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Identifying the growth effect of internet penetration[☆]

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ABSTRACT

This paper investigates the growth effect of broadband internet using China's city-level data from 2005 to 2019. The baseline OLS results suggest that on average a 10-percentage-point increase in broadband penetration growth is associated with a 0.4-percentage-point increase in real GDP per capita growth. A physical internet availability constructed from the location of mobile base stations predicts similar growth effects. A cost–benefit analysis translates the estimate into a 21% rate of return for investment in broadband internet infrastructure. We exploit historical and topographical instrumental variables to address the potential endogeneity. Utilizing the temporal and spatial variations from the Broadband China Pilot City Program, our staggered difference-in-differences analysis reveals innovation and entrepreneurship as two potential mechanisms underlying the growth effect.

1. Introduction

Recent years have witnessed a stunning transformation of how digital technology changes economic activities (Brynjolfsson and McElheran, 2016; Goldfarb and Tucker, 2019). Such transformation is impossible without broadband internet. Broadband represents a significant advancement in internet technology, characterized by always-on, wide-bandwidth, and particularly, high-speed data transmission. It includes a variety of internet connection types, each utilizing distinct technologies, such as digital subscriber line (DSL), cable internet, fiber-optic broadband, satellite broadband and more recently, wireless broadband. It therefore allows continuous transmitting of text, image, voice, and video across long distances and at high speeds, and enables a wide range of digital technologies. The rapid advancement and application of digital technologies, such as artificial intelligence (AI), block chain, clouding computing, and big data, leads to an ever-increasing demand for the capacity of broadband.[1] This implies that investment in broadband internet is an ongoing agenda for almost every country.

Starting from the emergence of internet in the United States, to its fast diffusion to the rest of world, both developed and developing economies have been heavily investing in the deployment of broadband internet infrastructure (Greenstein and McDevitt, 2009; World Bank, 2016), with a high expectation on "the greatest invention of our time" (The Economist, 2012). However, there is a continuing dispute among policymakers and researchers on the effects of broadband internet on economic outcomes, known as the Modern Productivity Paradox (Brynjolfsson et al., 2018). It refers to the contrast between rapid technological advancements, particularly in internet-empowered technologies, and the relatively slow growth in aggregate productivity

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[1] According to the 2010 report by Federal Communications Commission (FCC), broadband internet refers to internet service with download and upload speeds of at least 4 and 1 megabits per second (Mbps), respectively. In 2015, it increased the minimum download speed to 25 Mbps and the minimum upload speed to 3 Mbps. And in 2024, it further increased the minimum download and upload speeds to 100 Mbps and 20 Mbps. The FCC's long-term goal is to have 1 gigabits (Gbps) downloads and 500 Mbps uploads.

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statistics such as aggregate labor productivity and total factor productivity (TFP) in the U.S. (Byrne et al., 2016). The deceleration is not limited to a specific region but is prevalent across the OECD countries, and has recently been observed in several major emerging economies (Syverson, 2017).

On the other hand, there has been compelling case-study or micro-level evidence on the causal effect of broadband internet on economic outcome. This includes reducing various costs (Goldfarb and Tucker, 2019), alleviating information asymmetries (Kuhn and Skuterud, 2004), improving labor productivity (Akerman et al., 2015), creating jobs (Hjort and Poulsen, 2019), enhancing market access (Fan et al., 2018), ameliorating organizational structure (Bresnahan et al., 2002), promoting management practices (Bloom and Van Reenen, 2007), fostering innovation (Paunov and Rollo, 2016; Yang et al., 2022), promoting entrepreneurship (Dai and Zhang, 2015), and increasing resilience to shocks (Bai et al., 2021; Cong et al., 2024), among many others.[2] The gap between the micro foundations and the macro statistics has motivated investigations that lead to several explanations. Some point to the possibility that output and productivity may not be accurately measured, and the gains brought by these technologies may not be fully captured, especially in terms of quality improvements and new product innovations (Smith, 2015). Others suggest that there could be a lag in realizing productivity gains from new technologies, implying that benefits might become more apparent over time (Brynjolfsson et al., 2021).

This paper aims to understand the gap by estimating the growth effect of broadband internet using data on China's prefecture-level cities from 2005 to 2019. China per se is an interesting research subject as it has experienced rapid economic growth and fast broadband expansion in the past two decades. The success or the lesson of China provides an important reference to other emerging economies that are still in the catch-up stage. Furthermore, exploiting recent city-level data of China has several advantages for our research design. First, China has relatively high quality city-level administrative panel data among developing economies. It allows us to implement a growth accounting framework covering the vast majority of the economy in obtaining an aggregate growth effect of broadband internet that is often lack in micro-level studies. Second, as the world second largest economy, China is also well-known for its huge heterogeneity across regions in historical endowment, topographical condition and economic development. This provides a potential identification by utilizing how broadband internet rollout depends on the historical and topographical conditions across cities. Finally, as a hybrid of the planned and market economy, China has implemented some top-down place-based policies in infrastructure investment, including the recent Broadband China Pilot City Program. The temporal and spatial variation in the rollout of the Program provides a quasi-experiment for us to further explore the mechanisms on how broadband internet promotes economic growth.

Under this empirical setting, and based on existing literature, we address three research questions in turn. First, does the penetration of broadband internet boost economic growth in China? If yes, is the positive relationship causal? Kolko (2012) estimates the 7-year growth effect of a 1% broadband expansion to be 0.06% by Ordinary Least Square (OLS) estimation and 0.64% by Instrumental Variable (IV) estimation over the period 1999–2006 throughout the United States. Czernich et al. (2011) suggests a 0.07% annual growth effect of broadband penetration rate by OLS and a 0.09% effect by Two-Stage Least Squares (2SLS) for 22 OECD countries during 1996–2007. However, a similar work by Koutroumpis (2009) finds a much lower effect, with an elasticity of 0.025, using a panel of 22 OECD countries from 2002 to 2007. This strand of the literature only focuses on developed countries, nevertheless, the effect in emerging countries may be different due to disparities in endowment, markets, and institutions. Kumar et al. (2016) focuses on China as a case study and conduct a time series analysis for the growth effect of five information and communication technologies (ICT). The paper finds an elasticity of ICT on economic growth ranging from 0.01 to 0.08, but also highlights a bidirectional causality between mobile cellular, telecommunication and economic growth. This suggest that there is still a lack of convincing causal evidence on the economic impact of the internet, especially in less developed countries including China.

Second, does the benefit of broadband internet exceed the cost, so that the investment in digital infrastructure is efficient? Recognizing the strategic role of digital technology in the China–US rivalry, both countries have invested or committed to invest massively in digital infrastructure. For example, the *New Infrastructure Initiative* in China, announced in 2020, focuses on building next-generation infrastructure, including 5G, AI, industrial internet, and data centers. The total investment under this initiative is estimated to exceed 10 trillion RMB (approximately $1.5 trillion) by 2025. On the second day of taking office in the White House, alongside CEOs of top tech firms, Donald Trump announced the *Stargate Project* that will invest $100 billion to start, with plans to pour up to $500 billion in the coming years, in order to build "the physical and virtual infrastructure to power the next generation of AI". In contrast to this massive investment, there is a paucity of research in calculating the aggregate rate of return for investment in digital infrastructure, including the broadband internet. More broadly, many countries in the developing world are still making significant investments in internet infrastructure, with the hope that connectivity can facilitate economic progress. A clearer sense on the costs and benefits could provide an evaluation on the existing investment and a better guidance for future public expenditure in this area.

Lastly, what is the mechanism of the growth effect of broadband that could be captured using city-level data? So far the outcomes of specific mechanism identified in the literature that largely employ firm-level or household-level data are usually difficult to measure at the city-level, with innovation and entrepreneurship being two exceptions. Meanwhile, innovation and entrepreneurship are two well recognized factors to productivity (Romer, 1990; Baumol, 1996), the ultimate source of long-run economic growth. In China's context, Yang et al. (2022) finds a positive effect of broadband internet on firm innovation, mainly through improving R&D personnel quantity and quality, stimulating firm's willingness to innovate, and attracting more financial support. In addition, Dai and Zhang (2015) shows that the spread of e-commerce reduces transaction costs and broadened the scope for entrepreneurship. This shift enables more people, including those previously limited by financial and social capital constraints, to become entrepreneurs. This motivates us to investigate whether there is a causal effect of broadband internet on innovation and entrepreneurship in China at the city-level, if we do find broadband internet impact economic growth.

To investigate these research questions, we apply a conceptual framework derived from Mankiw et al. (1992) to data on prefecture-level cities in China during 2005–2019. The baseline OLS result suggests that a 10-percentage-point increase in broadband internet penetration growth is associated with a 0.41-percentage-point increase in annual GDP per capita growth. We also adopt a physical measure of digital infrastructure availability based on the geographic distribution of 2G/3G/4G mobile base stations from OpenCelliD, which yields consistent results. The inferred social rate of return to investment in broadband internet infrastructure is 21% during the sample period. This is higher than both the private rate of return to investment in ICT firms and the social rate of return to investment in traditional infrastructure.

The 2SLS approach is utilized to mitigate the endogeneity problem, where we explore the number of telephones in 1984 as a historical

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[2] See survey papers of Goldfarb and Tucker (2019) and Hjort and Tian (2024) for research on "digital economics" in rich countries and "internet connectivity" in developing economies.

IV and the relief degree of land surface (RDLS) of each city as a topographical IV. Since these factors may also influence economic growth through other channels beyond broadband access, we interact them with national broadband penetration to extract the component of growth attributable specifically to broadband internet infrastructure. Results indicate that a 10-percentage-point increase in broadband penetration growth leads to a 1.50–2.07 percentage point increase on average in GDP per capita growth. The estimates remain stable even after we further include highway freight and passenger volumes growth in each city to control the potential channel of how historical and topographical conditions might affect economic growth. We also conduct a set of robustness checks for the causal inference, such as alternative measures of internet penetration, exclusion of internet nodal cites, alternatives of historical IV in 1984, and make use of the financial indicators from China's major broadband infrastructure providers to further addresses the exclusion restriction.

Exploiting the temporal and spatial variation provided by the Broadband China Pilot City Program, the staggered difference-in-differences (DID) results further suggests innovation and entrepreneurship are the two mechanisms of the economically and statistically significant growth effect of broadband internet. Finally, we provide additional evidence that firms located in cities that participated in the program at an earlier stage exhibit notably higher levels of digital adoption. This phenomenon, in turn, underscores the pivotal role of city-level broadband internet infrastructure in facilitating and manifesting its impact on innovation, entrepreneurship, and overall economic growth.

Our paper contributes to the literature in three aspects. First, this paper identifies the growth effect of broadband internet using cite-level data and provides an efficiency evaluation for China at the national level. This complements many existing literature that estimates the causal impact of the internet in particular contexts. Second, although there has been a large literature on the causal effect of traditional infrastructure on economic outcome, especially on the transportation infrastructure in China, such as Faber (2014), Banerjee et al. (2020), and Wu et al. (2021), there is relatively scare research on digital infrastructure. This paper contributes to the nascent yet growing literature on the economic effect of internet connectivity. Finally, existing literature on the causal inference on broadband internet in China has used IV or DID approach and employed some arguably exogenous shocks in earlier years, such as the Speed up of Major Backbone Networks in 2000 (Chen and Liu, 2020) and the North–South separation reform of China Telecom in 2002 (Yang et al., 2022). In this paper, we explore the more recent and relatively understudied Broadband China Pilot City Program in 2014–2016 using a staggered DID approach.

The remainder is organized as follows. Section 2 provides the background of broadband deployment in China. Section 3 introduces the baseline growth model. Section 4 addresses the endogeneity issue by 2SLS approach. Section 5 performs further analysis and robustness checks. Section 6 investigates the mechanisms based on a staggered DID design. Section 7 concludes the paper.

2. The broadband internet penetration in China

2.1. Broadband internet: Who, where, why, and how

In this section, we provide a summary of broadband deployment in China about the roles of central government, local governments, and the major telecommunication service operators in China. Detailed information is provided in the Online Appendix B.

The central government of China has played a proactive and strategic role in broadband internet development, integrating it into a series of national informatization and industrial plans since the late 1990s. From setting ambitious targets in early five-year plans to launching successive generations of mobile technology, the government's approach has evolved to be both supply- and demand-driven. Special initiatives like the Broadband China Pilot City Program demonstrate targeted efforts to accelerate access, particularly with a staggered rollout between 2014 and 2016. In addition to promoting growth, the central government has emphasized digital equity, mandating universal telecommunication service obligations and prioritizing underserved rural areas through various regulatory and strategic plans.

Local governments, operating under China's regionally decentralized authoritarian system, are instrumental in executing national broadband goals, as their performance is closely tied to economic outcomes like GDP growth (Xu, 2011). Incentivized by promotion mechanisms, local officials often turn to infrastructure investment to boost short-term growth and long-term productivity (Wu et al., 2021). However, their ambitions are constrained by budgetary limits and central regulations (Xiong and Song, 2024). After 2008, financing through Local Government Financing Vehicles (LGFVs) surged, but mounting debt prompted the central government to impose strict debt ceilings from 2014 onward. Consequently, local governments face a tradeoff between investing in broadband and other infrastructure projects, especially given limited fiscal space.

