coefficients from fictitious treatment timings and treatment status with 100 repetitions.

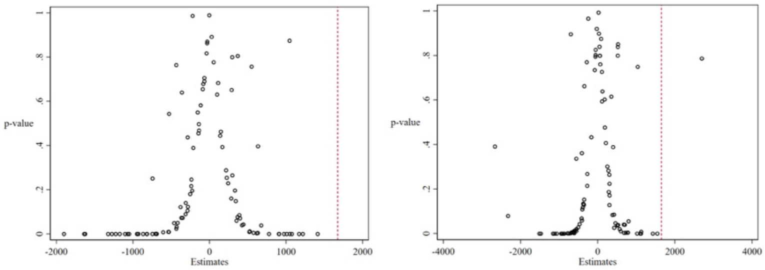
Figure A9 Placebo test: Net income by household income type




Low income | Middle income | High income

Note: The red vertical line is the estimated coefficient from baseline specification. This figure reports the estimated CSDID coefficients from fictitious treatment timings and treatment status with 100 repetitions.

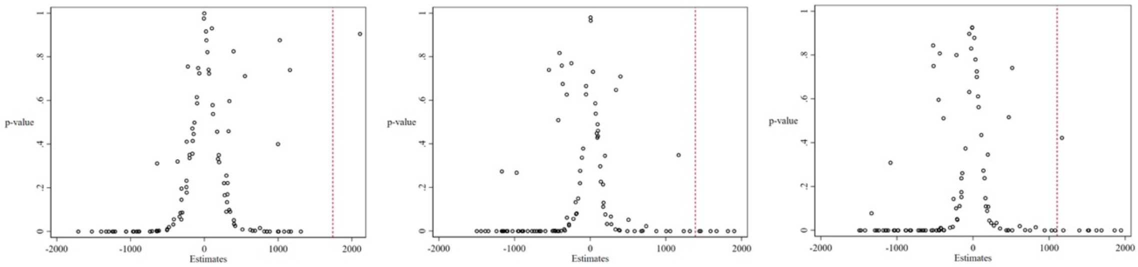
Figure A10 Placebo test: Labor income by household income type




Low income Middle income

Note: *The red vertical line is the estimated coefficient from baseline specification. This figure reports the estimated CSDID coefficients from fictitious treatment timings and treatment status with 100 repetitions.*

Figure A11 Placebo test: Other income by household income type




Low income Middle income High income

Note: *The red vertical line is the estimated coefficient from baseline specification. This figure reports the estimated CSDID coefficients from fictitious treatment timings and treatment status with 100 repetitions.*