Broadband construction in China is dominated by three major telecommunication service operators, China Mobile Limited (China Mobile), China Telecom Corporation Limited (China Telecom), and China United Network Communications Group (China Unicom), each among the largest global players by revenue and subscribers.[3] Despite being profit-driven, publicly listed firms on the New York Stock Exchange (NYSE) and the Hong Kong Exchanges and Clearing Limited (HKEX), until their late home-return to the Shanghai Stock Exchange (SSE), these operators are also instruments of state policy, particularly in extending broadband to less profitable rural regions. While financial incentives discourage them from expanding in hard-to-reach areas, state ownership ensures compliance with national goals such as the Village Connection Project. As a result, substantial investments have been made to bring broadband to thousands of towns and villages, helping close the rural–urban digital divide.

In sum, broadband infrastructure development in China relies on the planning of central government, collaboration between telecommunication service operators and local governments through policy coordination, resource sharing, and joint investments, subject to the incentives and constraints of each stakeholder.

2.2. Broadband internet development in China

This paper exploits the variation overtime and across cities to identify the growth effect of broadband internet penetration. Fig. 1 depicts the evolution of the spatial distribution of the number of broadband internet subscribers per 100 households and GDP per capita from 2005 to 2019. The pattern of the figures highlights the continual and substantial growth of both internet subscribers and GDP per capita. The number of cities with broadband internet penetration rates over 70% in 2005 is only 18, and this number increases to 51 after a decade, while in 2019, it surges to 223. During the same sample period, there is a marked acceleration in GDP per capita in China. In 2005, a mere 24 cities reports a GDP per capita surpassing 40,000 yuan ($5500). This statistic grows to 63 in 2010, expands to 142 by 2015, and reaches 184 by 2019.

Furthermore, Fig. 1 reveals an uneven expansion of broadband internet across China. The penetration rate in northeastern China has been lagged behind the national average throughout the two decades. In contrast, the coastal cities in the southeast witnessed a rapid surge in broadband internet penetration from 2010 onwards, consistently

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[3] In July 2014, the tower assets and operations of these three operators were consolidated into China Tower Corporation Limited, a state-owned company specializing in telecommunication tower construction, maintenance, and ancillary facilities management throughout Mainland China. This restructuring aimed to improve efficiency and reduce redundant infrastructure development.

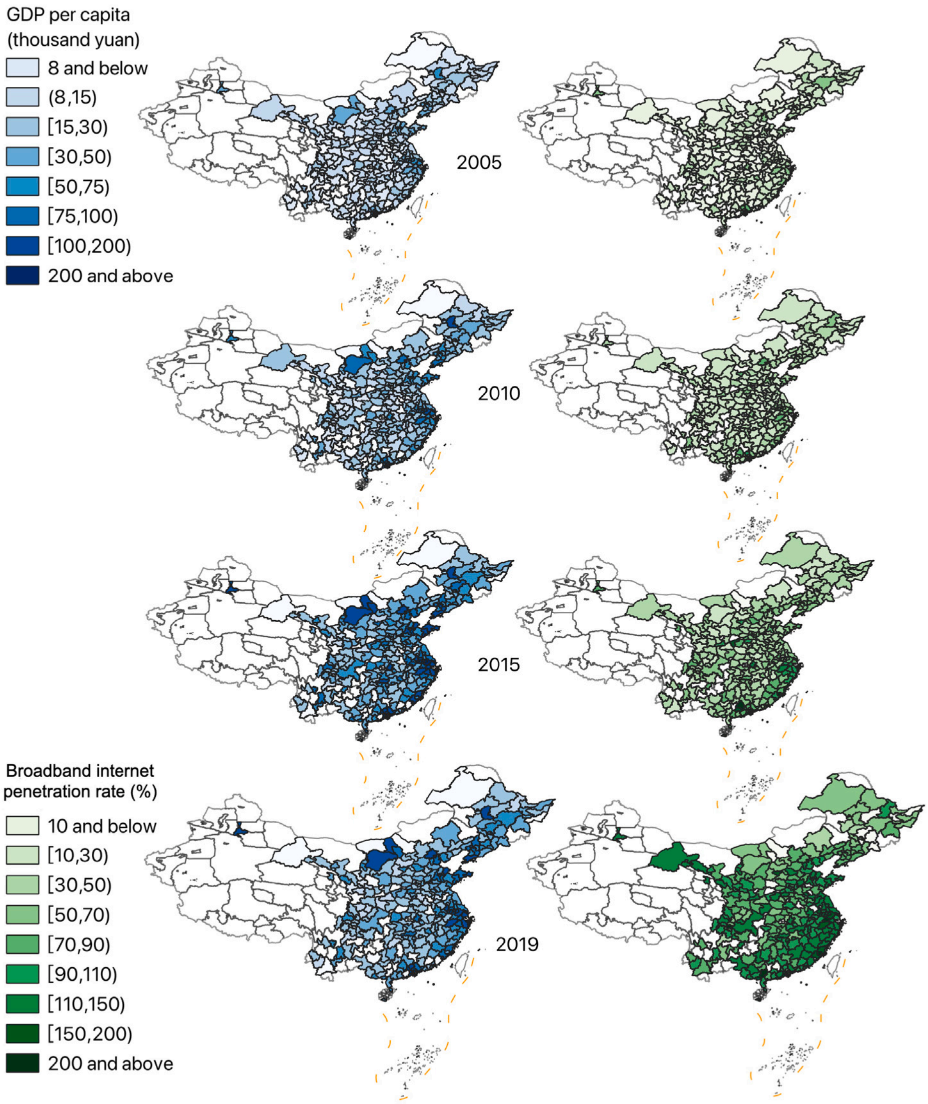

Fig. 1. The spatial distribution of GDP per capita and broadband penetration,
Notes: The left panel is for GDP per capita, while the right panel reflects broadband penetration that is defined as the number of broadband internet subscribers per 100 households. The areas with data unavailable are colored in white. Regions with darker color have greater values of broadband penetration or GDP per capita. The base map is sourced from the Ministry of Natural Resources of the People's Republic of China with the Map Approval Number: GS(2020)4624.
Source: Calculated by authors according to the CCSY and the CEIC database.

outpacing other cities. The spatial distribution of GDP per capita mirrors that of broadband internet penetration. The correlation coefficient between GDP per capita and broadband internet penetration rate stand at 0.773 during our sample period. The rest of the paper investigates whether there is a causal relationship underlying the positive correlation.

3. Growth effect of broadband penetration

3.1. Baseline growth model

This paper follows Czernich et al. (2011) that starts from the steady-state equation of a three-input production function proposed by Mankiw et al. (1992):

$$\ln y_{it} = \ln A_{it} + \beta_1 \ln s_{it} + \beta_2 \ln h_{it} + \beta_3 n_{it}, \tag{1}$$

where y_{it} is GDP per capita in city i and year t; A_{it} is the level of technology; s_{it} is the share of GDP invested in physical capital; h_{it} is the human capital accumulation; and n_{it} is the growth of population.

We assume TFP evolves exponentially over the year:

$$A_{it} = A_{i0} \mathrm{e}^{\lambda_{it}}, \tag{2}$$

where A_{i0} is the city-specific initial level of TFP, and $\mathrm{e}^{\lambda_{it}}$ is the growth factor in city i and year t.

To model the effect of broadband internet on TFP, we further assume that the growth factor follows:

$$\lambda_{it} = \alpha_0 t + \alpha_1 \ln B_{i,t-1} + \epsilon_{it}, \tag{3}$$

where $B_{i,t-1}$ is the broadband penetration level in the city i and year $t-1$. The lagged timing reflects the time-to-build assumption.

The intuition behind Eq. (3) is that the city-specific growth of TFP can be divided into three parts. First, $\alpha_0 t$ is a common growth trend over the whole nation, with an average annual growth rate α_0. Second, $\alpha_1 \ln B_{i,t-1}$ is the contribution of broadband penetration in city i. Third, ϵ_{it} is an unobserved city- and year-specific shock to the growth factor. The term ϵ_{it} captures all factors other than national average and city-specific broadband that affect the technology growth, such as the construction of traditional infrastructure like high-speed railways.

Table 1
Summary statistics for variables in regression.
Source: Calculated by authors according to the CCSY and the CEIC database.

Variable	Definition	N	P25	Mean	Median	P75	Std. Dev.
$\Delta \ln y$	Growth rate of real GDP per capita	2608	5.597	8.602	8.702	11.981	6.402
$\Delta \ln B$	Growth of broadband subscribers per 100 households	2608	5.208	15.227	14.107	23.921	17.722
$\Delta \ln M$	Growth of mobile phone penetration	2608	1.592	10.446	8.696	17.258	15.967
$\Delta \ln R$	Growth of per capita telecommunication revenue	2541	−0.534	6.259	5.854	12.270	19.392
$\Delta \ln s$	Growth of (fixed asset - residential investment)/real GDP	2608	−3.521	2.869	5.122	11.436	17.870
$\Delta \ln h$	Growth of number of college students/local residents	2608	−0.321	5.543	3.656	9.650	14.759
Δn	First difference of residential population growth	2608	−0.635	−0.064	0.001	0.586	4.455
$\ln y_0$	Natural logarithm of real GDP per capita in 2005	2608	8.901	9.361	9.311	9.726	0.629

Notes: All the growth rates are obtained by the differences between the natural logarithm of the current-year value and the previous-year value, and in terms of percentage %.

Under the general assumption as Eq. (3), Eq. (1) becomes:

$$\ln y_{it} = \ln A_{i0} + \alpha_0 t + \alpha_1 \ln B_{it-1} + \beta_1 \ln s_{it} + \beta_2 \ln h_{it} + \beta_3 n_{it} + \epsilon_{it}. \tag{4}$$

By taking the first differences, introducing $\ln y_{i0}$, the GDP per capita in initial year (Barro, 1991), and rewriting the first difference of the error term, $\varepsilon_{it} = \Delta\epsilon_{it}$, we propose the economic growth regression model with the impact of broadband internet as Eq. (5):

$$\Delta \ln y_{it} = \alpha_0 + \alpha_1 \Delta \ln B_{it-1} + \beta_1 \Delta \ln s_{it} + \beta_2 \Delta \ln h_{it} + \beta_3 \Delta n_{it} + \beta_4 \ln y_{i0} + \varepsilon_{it}. \tag{5}$$

Although our empirical foundation remains closely aligned with the original growth-accounting logic in Czernich et al. (2011), our key explanatory variable is different. Specifically, Czernich et al. (2011) relies on the variation in broadband penetrate level across OECD countries to explain the cross-country growth rate of GDP per capita. We instead calculate the growth rate of broadband penetration as a measure for broadband internet development. This choice might be more appropriate in the context of China, given the large dynamism and nonlinear rollout patterns in China's broadband development. Of course, the corresponding interpretation on the regression outcome is also different. While Czernich et al. (2011) reports a level to growth rate effect, we report a growth rate to growth rate effect.

The parameter of our primary interest is α_1, capturing the average effect of broadband penetration growth on annual GDP per capita growth, after controlling for other factors. In the set up of Eq. (5), the first differences eliminates the city fixed effect ($\ln A_{i0}$) and the year fixed effect ($\alpha_0 t$) in Eq. (4). We could add a year fixed effect, and this is only to accommodate α_0 to be year-specific. OLS estimates for α_1 would be consistent if $corr(\Delta \ln B_{i,t-1}, \varepsilon_{i,t}) = 0$. This requires the shock to the productivity growth rate in a city is not correlated with the lagged broadband penetration growth in that city. This assumption is much weaker than $corr(\ln B_{i,t-1}, \epsilon_{i,t}) = 0$. Nevertheless, we still estimate α_1 using the 2SLS approach in case this assumption does not hold.

3.2. Data

We obtain China's prefecture city-level panel data between 2005 and 2019 from the China City Statistical Yearbooks (CCSY) and the China Premium Database of CEIC separately for cross-checks. In Eq. (5), y_{it} is measured by real GDP per capita in city i and year t; B_{it-1} is the number of broadband internet subscribers per 100 households by residence in city i and year $t-1$; the proxy of k_{it} is the share of fixed asset investment deducted by residential housing investment in real GDP; h_{it} is the number of college students normalized by residential population; n_{it} is the residential population growth rate; and y_{i0} is the real GDP per capita in city i in the year 2005.

The definitions and summary statistics of key variables in regression are reported in Table 1. For those cities with changing boundaries or missing data, we exclude them from our sample following Banerjee et al. (2020). This leaves us an unbalanced panel of 241 cities and 2608 observations. We report the details of data cleaning process and panel structure of the final sample in the Online Appendix C.

According to Table 1, the average annual real GDP per capita growth rate is 8.6%. This is consistent with official statistics at the more aggregate level. Broadband penetration on average increases by 15.2% every year. Specifically, the average penetration rates over these cities in 2006, 2014 and 2019 are 18.1%, 52.3%, and 106.6%, respectively. In later years, the subscription ratio exceeds 100% in some cities. This is because the number of broadband internet subscribers are collected from the three major telecommunication service operators, which includes users from organizations such as firms, governments, and universities. This may result in double counting for some individuals. One thing should be noted is that our measure of broadband penetration refers to the broadband subscription intensity, not engineering-level broadband internet capability. Specifically, the CCSY reports only the total number of broadband subscribers registered with the three major telecommunications operators. No information is available on within-city network topology, such as Asymmetric Digital Subscriber Line (ADSL) loop lengths, local exchange boundaries, or copper-line geometry, which determine achievable internet speeds. Consequently, broadband penetration should be interpreted as capturing the extent of broadband access and adoption, rather than physical speed capacity at sub-city levels. In Section 4.1, we discuss the potential bias caused by such measurement errors.

3.3. Baseline results

Table 2 presents the OLS results for the growth model Eq. (5). Column (1) reports the estimates of our baseline setup. On average, a 10-percentage-point increase in the growth of broadband penetration is associated with a 0.41-percentage-point increase in real GDP per capita growth, ceteris paribus. In addition, the signs and magnitudes of coefficients on the other variables are as expected (Mankiw et al., 1992). Column (2) only keeps the initial level of real GDP per capita without the other factors of production. The coefficient on the lagged growth of broadband penetration in column (2) is slightly lower than that in column (1). This is true as the key independent variable is negatively correlated with one of the control, the first difference of population growth, given that broadband penetration is normalized by population size.

To make the magnitude more intuitive, we provide a concrete example using national averages: during 2006 to 2018, broadband penetration expanded at approximately 17% per year, and GDP per capita grew at 8.6% annually from 2007 to 2019. Therefore, an increase in broadband penetration growth from 17% to 27% would raise GDP per capita growth from 8.6% to approximately 9.11%.

Although Eq. (5) is obtained by taking the first differences that eliminates the city fixed effect, we could add a year fixed effect to show the robustness of our results in column (3). Furthermore, we include both city and year fixed effects and present the results in column (4). Including such fixed effects allows the growth rate beyond the contribution of broadband internet to be city- and year-specific. The robust evidence suggests that even under this most relaxed assumption,

Table 2
Growth effect of broadband internet: Baseline OLS results.

Dep: GDP per capita growth	(1) Baseline model	(2) Without control	(3) Baseline with year FE	(4) Baseline with TWFE
Lag of broadband penetration growth	0.041***	0.027***	0.041***	0.018***
	(0.007)	(0.007)	(0.008)	(0.007)
Saving rate growth	0.131***		0.127***	0.102***
	(0.014)		(0.016)	(0.018)
Human capital growth	0.033***		0.035***	0.022**
	(0.009)		(0.010)	(0.010)
First-difference of population growth	−0.307***		−0.310***	−0.304***
	(0.030)		(0.031)	(0.030)
Logarithm of GDP per capita in 2005	−1.324***	−1.915***		
	(0.174)	(0.174)		
Constant	19.549***	25.841***	7.166***	9.010***
	(1.689)	(1.644)	(0.149)	(0.349)
City FE	NO	NO	NO	YES
Year FE	NO	NO	YES	YES
Observations	2608	2608	2608	2608
R-squared	0.221	0.046	0.182	0.347

Notes: Column (1) is the baseline result that includes all variables in the theoretical framework. Column (2) only includes the key independent variable and the GDP per capita in the initial year 2005. Column (3) controls for the year fixed effect. And column (4) includes both year and city fixed effect. Clustered (at city level) robust standard errors are reported in parentheses. $***$ indicates $p < 0.01$; $**$ indicates $p < 0.05$; $*$ indicates $p < 0.1$.

the broadband penetration growth still has a positive and significant effect on economic growth.

Compared with the findings of Kolko (2012) in the U.S., where the economic effects of broadband rollout appear more gradually, the effects found in China seem to be faster. This accelerated effects could be attributed to China's position as a technological follower rather than a frontier innovator in broadband infrastructure. Moreover, the top-down implementation strategy through initiatives like the Broadband China Pilot City Program might also contribute to the faster diffusion of broadband internet and economic growth. The combination of ready-made technology and policy-driven deployment significantly shortens the lag between broadband expansion and measurable economic outcomes.

To account for the substantial technological upgrade in China's fixed broadband infrastructure over our sample period, we further separate the analysis into two sub-periods that correspond to the dominant access technologies in each era. The first sub-period,2007–2014, reflects a pre-fiber-dominant phase during which ADSL and cable modem connections constituted the main forms of fixed broadband. The second sub-period,2015–2019, corresponds to the fiber-to-the-home (FTTH) era, following the nationwide fiber rollout that accelerated after 2013. The timing of this break is consistent with industry evidence: China Telecom's 2015 Annual Report indicates that FTTH accounted for nearly 40% of broadband users by the end of 2014 and exceeded 60% by the end of 2015, a transformation further reinforced by MIIT's 2013 mandate requiring fiber-ready installation in newly built housing units in fiber-covered areas. By 2020, China had installed more than 860 million fiber access ports, with FTTH penetration rates surpassing 92% nationwide. As the average download speeds of ADSL and FTTH are around 24 Mbps and at least 100 Mbps, this evolution represents a marked shift in technological capability and service quality, making the distinction between pre-fiber and fiber-dominant periods economically meaningful.

Table 3 presents the results from these two periods. Columns (1) and (2) show the OLS and 2SLS estimates in the pre–fiber-dominant era. The estimated growth effect is positive but modest, consistent with the more limited speed, stability, and capacity of copper-based networks. Columns (3) and (4) indicate in the fiber-dominant period, the estimated broadband coefficient nearly doubles in size relative to the earlier period. This substantial increase aligns with the technological upgrade: fiber connections deliver significantly faster and more reliable bandwidth, enabling broadband to exert a much stronger growth effect.

The comparison across periods suggests that the economic impact of broadband penetration is closely tied to underlying technological capability and quality of the network. Broadband mattered even during the copper era, but its growth effect became materially stronger only after fiber became the dominant access technology. This pattern reinforces the interpretation of broadband as a genuine form of productive infrastructure rather than a simple household communication good.

4. 2SLS approach

4.1. Endogeneity

The consistency of OLS estimates for α_1 in Eq. (5) depends on the assumption that $corr(\Delta \ln B_{i,t-1}, \epsilon_{i,t}) = 0$. This assumption could be challenged for several reasons, so that the OLS estimates could be biased.

On the one hand, the OLS estimates could be upward biased due to positive reverse causality, omitted variables, and endogenous location choice. First, local governments with higher GDP growth rates ($\Delta \ln y_{it}$) may foresee the demand for more, faster, and better broadband internet infrastructure from high-growth firms and high-income households. To meet this demand, they tend to speed up the construction of broadband internet, reflected by a higher broadband penetration growth rate ($\Delta \ln B_{it-1}$). Furthermore, meeting this demand is consistent with profit-maximization of the three major telecommunication service operators. Given there is economics of scale of infrastructure investment, rolling out broadband infrastructure in those fast-growing cities implies more revenue and higher rate of return. As a result, there could be a positive correlation between broadband penetration growth and GDP per capita growth, even if there is no causal effect that we are trying to identify. Second, a turnover in city leadership, particularly the arrival of a more ambitious and competent mayor, could drive various growth-enhancing initiatives simultaneously, in addition to broadband infrastructure investment. Such omitted concurrent policy initiatives could lead to upward-biased OLS estimates. Finally, firms with higher productivity and households with higher income are more likely to adopt broadband internet services and use more intensively after adoption. Consequently, they are inclined to locate in cities with

Table 3
Growth effect of broadband internet: Different generations of broadband.

Dep: GDP per capita growth	(1)	(2)	(3)	(4)
	Pre-fiber-dominant: 2006–2014		Fiber-dominant: 2015–2019	
	OLS	2SLS	OLS	2SLS
Lag of broadband penetration growth	0.024***	0.109	0.047***	0.104**
	(0.007)	(0.071)	(0.018)	(0.044)
Saving rate growth	0.050***	0.060***	0.122***	0.141***
	(0.012)	(0.013)	(0.020)	(0.025)
Human capital growth	0.023*	0.023*	0.029	0.061**
	(0.012)	(0.012)	(0.024)	(0.031)
First-difference of population growth	−0.309***	−0.365***	−0.288***	−0.345***
	(0.028)	(0.068)	(0.080)	(0.123)
Logarithm of GDP per capita in 2005	−1.708***	−1.386***	−1.430***	−0.790*
	(0.254)	(0.412)	(0.429)	(0.473)
Constant	25.243***	20.797***	17.610***	10.931**
	(2.444)	(4.923)	(4.005)	(4.645)
R-squared	0.142	0.04	0.229	0.253
Observations	1812	1464	796	626

Notes: Columns (1) and (2) report the estimation for the pre-fiber-dominant period 2006–2014 (inclusive). Columns (3) and (4) are for the fiber-dominant period 2015–2019 (inclusive). Columns (1) and (3) show the OLS estimates, while columns (2) and (4) are the second-stage results of 2SLS estimates using the same historical and topographical IVs. Clustered (at city level) robust standard errors are reported in parentheses. $***$ indicates $p < 0.01$; $**$ indicates $p < 0.05$; $*$ indicates $p < 0.1$.

better internet infrastructure. This self-selection effect can also result in an upward bias in OLS estimates.

On the other hand, the OLS estimates could exhibit a downward bias attributed to negative reverse causality, omitted variable bias, and measurement error. First, the central government of China has committed to narrowing the digital divide between urban and rural areas and specifies the requirements for telecommunications universal service in various planning policies, as discussed in Section 2. Therefore, the three major telecommunication service operators, which are SOEs by nature, are compelled to invest more in the less developed areas as mandated by the regulation and supervision of the central government. Such investment may contradict the profit-maximization rationale, as these areas often possess inadequate logistic infrastructure, scattered populations, less productive firms, and lower demand for internet service. It is consistent with the lower market valuation for the three telecommunication service operators, compared with their counterparts in the US. This suggests there could be a negative correlation between GDP per capita growth and internet penetration growth.

Second, the local governments in China may have other local infrastructure projects in addition to broadband internet infrastructure. If the fiscal budget constraint is binding, there could be a negative correlation between investment in competing infrastructure projects. The first difference of Eq. (5) may eliminate the negative correlation between internet and other infrastructure in level. However, it may not completely eliminate the negative correlation in their growth rate. If so, in Eq. (5), the growth of other infrastructure, such as high-speed railways and electricity grids, is subsumed within ε_{it}. In the literature, infrastructure of transportation and electricity is generally found to have a positive growth effect (Baum-Snow, 2007; Faber, 2014; Agrawal et al., 2017; Banerjee et al., 2020; Wu et al., 2021). Omitting such variables may lead to a downward bias of OLS estimates for α_1.

Lastly, OLS estimates may suffer from attenuation bias due to potential measurement error in broadband penetration. Broadband penetration is measured as the number of broadband subscribers per one hundred households. While this measure is standard and widely used in both academic and policy research, it is inherently imperfect. For example, heterogeneity in household size across Chinese prefectural cities may distort the per-100-household denominator, as cities with larger households mechanically exhibit lower measured penetration even when the number of subscriptions per person is comparable. Furthermore, as elaborated in the Online Appendix C,[4] the average registered household size tends to be larger than the residential household size, since the labor force flows into cities and one registered household breaks out into two residential households in two different cities, for example, reducing the residential household size in each city. Thus, the inferred number of residential households is underestimated, and as a result, the broadband penetration rate is overestimated systematically. Moreover, the data may not distinguish clearly between residential and institutional accounts: commercial or government subscribers may be counted as household subscribers, and single households may maintain multiple subscriptions for work, business, or rental purposes. This is the reason why the number of broadband internet users is larger than the number of households in cities with a plethora of firms and universities such as Shenzhen, Shanghai, and Wuxi. These sources of noise directly attenuates the OLS estimate toward zero. In addition, the measure aggregates all subscribers within a city and therefore masks within-city differences in physical network conditions. In the ADSL-dominant era, achievable broadband speed depended heavily on the average loop length between premises and local exchanges. Longer copper loops may reduce attainable speeds even for users counted equally in subscriber totals. Because engineering-level data on loop lengths and exchange topology are not available for Chinese city, our penetration measure may mask this variation. This limitation implies that our broadband measure captures access intensity rather than line-quality. This concern further motivates the period-specific analysis in Section 3.3 and Table 3, where we show that the estimated broadband coefficient nearly doubles in the fiber-dominant period after 2014, consistent with the substantial improvement in physical network capability.

4.2. Instrumental variables

To address the potential endogeneity issue, we use the 2SLS estimation to identify the causal effect of broadband penetration growth on

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[4] Due to unavailability of the number of local (different from registered household) households, we use local residence divided by the average household size to infer the number of local households, where the average household size is calculated as registered population over registered household. The underlying assumption is the average household sizes for registered households and for local households are the same. In this way, we can obtain the broadband penetration rate normalized by local households.

GDP per capita growth. This paper proposes two types of IVs that are popular in literature: historical IV and topographical IV.

First, the historical IV refers to the variable that contains information from a long time ago. Owning to a longtime interval, the correlation between this historical information and the error term of recent economic status fades away as time goes by. Following Czernich et al. (2011), this paper uses the number of telephones in 1984, the earliest available prefecture-level data from the CCSY, as a historical IV. This choice is particularly suitable in the Chinese context due to the institutional and technological evolution of China's telecommunications infrastructure. Broadband internet in China initially relied heavily on existing copper-wire telephone networks, as evidenced by the three-network integration process.[5] The predetermined number of telephones strongly predicts subsequent broadband internet development, particularly for ADSL, cable, and early fiber-optic services. Moreover, this historical measure is plausibly exogenous to contemporary economic growth, as GDP per capita growth rates after 1984 were primarily driven by economic reforms and opening-up policies rather than pre-existing telecommunications infrastructure. We also experiment with alternative historical IVs, including the number of post offices and telecommunication revenue in 1984, as robustness checks.

Although the level of fixed-line telephone adoption in China remained modest in 1984, the cross-city variation in the CCSY data is substantial and meaningful for identification. The mean number of telephones across prefecture-level cities is 0.84 per 100 people. Importantly, the dispersion across space is large: several coastal and industrialized cities, such as Shanghai, Tianjin, and Guangzhou, had penetration rates exceeding 2 telephones per 100 people, whereas many interior and western cities had fewer than 0.2. This heterogeneity captures long-standing differences in early telecommunications development, administrative importance, and industrial structure, which subsequently shaped local capacity to adopt ADSL and cable modem broadband technologies during the 2000s.

To provide a clear visualization of this identifying variation, Fig. 2 displays a map of the spatial distribution of fixed-line telephone penetration in 1984. The geographic pattern reveals a pronounced east–west divide, with higher values concentrated along the eastern coastal area and significantly lower penetration in the western inner land. This spatial structure highlights the historical foundations of China's uneven telecommunications landscape and illustrates how the predetermined telephone network provides substantial variation relevant for later broadband rollout.

Second, the topographical IV denotes the physical and geographical characteristics of a city. Such variable describes the variations made by nature, as a result, it is usually regarded as exogenous and used as an IV for broadband internet. For example, Kolko (2012) uses the average slope of terrain as an instrument for broadband availability, while Ahlfeldt et al. (2017) exploits how ADSL depends on the distance from the premise to the nearest connection point for identification. Since the underlying technology of broadband internet studied in this paper evolves from the early ADSL cable technology to the recent mobile technology, the topographical IV proposed in this paper is the RDLS of each city, constructed by You et al. (2018). RDLS captures both slope and elevation of the terrain: the larger slope and the higher elevation of the terrain, the greater is the RDLS value.

The RDLS measure also exhibits rich spatial variation. Across the cities in our sample, RDLS values range from near zero in flat alluvial plains such as the Yangtze River Delta to very high levels in mountainous regions including Yunnan, Guizhou, and parts of Sichuan. This spatial heterogeneity reflects meaningful differences in engineering cost structures: areas with higher RDLS values face greater difficulty in laying and maintaining buried telecommunication cables, higher construction costs, and increased risks of physical damage. As a result, the RDLS measure provides rich cross-sectional variation that strongly predicts subsequent broadband penetration rates through supply-side constraints inherent in the physical terrain.

To illustrate this variation, Fig. 3 reports a city-level map of the RDLS distribution. The map highlights the natural clustering of high-RDLS cities in southwestern and northwestern China, contrasted with expansive low-RDLS regions in the eastern plains. The geographic pattern underscores the role of terrain-induced cost heterogeneity in shaping the path of broadband rollout.

Both IVs are inherently time-invariant. To introduce necessary time variation for panel analysis, we follow Nunn and Qian (2014) and interact these city-level IVs with the yearly national broadband penetration rate. The underlying rationale lies in that the broadband internet rollout takes place earlier and faster in cites with superior pre-existing telecommunications infrastructure and more favorable topographical conditions. This interaction strategy also addresses the exclusion restriction by design. Under this specification, the interaction term captures how historical and topographic conditions affect the GDP per capita growth rate via how broadband internet has been rolling out in China.

In robustness checks, we explore alternative specifications for the time-varying component. Instead of national broadband penetration, we interact our time-invariant IVs with the lagged one-year growth of operating revenue from China Mobile, China Telecom, China Unicom, and China Tower. This alternative leverages operator-specific financial data to capture the telecommunications sector's expansion and capacity to supply broadband infrastructure.

The exclusion restriction would require the model to estimate how the historical and topographical IVs affect economic growth solely through their influence on broadband penetration, without exerting any independent or direct effect on GDP per capita growth. Specifically, the exclusion restriction holds if these IVs are unrelated to the error term in the second-stage equation. However, there are some potential threats to this assumption. For instance, historical telecommunications infrastructure, such as the number of telephones, may have facilitated information flows and trade connectivity even before the broadband era, thereby directly influencing local economic outcomes. Similarly, topographical features like slope and elevation may shape economic development by affecting transportation costs and the movement of goods and people. To mitigate these concerns and reduce the risk of violating the exclusion restriction, this paper explicitly controls for the growth of city-level highway passenger volumes and freight volumes, which serve as proxies for local trade, mobility, and transportation infrastructure.

Concerns may remain that the controls of passenger volumes and freight volumes may not fully address the exclusion restriction, we conduct a placebo regression in which GDP per capita growth during the pre-critical-mass period (2001–2007) is regressed on the historical fixed-line instrument and the topographical instrument, along with the

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[5] The term three-network integration refers to the convergence of telecommunications, broadcasting, and the internet, aimed at delivering voice, data, and video services over a unified broadband infrastructure. In China, the push for integration began in the late 1990s, with the 10th Five-Year Plan (2000–2005) calling for accelerated broadband construction and the development of next-generation networks. The 11th Five-Year Plan (2006–2010) further emphasized the strategic importance of network integration. A milestone came in 2009 when China's third major telecom industry restructuring, coupled with the rollout of 3G services, promoted full-service competition among the major operators. This period marked a rapid expansion of the broadband backbone, largely built upon the legacy copper-wire telephone network and complemented by cable TV and optical fiber upgrades. The three-network integration initiative laid the institutional and technical foundation for China's broadband boom in the 2010s. Consistent with this, annual reports of China Mobile, China Unicom, and China Telecom during the late 2000s and early 2010s repeatedly highlight investments in fixed-mobile convergence, the integration of voice, broadband, and IPTV services, and the upgrade of copper-based networks into hybrid fiber-coaxial systems, demonstrating how historical telephone infrastructure was central to their broadband strategies.

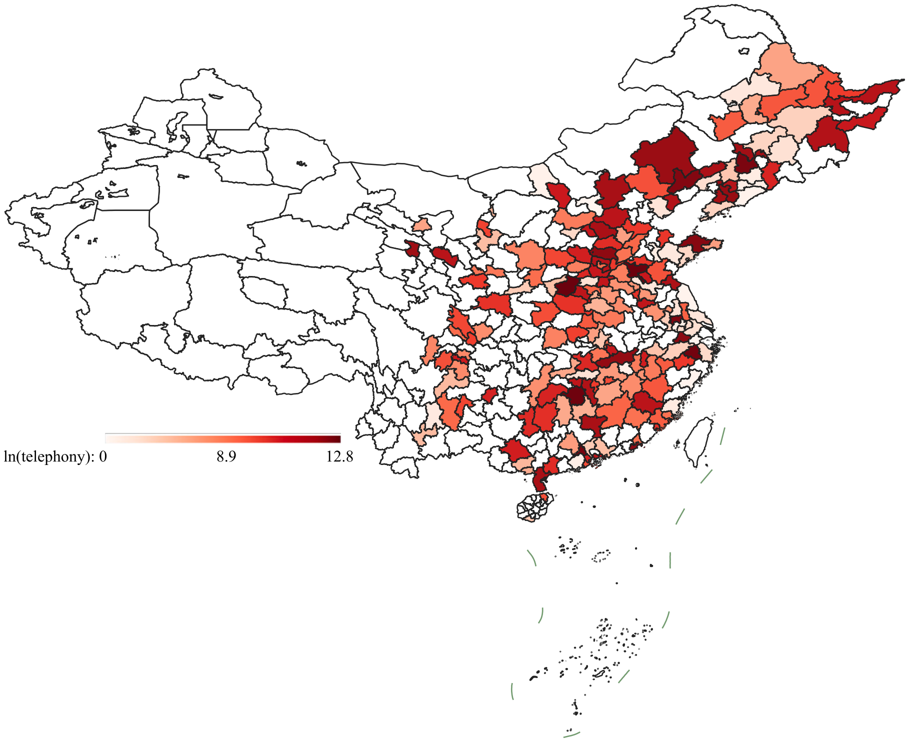

Fig. 2. The spatial distribution of telephony in 1984.
Notes: The areas with data unavailable are colored in white. Regions with darker color have greater values of telephony in 1984. The base map is sourced from the Ministry of Natural Resources of the People's Republic of China with the Map Approval Number: GS(2020)4624.
Source: Presented by authors according to the CCSY database.

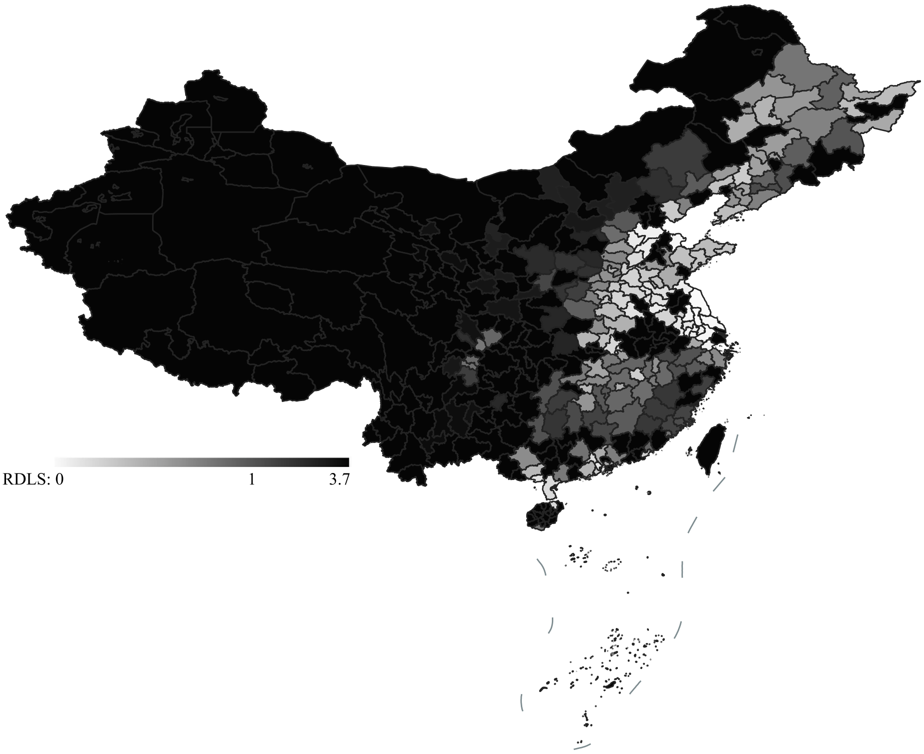

Fig. 3. The spatial distribution of RDLS.
Notes: The areas with data unavailable are colored in black. Regions with darker color have greater values of RDLS. The base map is sourced from the Ministry of Natural Resources of the People's Republic of China with the Map Approval Number: GS(2020)4624.
Source: Presented by authors according to You et al. (2018).

same control variables used in our baseline specification. This approach aligns with the idea of balance check in Xu (2022):

$$\Delta \ln y_{it} = \theta_0 + \vartheta' \boldsymbol{Z}_{it} + \theta_1 \Delta lns_{it} + \theta_2 \Delta lnh_{it} + \theta_3 \Delta n_{it} + \theta_4 \ln y_{i0} + \xi_{it}, \tag{6}$$

where $\boldsymbol{Z}_{it}$ denotes the historical and topographical IVs, and the other variables are exactly the same as those in the baseline model Eq. (5). In our study, we estimate Eq. (6) for two periods, i.e., 2001–2007 and 2008–2019, based on the broadband penetration rate.

City-level broadband subscriber data in China first became available in the year 2001.[6] Statistics from China Center for Information Development (CCID) indicates that in 2001 only 1.17% of users accessed the internet through local area network (LAN) broadband, and only 0.53% used ADSL. This extremely low usage explains why the CCSY began reporting broadband subscribers only in 2001, and the reported penetration rate was merely 2.324 subscribers per 100 persons at that time. These statistics indicate that broadband infrastructure before 2001 was too sparse to meaningfully affect economic activity, making pre-2001 data unsuitable for any exclusion restriction evaluation.

We therefore focus on the period after 2001 but before broadband networks reached economically meaningful density. We consider the critical mass issue in the network effect, as highlighted by engineering studies (Arroyo-Barrigüete et al., 2010), the ITU's digital infrastructure reports (Sector, 2020), and the broadband-economics literature (Czernich et al., 2011). Studies such as note that broadband externalities typically emerge only after adoption reaches 20% of households. Below this threshold, the network is too sparse to generate substantial effects. In China, broadband penetration exceeded 20 percent at the national level for the first time in 2008. Therefore, we treat 2001–2007 as the pre-treatment period during which broadband penetration was too low to affect GDP per capita growth.

We estimate a placebo regression in which GDP per capita growth from 2001–2007 is regressed on the historical instrument and the topographical instrument, along with the same controls as in the baseline model. Our expectation is that neither instrument can predict economic growth prior to 2008. If these instruments operated through non-broadband channels such as historical trade patterns, administrative hierarchy, or transportation networks, their effects would have appeared in this early period. The absence of correlation could support the exclusion restriction. After 2008, once broadband surpasses the critical-mass threshold, the instruments should begin to correlate significantly with GDP per capita growth.

4.3. 2SLS results

Table 4 presents the 2SLS regression results. Panel A conducts the second-stage 2SLS regression while panel B reports the first-stage results. Column (1) is the estimation using historical IV, the number of telephones in 1984, column (2) is the RDLS topographical IV, and column (3) includes both IVs to allow for the overidentification test. Panel A of Table 4 suggests that, in general, a 1 percentage point increase in broadband penetration growth promotes real GDP per capita growth by 0.15–0.21 percentage point. And the effect is significant in all the three settings.

The first-stage results in panel B verify the relevance condition of the IV: The historical number of telephones is positively associated with the recent broadband penetration growth, while the tougher topographic characteristic is correlated with lower broadband internet penetration growth. The reported Kleibergen–Paap rank Wald F statistics for the first-stage regression, benchmarked with Stock-Yogo critical values 5.53–16.38 for one IV and 7.25–19.93 for two IVs, indicate that there is no concern about the weak IV problem. Moreover, the overidentification test of the both-IVs model cannot reject the null hypothesis on exogeneity of the IVs.

Columns (4) to (6) of Table 4 present the results after explicitly addressing the exclusion restriction, where we include two additional controls: freight volume (highway freight volume normalized by local real GDP) and passenger volume (highway passenger volume normalized by local resident population). Consistent with our baseline specification in growth form, we use the growth rates of these variables as controls. The estimated coefficients on broadband penetration growth remain reassuringly stable in magnitude and significance compared to the baseline specifications in columns (1) to (3). Specifically, the coefficients remain positive and highly significant across specifications, suggesting that the positive effect of broadband penetration on GDP per capita growth is robust to controlling for local trade and transportation activities. This stability in the results provides supporting evidence that is consistent with the exclusion restriction and that the instruments primarily operate through the broadband channel.

We further present Table 5, which evaluates the exclusion restriction using a placebo regression in which GDP per capita growth during the pre-critical-mass period (2001–2007) is regressed on the historical fixed-line instrument and the topographical instrument, along with the same control variables used in our baseline specification. Columns (1) and (3) of Table 5 shows that, consistent with the expectation that broadband was not sufficiently developed to influence economic growth, neither instrument has explanatory power for GDP per capita growth before 2008. This suggests that although the historical telephony instrument captures deeper structural features such as administrative hierarchy, long-run trade networks, or industrial composition, and the RDLS instrument reflects constraints relevant for non-digital infrastructure such as road or rail transportation, conditional on a set of controls in the growth regression model, these factors alone do not explain systematic GDP per capita growth variation across cites before broadband rollout reaches a critical mass. This finding is important because if these alternative channels through historical telephony or the RDLS instruments were at work, then they would have manifested even before broadband networks were economically relevant.

In contrast, after 2008, as shown in column (2), once broadband adoption surpasses the required network density, the instruments begin to correlate with GDP per capita growth in a manner consistent with the broadband channel. Moreover, when we interact each instrument with national broadband penetration growth in column (4), the coefficients on these interactions become significantly larger and strongly statistically significant. This pattern indicates that the instruments' influence on economic outcomes is amplified only when broadband itself becomes an operative channel, which provides additional support for the exclusion restriction.

While the placebo test using pre-2008 GDP growth provides supportive evidence for the exclusion restriction, we acknowledge that some unobserved and time-varying channels cannot be fully ruled out by this exercise. Specifically, the placebo test helps rule out time-invariant or smoothly evolving confounding factors that would have affected economic growth prior to the large-scale diffusion of broadband infrastructure. However, it does not fully exclude the possibility of alternative channels through which the instrumental variables may influence post-2008 growth. For example, infrastructure-related complementarities such as transport investments, changes in economic geography, or agglomeration dynamics may become operative only once cities reach a certain scale or growth threshold, which may coincide with the period of rapid broadband expansion.

The 2SLS coefficients (0.150, 0.207, and 0.162) reported in Table 4 are larger than the OLS coefficient (0.041) as presented in Table 2, which is a common pattern in the infrastructure literature. This suggests that on average the bias in OLS estimator arising from the negative reverse causality, omitted variable bias, and measurement error may dominant the positive reverse causality and endogenous location choice discussed in Section 4.1.

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[6] It should be noted that the reasons for starting our sample in 2005 in the baseline estimation are outlined in the Online Appendix C, primarily due to the accuracy concerns regarding the measure of local residence population.

Table 4
Growth effect of broadband internet: 2SLS results.

	(1) Historical	(2) Topographical	(3) Both IVs	(4) Historical	(5) Topographical	(6) Both IVs
Panel A						
Lag of broadband penetration growth	0.150***	0.207***	0.162***	0.145***	0.210***	0.158***
	(0.043)	(0.053)	(0.038)	(0.043)	(0.055)	(0.038)
Saving rate growth	0.145***	0.147***	0.145***	0.148***	0.151***	0.149***
	(0.017)	(0.017)	(0.015)	(0.018)	(0.018)	(0.017)
Human capital growth	0.037***	0.035***	0.037***	0.037***	0.035***	0.037***
	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
First-difference of population growth	−0.382***	−0.414***	−0.389***	−0.372***	−0.409***	−0.379***
	(0.048)	(0.050)	(0.056)	(0.048)	(0.051)	(0.056)
Logarithm of GDP per capita in 2005	−0.782**	−0.472	−0.719**	−0.750**	−0.402	−0.681**
	(0.324)	(0.365)	(0.281)	(0.322)	(0.376)	(0.283)
Freight volume growth				−0.213	−0.308	−0.231
				(0.503)	(0.539)	(0.506)
Passenger volume growth				1.273***	1.131***	1.245***
				(0.379)	(0.424)	(0.381)
Constant	12.808***	9.064**	12.050***	12.615***	8.379**	11.774***
	(3.621)	(4.121)	(3.075)	(3.587)	(4.262)	(3.102)
Overidentification p-value			0.308			0.246
Observations	2090	2090	2090	2074	2074	2074
R-squared	0.147	0.031	0.127	0.157	0.025	0.136
Panel B						
Telephony in 1984 × national penetration	8.047***		7.070***	8.031***		7.056***
	(0.881)		(0.882)	(0.884)		(0.890)
RDLS × national penetration		−11.524***	−6.016***		−11.467***	−5.845***
		(1.544)	(1.584)		(1.571)	(1.608)
Controls	YES	YES	YES	YES	YES	YES
Kleibergen–Paap rank Wald F statistics	83.529	55.714	45.999	82.617	53.259	50.395
Observations	2090	2090	2090	2074	2074	2074
R-squared	0.095	0.069	0.099	0.097	0.072	0.101

Notes: Panel A performs the second-stage regression while panel B presents the first-stage results. Column (1) reports the estimation based on the historical IV which refers to the natural logarithm of the number of telephones in 1984 interacted with the lagged national average of the broadband penetration growth. Column (2) is based on the topographical IV which refers to the natural logarithm of the Relief Degree of Land Surface with the same interaction as the historical IV. And Column (3) uses both IVs thus can conduct the overidentification test. Columns (4) to (6) mimic the layout of Columns (1) to (3) while including the growth rates of highway freight and passenger volumes to test exclusion restriction. Clustered (at city level) robust standard errors are reported in parentheses. ∗∗∗ indicates $p < 0.01$; ∗∗ indicates $p < 0.05$; ∗ indicates $p < 0.1$.

Table 5
Exclusion restriction test: The effect of the IVs on real GDP per capita growth.

Dep: GDP per capita growth	(1) Below 20%: 2001–2007	(2) Above 20%: 2008–2019	(3) Below 20%: 2001–2007	(4) Above 20%: 2008–2019
ln(Telephone)	−0.172	0.220*		
	(0.192)	(0.126)		
ln(RDLS)	0.147	−0.253***		
	(0.133)	(0.087)		
Historical IV			−0.035	1.293***
			(0.072)	(0.367)
Topographical IV			0.374	−1.955***
			(0.337)	(0.623)
Saving rate growth	0.031***	0.142***	0.036***	0.146***
	(0.010)	(0.007)	(0.013)	(0.017)
Human capital growth	0.034***	0.041***	0.035*	0.045***
	(0.010)	(0.012)	(0.020)	(0.011)
First-difference of population growth	−0.193***	−0.295***	−0.193***	−0.285***
	(0.027)	(0.036)	(0.038)	(0.040)
Logarithm of GDP per capita in 2005	0.922**	−2.195***	0.673	−2.123***
	(0.393)	(0.255)	(0.439)	(0.216)
Constant	3.384	25.902***	3.929	25.679***
	(3.210)	(2.089)	(4.144)	(2.017)
Observations	928	1949	928	1949
R-squared	0.087	0.239	0.087	0.250

Notes: Columns (1) and (3) use the sub-sample of years between 2001 and 2007 (inclusive), when the national average of broadband penetration rate was below 20%. Columns (2) and (4) report the results for years between 2008 and 2019 (inclusive), when the national average of broadband penetration rate was over 20%. In columns (1) and (2), ln(Telephone) is the natural logarithm of the number of telephones in 1984, and ln(RDLS) is the natural logarithm of the Relief Degree of Land Surface (RDLS). In columns (3) and (4), the historical IV is the same as that in Table 4, which refers to the natural logarithm of the number of telephones in 1984 interacted with the lagged annual national average of broadband penetration growth. And the topographical IV refers to the natural logarithm of RDLS with the same interaction as the historical IV. Clustered (at city level) robust standard errors are reported in parentheses. ∗∗∗ indicates $p < 0.01$; ∗∗ indicates $p < 0.05$; ∗ indicates $p < 0.1$.

Another possibility is the heterogeneous effects of broadband internet on economic growth across compliers and non-compliers in our IV design. In our context, the historical IV compliers refer to cities whose broadband penetration growth rates are higher with a greater historical number of telephone users and are lower with a smaller number of telephone users. The non-compliers are those whose broadband penetration growth rates are higher despite of fewer telephone users and are lower despite of more telephone users. Similar definition also applies to the topographical IV, as illustrated in Table A1 in the Online Appendix A. The 2SLS estimator reveals the local average treatment effect (LATE) for compliers (Angrist and Imbens, 1995; Angrist and Pischke, 2009), while the OLS estimator is the average treatment effect (ATE) for both compliers and non-compliers.

Hence, the 2SLS coefficients may exceed the OLS counterparts because the compliers enjoy a larger growth effect of broadband than the non-compliers. This heterogeneity in the average treatment effect is demonstrated in Table A2 (OLS) and Table A3(2SLS). For both tables, since coefficients on internet penetration growth in columns (1), (3), and (5) are greater than those in (2), (4), and (6), respectively, it is verified that the ATE for compliers is higher than that for non-compliers. Additionally, the estimations in Tables 2 and 4 are all between the corresponding estimations for compliers and non-compliers.

5. Further analysis

5.1. Availability of mobile base stations

Ideally, an empirical measure of broadband penetration would reflect three components: availability, adoption, and capacity. In practice, however, data limitations constrain how these dimensions are observed. Our baseline measure captures availability and adoption, with capability examined indirectly through the technological-period subgroup analysis in Section 3.3.

To further separate these components, we construct a physical measure of availability alone using an innovative dataset on mobile network base stations. We obtain the universe of 2G, 3G, and 4G mobile base stations from OpenCelliD,[7] the world's largest open-source database of cellular infrastructure. All cell towers are recorded with information on their longitude-latitude coordinates, network technology generations, and date of constructions. We aggregate the tower counts at the prefecture-city level. We then construct annual growth rates of base station density, similar to our baseline measure, the growth rates of broadband internet penetration.

Because base-station density reflects availability but not adoption, we include city and year fixed effects in the specification. The two-way fixed effects design absorbs city-specific time-varying adoption patterns as well as national demand shocks, allowing the coefficient on tower growth to isolate the contribution of physical network availability to GDP per capita growth.

Table 6 reports the estimates using the growth rate of mobile base stations as the alternative independent variable. Column (1) uses the overall tower density, while columns (2)–(4) show details on different technologies of 4G, 3G, and 2G, respectively. Across all specifications, the growth in mobile base-station density has a strong positive association with city-level GDP per capita growth. The coefficient on total base-station growth in column (1) is 0.087, implying that a 10-percentage-point increase in tower availability is associated with a 0.87-percentage-point increase in GDP per capita growth. This larger magnitude is consistent with the previous discussion on the attenuation bias in the subscriber-based measure.

Columns (2)–(4) reveal distinct contributions by technology generation. Growth in 4G base stations shows a large estimated effect of 0.141, consistent with the superior speed and capacity of 4G networks. 3G expansion exhibits an even larger coefficient of 0.177, reflecting its pivotal role during the early 2010s when mobile internet adoption surged. And 2G infrastructure also contributes positively, though at a lower magnitude, which is consistent with its more limited data transmission capability.

By relying on a purely physical, engineering-based proxy for availability, independent of subscriber behavior, the estimates presented in Table 6 offer an additional layer of credibility to our identification strategy and reinforce the broader conclusion that digital infrastructure expansion plays a meaningful role in driving economic growth in China.

5.2. A cost–benefit analysis

There has been many inspirational case studies characterizing the benefits of broadband internet, including alleviating information asymmetries, stimulating productivity, encouraging innovation, improving organizational structure, and promoting management practices. However, from a social planner's point of view, the overall benefit that aggregates all potential gains needs to be evaluated with the corresponding cost. In the following, we conduct a cost–benefit analysis utilizing our estimation to check the efficiency of investment in information and communication technology infrastructure. The conservative OLS baseline result in Table 2 indicates:

$$\Delta \ln y_{it} = 0.041\Delta \ln B_{it-1} + \text{other factors}, \tag{7}$$

which suggests a linear relationship between GDP per capita growth rate and broadband penetration growth rate, all else being equal. According to the China Statistical Yearbooks, during 2006–2018, broadband penetration grows at 17.01% per year. This translates into an additional increase in annual GDP per capita growth by 0.697% (i.e., $17.01\% \times 0.041$). As the annual GDP per capita grows at 8.6% during 2007 to 2019, broadband internet penetration growth counts about 8% in China's GDP per capita growth.

Since the average GDP per capita during 2007–2019 is 43,248 yuan, this implies on average every year increase in GDP per capita due to broadband penetration would be 301.61 yuan (i.e., $43,248 \times 0.697\%$). With an average population 1361.35 million in China during our sample period, this translates into an increase of approximately 410,605 million yuan in GDP (301.61 yuan $\times 1361.35$ million people). This 410,605 million yuan can be regarded as the aggregate benefit of broadband penetration.

According to the MIIT, during 2006–2018, the average annual fixed asset investment in broadband infrastructure was 339,342 million yuan, which is the construction cost of broadband internet. Therefore, the annual rate of return of broadband infrastructure investment is estimated to be $(410,605 - 339,342)/339,342 \times 100\% = 21\%$.

During the same sample period, if an investor has made a portfolio investment including the stocks of the three major telecommunication service operators, he would have obtained an annual rate of return about 6%.[8] The fact that the social rate of return of investment in broadband internet exceeds the private rate of return highlights its nature of positive externality.

To understand the magnitude of the broadband effect, it is useful to compare our estimates with those found in the empirical literature on traditional and tangible infrastructure investments in China. A growing body of work quantifies the economic returns to highways, expressways, and high-speed rail. For example, Li et al. (2017) find

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[7] See https://opencellid.org/.

[8] Based on the Forms 20-F filings of China Mobile Limited (See https://www.chinamobileltd.com/sc/ir/reports.php), China Telecom Corporation Limited (See https://www.chinatelecom-h.com/sc/ir/reports.php?year=2018), and China Unicom Limited (See https://www.chinaunicom.com.hk/sc/ir/report_form2018.php), we calculate the rate of return as the sum of annual market capitalization appreciation and dividend yield, at 4.92%, 2.57%, and 10.70%, respectively during 2006–2018.

Table 6

Growth effect of broadband internet: Availability of mobile base stations.

Dep: GDP per capita growth	(1) All	(2) 4G	(3) 3G	(4) 2G
Lag of mobile base stations growth	0.087***			
	(0.018)			
Lag of 4G base stations growth		0.141***		
		(0.035)		
Lag of 3G base stations growth			0.177***	
			(0.039)	
Lag of 2G base stations growth				0.135***
				(0.026)
Saving rate growth	0.105***	0.106***	0.105***	0.104***
	(0.020)	(0.021)	(0.021)	(0.021)
Human capital growth	0.011	0.010	0.009	0.011
	(0.013)	(0.013)	(0.013)	(0.013)
First-difference of population growth	−0.309***	−0.309***	−0.310***	−0.312***
	(0.036)	(0.036)	(0.036)	(0.036)
Constant	10.987***	11.002***	11.009***	10.992***
	(0.341)	(0.342)	(0.344)	(0.343)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1908	1908	1908	1908
R-squared	0.368	0.366	0.365	0.367

Notes: Column (1) uses the total number of mobile base stations as the availability proxy. Columns (2)–(4) separately use 4G, 3G, and 2G base stations. All other variables are the same as those in Table 2. Clustered (at city level) robust standard errors are reported in parentheses. $***$ indicates $p < 0.01$; $**$ indicates $p < 0.05$; $*$ indicates $p < 0.1$.

the annual rate of return to road investment is approximately 11% in China from 1998 to 2007. Wu et al. (2021) estimates the annual rate of return for investment in electricity, gas, and water, and transportation infrastructure in China during 1998–2007 is around 6%. By comparison, our cost–benefit calculation suggests that broadband infrastructure generates an annual social rate of return of approximately 21%, using the conservative OLS estimate. This magnitude is notably larger than the returns estimated for traditional physical infrastructure. The comparison highlights the increasingly central role of digital connectivity in driving modern economic growth.

Although our cost–benefit calculation captures the aggregate gains internal to each city, it is important to note that the city-level analysis does not fully account for broader agglomeration and spillovers generated by digital infrastructure. This interpretation aligns closely with existing national-level findings. In particular, Feng et al. (2025) estimate a 48.6% return to digital infrastructure for China as a whole, a substantially larger figure that incorporates cross-city spillovers, network externalities, and nationwide agglomeration effects that cannot be observed in our prefecture-level data. The comparison between our local estimate and their national estimate underscores that digital infrastructure generates both within-city gains, which we identify, and between-city and national spillovers, which fall outside the scope of our data but remain economically important. Recognizing this distinction strengthens the interpretation of our results and situates our estimates more carefully within the broader development and infrastructure literature.

5.3. Robustness checks

We conduct a battery of robustness checks on our empirical results. To begin with, we consider alternative measures of our independent variable. We collect the number of broadband internet subscribers, number of mobile phone users, and telecommunication revenue from CCSY, all normalized by the number of residential population. Tables A4 and A5 in the Online Appendix A mimic Tables 2 and 4, respectively, using the different three measures of the independent variables. The results remain robust.

To address the potential concern of the non-random placement of broadband infrastructure, we first exclude Beijing, Shanghai, and Guangzhou, as these three cities are the access points to the world's internet backbone. We also experiment by excluding the eight nodal cities (Beijing, Shanghai, Guangzhou, Shenyang, Nanjing, Wuhan, Chengdu, and Xi'an) of the CHINANET, the largest Internet Backbone Provider (IBP) in China. The remaining cities are arguably more like to be unintended or inconsequential units of the broadband intervention. The corresponding 2SLS results based on both-IVs with four different measures of independent variables are reported in Table A6.

In addition, since the number of post offices in 1984 is also a popular IV for internet penetration in the literature, such as Wongsurawat (2006), Table A7 reports the results exploring this IV. In addition, we use the telecommunication revenue in 1984 as another alternative of our historical IV as shown in Table A8. Comparison across Tables A7 A8 and Table 4 indicates our results are not sensitive to the choice of alternative IVs.

Lastly, to further validate our IV strategy, we explore alternative specifications for the time-varying component that leverage China's unique institutional context. Instead of interacting our time-invariant IVs with national broadband penetration, we use the lagged one-year growth rate of operating revenue from China's major internet infrastructure providers—China Mobile, China Telecom, China Unicom, and China Tower. This approach offers several advantages. First, it captures the telecommunications sector's expansion dynamics through direct financial performance metrics of the key market players responsible for broadband infrastructure deployment. Second, it provides an institutional perspective on broadband rollout timing, as these state-owned enterprises' revenue growth reflects both policy directives and market conditions driving network expansion. Third, the use of lagged revenue growth addresses potential simultaneity concerns while maintaining the temporal structure necessary for identification. The results using these operator-specific financial metrics remain robust and are presented in Table A9. The stability of our estimates across both national penetration rates and operator revenue specifications reinforces the validity of our identification strategy and suggests that our instruments effectively isolate the causal impact of broadband expansion on economic growth.

6. Mechanisms: Broadband China Pilot City Program

In our conceptual framework, the broadband penetration enters the model by affecting productivity, as indicated by Eq. (3). Productivity is the ultimate source of economic growth. Since innovation (Romer, 1990) and entrepreneurship (Baumol, 1996) have been highlighted as two of the most important sources of productivity, in this section, we test whether broadband internet leads to economic growth by promoting both innovation and entrepreneurship.

Leveraging the multi-period implementation of the Broadband China Pilot City Program, we examine the intensive margin by evaluating its effect on innovation, and the extensive margin by assessing its impact on entrepreneurial activity. Finally, we investigate whether the Broadband China Pilot City Program significantly facilitates firms' digital technology adoption.

6.1. Staggered DID identification strategy

The Broadband China Pilot City Program aims to accelerate the development of broadband infrastructure in China and improve internet quality in designated cities. The program is launched by the central government in January 2014, with the goal of providing high-speed internet access to all households and promoting the use of broadband technology in various sectors, such as education, healthcare, and e-commerce. All cities satisfying at least four conditions out of six can apply for the title "Broadband China Pilot City".[9] In each year of 2014 to 2016, 39 cities are designated as Broadband China Pilot Cities.

The designation of Broadband China Pilot City brings at least three benefits for the eligible cities. First, the title indicates a better internet infrastructure in the city, which provides an important advantage in competing for domestic and foreign direct investment among otherwise similar peers. Second, in the subsequent three years after receiving the title, the central government would provide specific funds to subsidize investment in the universal telecommunication service in the city. Third, the related authorities, including the Commission of Housing and Urban–Rural Development, the Industry and Information Technology Bureau, the Bureau of Housing, and the Development and Reform Commission, would collaborate in various aspects such as policy formulation, allocation of resources, and regulatory support. This substantially reduce institutional costs in developing and expanding broadband infrastructure.

As a result, in pilot cites, the local governments receive special funds on broadband internet from the central and provincial governments. This additional resources are specified to compensate the costs in laying fiber-optic cables, subsidize electricity consumption associated with internet, and attract talents specializing in internet. Furthermore, the approval procedure of the base station site and land acquisition processes in those pilot cities also becomes much simpler and quicker.[10]

Although official policy documents state that eligibility for the Broadband China Pilot City designation is based exclusively on observable, pre-specified technical criteria related to broadband and mobile internet infrastructure, such as broadband accessibility, penetration rates, and 3G/LTE mobile phone adoption, the assignment and timing of cities may nonetheless have been influenced by political economy factors in practice. In particular, meeting these technical thresholds requires substantial upfront investment, administrative coordination, and implementation capacity, which may differ across cities. Cities with stronger fiscal resources, greater administrative capacity, or more experience in policy implementation may have been better positioned to satisfy the eligibility requirements earlier and to coordinate effectively with central ministries during the application and evaluation process (Nie, 2017). As a result, while the formal criteria are rule-based, the timing of designation may still correlate with broader development characteristics that are relevant for economic growth.

These considerations motivate the use of a staggered difference-in-differences design. Identification does not rely on random assignment of the designation, but on the assumption that, conditional on city fixed effects, year fixed effects, observed covariates, and pre-treatment trends, treated and untreated cities would have followed parallel growth trajectories in the absence of the Program. To support this assumption, this paper conducts a series of diagnostic exercises, including conditional pre-trend tests and permutation-based placebo analyses, while interpreting the estimated effects with appropriate caution.

In this paper, we investigate the effect of broadband internet penetration on innovation and entrepreneurship. In terms of the intensive margin, we employ the growth rate of granted invention patents as the measure of innovation outcome. Data on patents are collected by indexing the granted invention patents by city-year from the website of the China National Intellectual Property Administration.[11] Regarding the extensive margin, especially on small and medium-sized firms, we utilize the number of newly registered firms with registered capital below 2 million yuan (Dai et al., 2021), normalized by the residential population.[12] To obtain the data on newly registered firms, we manually collect data on the firms established in each city and year, along with their registered capital, and then aggregate the information at the city-year level.[13]

First, we use the event study approach to show the effects of being designated as a Broadband China Pilot City on innovation and entrepreneurship. Specifically, we estimate the model:

$$Outcome_{it} = \beta_0 + \sum_{m=2}^{9} \gamma_m T_{i,t-m} + \sum_{n=0}^{5} \gamma_n T_{i,t+n} + \boldsymbol{\delta}' \boldsymbol{X}_{it} + \eta_i + \mu_t + \zeta_{it}, \tag{8}$$

where $Outcome_{it}$ denotes the innovation and entrepreneurship in city i and year t in two separated regressions, and $T_{i,t-m}$ and $T_{i,t+n}$ are year indicators equal to 1 for m (n) year before (after) the city i is designated as the Broadband China Pilot City. Control vector $\boldsymbol{X}_{it}$ include physical capital level, human capital level, and population growth. Our data are between 2007 and 2019, and the first cohort of the Broadband China Pilot Cities is at the year 2014 while the last cohort is in 2016. And we set one year before the designation as the base year. Therefore, in Eq. (8), m starts from 2 and ends at 9, while n ranges from 0 to 5. The coefficients γ_m and γ_n denote the differences between innovation and entrepreneurship in the never-treated cities and the other cities, respectively, with the absence and presence of being designated as the Broadband China Pilot City.

Second, we estimate a conventional two-way fixed effects (TWFE) model, which is a widely adopted method in empirical research (Callaway and Sant'Anna, 2021):

$$Outcome_{it} = \phi_0 + \phi_1 D_{i,t} + \boldsymbol{\iota}' \boldsymbol{X}_{it} + \chi_i + \psi_t + \kappa_{it}. \tag{9}$$

where $D_{i,t}$ is a treatment dummy equal to 1 if city i is ever designated as the Broadband China Pilot City in year t. And χ_i and ψ_t are city and year fixed effects. The parameter of our primary interest is ϕ_1, which captures the average treatment effect of the Broadband China Pilot City designation.

Third, as there are emerging theoretical research pointing out the drawbacks of TWFE estimation (De Chaisemartin and d'Haultfoeuille,

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[9] Requirements: (i) 20 Mbps and above broadband accessibility rate in an urban area would reach 85%; (ii) 4 Mbps and above broadband accessibility rate in an urban area would reach 90%; (iii) broadband penetration rate would reach 55%; (iv) 3G/LTE mobile phone penetration rate would reach 40%; (v) 4 Mbps and above broadband penetration rate would reach 80%; and (vi) 8 Mbps and above broadband penetration rate would reach 35%.

[10] See representative examples of Hubei Province and Wuhan City. Information is from Hubei Government and Wuhan Government. Websites: www.hubei.gov.cn and www.wuhan.gov.cn. Policy report indices: 011043102/2019-69567 and K28044908/2020-800853.

[11] The information of granted invention patents was indexed from the website https://pss-system.cponline.cnipa.gov.cn/Disclaimer on the day 20th December 2021.

[12] To test the robustness of our findings, we conduct an additional analysis that considers newly registered firms with registered capital below 0.5 million yuan, and the results demonstrate a consistent pattern.

[13] The information was collected on the platform *Ai Qi Cha* (website: https://aiqicha.baidu.com/advancesearch) on the day 7th December 2021.

2020; Goodman-Bacon, 2021) , we use the approach proposed by Callaway and Sant'Anna (2021) to estimate the average treatment effect on the treated (ATT) of being designated as the Broadband China Pilot City on innovation and entrepreneurship. The key idea of this estimation is to decompose the sample according to different cohorts of treatment and estimate the ATT for each cohort and time, then aggregate the group-time ATTs into the aggregated ATT. This decomposition allows us to observe the changes in the outcome variable over time and how they relate to the timing of treatment, providing a more detailed understanding of the treatment effect.

Specifically, we estimate the group-time average treatment effect for all $t \geq g$:

$$ATT(g,t) = E\left[Outcome_t(g) - Outcome_t(0) \mid \boldsymbol{X}_t, G_g = 1\right] \tag{10}$$

where g is the designation cohort year and t is the calendar year. Since there are three cohorts of designated cities, G is defined as the year when a city first becomes treated. For all the Broadband China Pilot Cities, G denotes which cohort they belong to. For cities that are never designated, we set $G = 0$. Therefore, $G \in \{0, 2014, 2015, 2016\}$ in our setup. G_g is the dummy variable equal to one if the city is designated in year g and otherwise zero, i.e., $G_g = \mathbf{1}\{G = g\}$.

Subsequently, we aggregate the average effect of participating in the treatment among all cities in cohort g across all their post-treatment periods:

$$\xi(g) = \frac{1}{\mathcal{T} - g + 1} \sum_{t=g}^{\mathcal{T}} \mathbf{1}\{g \leq t\} ATT(g,t) \tag{11}$$

where $\mathcal{T}$ denotes the final year of our sample period 2019.

Finally, we compute the overall effect across all groups:

$$\xi^O := \sum_{g \in G}^{\mathcal{T}} \xi(g) P(G = g) \tag{12}$$

We also conduct aggregation by exploiting different aggregation methods provided by Callaway and Sant'Anna (2021). The overall treatment effect ξ^O reflects the effect of the Broadband China Pilot City Program across all groups that have ever been designated as the Broadband China Pilot Cities.

6.2. Empirical results of the mechanisms

To evaluate whether the Broadband China Pilot City Program affects innovation and entrepreneurship through credible causal channels, we begin by examining the dynamic treatment effects implied by Eq. (8). Figs. 4 and 5 plot the event-study coefficients for innovation and entrepreneurship, respectively. The estimates in all pre-designation years are statistically indistinguishable from zero, while positive and persistent effects emerge immediately after designation. For innovation, the treatment effect strengthens over the subsequent five years, consistent with the time required for R&D processes to materialize, whereas entrepreneurship responds more quickly and remains elevated for at least three years. These dynamic patterns support the view that treated and untreated cities followed parallel trajectories prior to the program.

Tables 7 and 8 present additional quantitative evidence in the staggered DID setting. Panel A presents results under an unconditional parallel-trend assumption, and we additionally report a formal pre-trend test based on the average of all pre-treatment coefficients. As expected, treated cities exhibit higher underlying levels of innovation ($p = 0.042$) and entrepreneurship ($p = 0.001$) before designation, reflecting the non-random criteria guiding the Program selection. To account for these differences, Panel B conditions on pre-treatment physical capital, human capital, and population growth. Under this conditional specification, the pre-trend p-values rise to 0.483 for innovation and 0.128 for entrepreneurship, providing no evidence of differential pre-treatment slopes once baseline differences in city characteristics are absorbed. The conditional specification thus serves as our preferred design.

The rows "TWFE" in both panels of Tables 7 and 8 present treatment effects estimated by the two-way fixed effects regression model, as described in Eq. (9). The conventional TWFE estimations suggest a statistically significant positive effect of being designated as a Broadband China Pilot City on innovation and entrepreneurship. Following Callaway and Sant'Anna (2021), we also report the aggregated group-time average treatment effects in Tables 7 and 8. For the intensive margin, the simple average aggregation in Table 7 suggests that the Broadband China Pilot City Program leads the innovation level of the pilot cities 7.4% higher than the others. As for the extensive margin, the simple average of the treatment effect in Table 8 indicates that entrepreneurial activity in Broadband China Pilot Cities is 31.2% higher than others as a result of the Program.

Additionally, we illustrate the heterogeneous treatment effects by calculating the partially aggregated estimates. In general, the three methods of aggregation, namely by cohort, calendar year, and length of exposure, consistently suggest the same positive patterns as the TWFE and simple average estimations. In particular, the rows "Cohort-Specific Effects" report ATTs for the three cohorts (2014, 2015, and 2016) of Broadband China Pilot Cities. The rows "Calendar Year Effects" report ATTs by calendar year, while the rows "Event Study" address ATTs by the length of exposure to the Program.

An interesting and intuitive story behind the difference between Tables 7 and 8 is that broadband internet benefits entrepreneurship immediately, while the benefits of innovation take a longer time to materialize. Broadband internet enables a variety of access to sales channels, convenient online payment platforms, and efficient electronic information systems. Entrepreneurs are quick to capitalize on these opportunities brought by broadband internet. As a result, we observe an instantaneous increase in the number of newly-registered small-and-medium-sized firms, which is a key measure of entrepreneurship in our analysis. In contrast to entrepreneurship, innovation is a more complex and time-consuming process that cannot be achieved through simple capital investments. The effects of broadband internet on innovation take time to be fully revealed. In our analysis, we use the number of granted invention patents as a proxy for innovation. It typically takes at least 20 months for a filed invention patent to be granted by China National Intellectual Property Administration as reported.[14] Thus, in Table 7, we only observe significant treatment effects on innovation starting from the third year of exposure to the Broadband China Pilot City Program.

To further strengthen identification, we implement a nonparametric placebo exercise adapted from Chetty et al. (2009), Li et al. (2016). Specifically, we randomly assign the same number of pilot-city designations to cities in each cohort to be Broadband China Pilot Cities without replacement, and once a city is selected it is dropped from the set for the next cohort's designation. Therefore, in this generated data set, there are 39 cities in each year selected as pseudo Broadband China Pilot Cities, serving as a placebo treatment group. This exercise is repeated 1000 times to obtain 1000 placebo estimates. We separately conduct this placebo test for innovation and entrepreneurship. Figures A1 and A2 in the Online Appendix A show the empirical cumulative distribution functions (cdf) and probability density functions (pdf) of these placebo effects on innovation and entrepreneurship respectively, together with the vertical solid lines denoting the benchmark TWFE estimates, from Panel B of Tables 7 and 8 respectively.

According to Figures A1 and A2, the distribution of these placebo effects is centered tightly around zero for both innovation and entrepreneurship, while the actual estimates fall entirely outside the simulated distributions. This exercise confirms that the significantly positive intensive and extensive margins are not spuriously driven by biased standard errors.

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[14] Source: https://www.tradecommissioner.gc.ca/china-chine/118690.aspx?lang=eng.

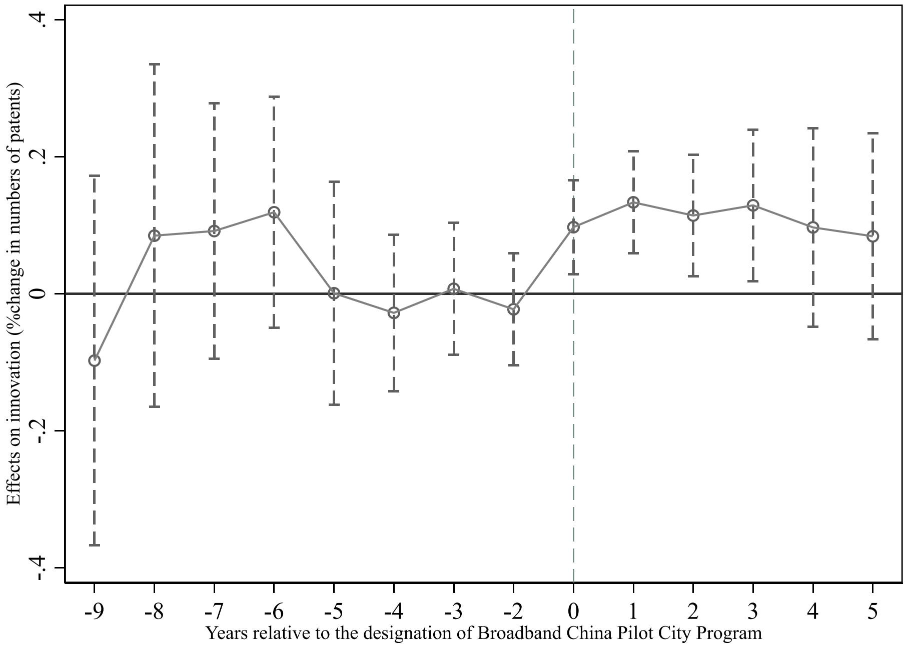

Fig. 4. Pre-trend of the Broadband China Pilot City Program on innovation.
Note: The horizontal axis denotes years relative to when a city is designated as a Broadband China Pilot City, with zero denoting the year of designation, negative values indicating years before designation (e.g., -2 is two years before) and positive values indicating years after (e.g., 5 is five years after). The reference year (−1, one year before designation) is omitted as it serves as the baseline for comparison. The vertical axis measures the effect on innovation, with 90% confidence intervals shown by dashed lines.

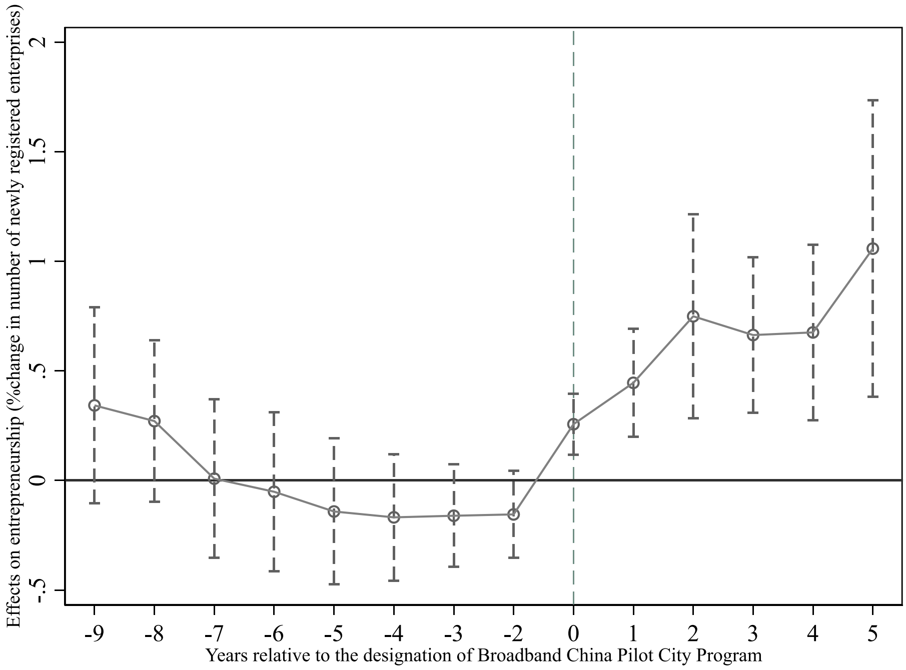

Fig. 5. Pre-trend of the Broadband China Pilot City Program on entrepreneurship.
Note: The format is the same as Fig. 4, while the vertical axis measures the effect on entrepreneurship.

6.3. Cross-validation of main results

Our main finding in Section 3.3 has identified a growth effect of broadband penetration on GDP per capita. The Broadband China Pilot City Program allows us to identify a causal effect of broadband penetration on innovation and entrepreneurship. If broadband affects economic growth via promoting innovation and entrepreneurship, we would expect the Program to improve broadband penetration and GDP per capita growth as well. To do this, we conduct a cross-validation to assess whether there is a causal effect of the Program on the growth of both broadband penetration and GDP per capita using the staggered DID framework. Specifically, we adopt the same methodology

Table 7
Mechanism: Effect of the Broadband China Pilot City Program on innovation.

Panel A: Under the unconditional parallel trend assumption							
	Aggregate Effect	Partially Aggregated Parameters					
TWFE	0.118***						
	(0.041)						
Simple Average	0.139**						
	(0.055)						
Cohort-Specific Effect		g = 2014	g = 2015	g = 2016			
	0.128**	0.210*	0.132*	0.037			
	(0.052)	(0.115)	(0.072)	(0.072)			
Calendar Year Effect		t = 2014	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019
	0.144**	0.135	0.247***	0.146**	0.162**	0.057	0.118
	(0.060)	(0.134)	(0.067)	(0.071)	(0.064)	(0.072)	(0.092)
Event Study		e = 0	e = 1	e = 2	e = 3	e = 4	e = 5
	0.141**	0.140***	0.160***	0.099	0.159**	0.124	0.163
	(0.063)	(0.051)	(0.052)	(0.064)	(0.064)	(0.080)	(0.140)
Panel B: Under the conditional parallel trend assumption							
TWFE	0.098**						
	(0.042)						
Simple Average	0.074*						
	(0.041)						
Cohort-Specific Effect		g = 2014	g = 2015	g = 2016			
	0.072*	0.061	0.117**	0.038			
	(0.038)	(0.075)	(0.054)	(0.064)			
Calendar Year Effect		t = 2014	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019
	0.061	−0.066	0.126**	0.038	0.100**	0.068	0.104**
	(0.041)	(0.085)	(0.063)	(0.065)	(0.049)	(0.055)	(0.052)
Event Study		e = 0	e = 1	e = 2	e = 3	e = 4	e = 5
	0.076*	0.042	0.076	0.011	0.135***	0.116**	0.077
	(0.044)	(0.044)	(0.047)	(0.056)	(0.050)	(0.055)	(0.090)

Notes: The dependent variable is the growth rate of the granted invention patents per 100 residence. Panel A presents estimations under the unconditional parallel trends assumption, while panel B allows conditional parallel trends with control variables including the pre-treatment value of saving rate growth, human capital growth, and the natural logarithm of GDP per capita. Pre-trend test p-values are 0.042 and 0.483 for the two panels respectively. The rows "TWFE" show the coefficients on treatment dummy in the conventional TWFE regressions. The rows "Simple Average" are the simple average of all group-time ATTs. The rows "Cohort-Specific Effects" report the ATTs for the three cohorts of the Program; g indexes the year that a city is first designated as the Broadband China Pilot City. The rows "Calendar Year Effects" present ATTs by calendar year; t indexes the calendar year. The rows "Event Study" report ATTs by the lengths of exposure to the Program; e indexes the length of exposure to the Program. The column "Aggregate Effect" presents the further aggregation of each type of parameters as the overall effects. Bootstrapped standard errors clustered at the city level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

as described in Eqs. (10), (11), and (12), with the outcome variables being the broadband penetration growth in Panel A and GDP per capita growth in Panel B in Table 9.

The table format mirrors the lower panels of Tables 7 and 8 with the set of controls included. Regardless of whether we consider the conventional TWFE or the staggered DID approach for multi-period implementation, our findings indicate that on average, the broadband penetration in pilot cities grows at least twice as faster as those non-designated cities, which aligns with the policy targets. Moreover, the Program significantly boosts GDP per capita growth. we estimate that GDP per capita in the designated cities grew by 57% more than in non-designated cities as a result of the Broadband China Pilot City Program. To illustrate the magnitude, consider that the average GDP per capita growth rate during the sample period after the Program (2014–2019) was 6.3% according to the World Bank, with 117 out of 241 cities (48.5%) designated as pilot cities. Based on the estimated effect, all else being equal, the control group's GDP per capita growth rate can be approximated at 4.9%, while the designated cities experienced a substantially higher growth rate of about 7.7%.

6.4. Additional evidence of digital technology adoption

The effect of broadband penetration on innovation, entrepreneurship, and economic growth would be materialized only when firms and individuals in fact use more technologies empowered by broadband internet. In this section, we examine whether the Program encourages and facilitates firms to integrate digital technologies into their business operations.

To carry out this analysis, we collect datasets that encompass firms engaged in various digital activities before 1st January 2020. These activities include the development and use of standalone applications, the operation of WeChat applets (also known as WeChat Mini Programs)that are integrated into WeChat without requiring separate downloads or installations, and the possession of Internet Content Provider (ICP) licenses from MIIT. Additionally, we consider firms that hold computer software copyrights, and operate Sina Weibo Accounts, and manage WeChat Official Accounts. Sina Weibo is a prominent microblogging social media platform in China, while WeChat Official Account is an official profile based on the WeChat platform. Both platforms enable businesses, organizations, and individuals to establish and manage accounts for information dissemination, engagement with followers, and conducting marketing and communication.

Whether firms embrace these digital technologies at the firm level serve as indicators of their levels of digitization. We collect and aggregate the number of firms participating in these six categories of digital technologies and social media channels at the city level. These counts are then normalized by the total number of firms operating within each respective city. The datasets of firm lists with the six categories of digital technologies are acquired from *Qi Cha Cha* website by the built-in function of advanced search.[15] It is an official enterprise credit information query system in China, registered with the government as an enterprise credit reporting agency.

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[15] Website: https://www.qcc.com.

Table 8

Mechanism: Effect of the Broadband China Pilot City Program on entrepreneurship.

Panel A: Under the unconditional parallel trend assumption							
	Aggregate Effect	Partially Aggregated Parameters					
TWFE	0.660***						
	(0.118)						
Simple Average	0.548***						
	(0.143)						
Cohort-Specific Effect		g = 2014	g = 2015	g = 2016			
	0.486***	1.110***	0.180	0.165			
	(0.122)	(0.291)	(0.132)	(0.153)			
Calendar Year Effect		t = 2014	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019
	0.558***	0.646***	0.522***	0.666***	0.505***	0.443***	0.564***
	(0.141)	(0.188)	(0.175)	(0.221)	(0.141)	(0.152)	(0.180)
Event Study		e = 0	e = 1	e = 2	e = 3	e = 4	e = 5
	0.625***	0.279***	0.438***	0.682***	0.546***	0.606***	1.197***
	(0.156)	(0.078)	(0.130)	(0.232)	(0.164)	(0.200)	(0.364)
Panel B: Under the conditional parallel trend assumption							
TWFE	0.640***						
	(0.118)						
Simple Average	0.312*						
	(0.184)						
Cohort-Specific Effect		g = 2014	g = 2015	g = 2016			
	0.277*	0.590	0.149	0.069			
	(0.164)	(0.381)	(0.143)	(0.169)			
Calendar Year Effect		t = 2014	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019
	0.335*	0.502**	0.372*	0.536**	0.292	−0.002	0.310
	(0.176)	(0.206)	(0.209)	(0.254)	(0.197)	(0.323)	(0.204)
Event Study		e = 0	e = 1	e = 2	e = 3	e = 4	e = 5
	0.329*	0.229***	0.311**	0.497*	0.303	0.034	0.598
	(0.198)	(0.086)	(0.151)	(0.276)	(0.212)	(0.399)	(0.402)

Notes: The dependent variable is the growth of registered firms per 100 residence with registered capital less than 2 million yuan. Panel A presents estimations under the unconditional parallel trends assumption, while panel B allows conditional parallel trends with control variables including the pre-treatment value of population growth, saving rate, and human capita. Pre-trend test p-values are 0.001 and 0.128 for the two panels respectively. The layout is the same as Table 7.

Table 9

Cross-validation: Effects of the Broadband China Pilot City Program on broadband growth and GDP per capita growth.

Panel A: Broadband penetration growth							
	Aggregate Effect	Partially Aggregated Parameters					
TWFE	2.218*						
	(1.339)						
Simple Average	4.008*						
	(2.142)						
Cohort-Specific Effect		g = 2014	g = 2015	g = 2016			
	3.478*	7.515*	2.870	−0.379			
	(2.004)	(4.186)	(1.963)	(3.396)			
Calendar Year Effect		t = 2014	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019
	3.850*	3.917	1.316	5.975*	4.245	4.171	3.477
	(2.308)	(4.943)	(3.214)	(3.612)	(2.743)	(2.724)	(2.332)
Event Study		e = 0	e = 1	e = 2	e = 3	e = 4	e = 5
	4.761**	3.042	0.830	4.820*	3.721	6.750**	9.404*
	(2.325)	(2.424)	(2.477)	(2.829)	(2.406)	(2.924)	(4.831)
Panel B: GDP per capita growth							
TWFE	0.573***						
	(0.166)						
Simple Average	0.809**						
	(0.358)						
Cohort-Specific Effect		g = 2014	g = 2015	g = 2016			
	0.790**	0.871	0.917*	0.571			
	(0.331)	(0.431)	(0.404)	(0.540)			
Calendar Year Effect		t = 2014	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019
	0.790**	0.410	1.238**	1.608**	0.410	0.472	0.597
	(0.351)	(0.409)	(0.506)	(0.658)	(0.332)	(0.323)	(0.350)
Event Study		e = 0	e = 1	e = 2	e = 3	e = 4	e = 5
	0.769**	0.938*	0.648	0.645	0.415	0.503	0.382
	(0.351)	(0.332)	(0.442)	(0.393)	(0.315)	(0.308)	(0.3817)

Notes: This table reports the effects of the Broadband China Pilot City Program on broadband penetration growth (Panel A) and GDP per capita growth (Panel B). Both panels are results under conditional parallel trends with control variables including the pre-treatment value of saving rate growth, human capital growth, and the natural logarithm of GDP per capita. Pre-trend test p-values are 0.653 and 0.207 for the two panels, respectively. The rows are the same as Table 7. Bootstrapped standard errors clustered at the city level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10

Long-difference: Broadband China and the digital adoption of firms.

	(1) APP	(2) Applet	(3) ICP	(4) Software	(5) Weibo	(6) WeChat
Panel A						
BC dummy	0.630***	0.403***	0.547***	0.794***	0.584***	0.374***
	(0.113)	(0.073)	(0.101)	(0.122)	(0.108)	(0.073)
Change in ln GDP	0.342***	0.128	−0.029	0.192	0.176	0.220***
	(0.125)	(0.084)	(0.120)	(0.137)	(0.120)	(0.084)
Change in ln residence	0.422***	0.352***	0.402***	0.635***	0.458***	0.234***
	(0.128)	(0.084)	(0.134)	(0.155)	(0.137)	(0.086)
Constant	0.486	1.851***	1.403	1.634	1.712*	2.839***
	(0.973)	(0.657)	(0.945)	(1.069)	(0.938)	(0.655)
Observations	283	283	283	283	283	283
R-squared	0.165	0.161	0.131	0.192	0.144	0.142
Panel B						
BC order	0.360***	0.226***	0.303***	0.439***	0.331***	0.213***
	(0.053)	(0.033)	(0.045)	(0.053)	(0.050)	(0.034)
Change in ln GDP	0.374***	0.149*	−0.001	0.232*	0.206*	0.240***
	(0.124)	(0.083)	(0.120)	(0.132)	(0.119)	(0.082)
Change in ln residence	0.352***	0.309***	0.343**	0.550***	0.394***	0.193**
	(0.127)	(0.083)	(0.135)	(0.153)	(0.138)	(0.086)
Constant	0.741	2.014***	1.625*	1.957*	1.948**	2.990***
	(0.966)	(0.649)	(0.939)	(1.032)	(0.933)	(0.643)
Observations	283	283	283	283	283	283
R-squared	0.240	0.226	0.188	0.269	0.209	0.206

Notes: Panel A is the result of long-difference regression with the key independent variable BC_1, or BC dummy, i.e., the dummy variable indicating whether a city participated in the Broadband China Pilot City Program. And the key independent variable BC_2, or BC order, in Panel B is an ordered indicator with value of 0, 1, 2, and 3 if the city never participated in the program, participated in the last batch (the year 2016), the second batch (the year 2015), and the first batch (the year 2014), respectively. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Similar to Kolko (2012), our empirical analysis employs a long-difference regression model from 2006 to 2019:

$$\Delta \ln Adoption_{ik} = \omega_{0jk} + \rho_{jk} BC_{ij} + \omega_{1jk} \Delta \ln Y_i + \omega_{2jk} \Delta \ln L_i + \upsilon_{ijk}, k = 1, \dots, 6; j = 1, 2 \tag{13}$$

where $Adoption_{ik}$ is the share of firms with applications ($k = 1$), applets ($k = 2$), ICP licenses ($k = 3$), software copyrights ($k = 4$), Weibo Accounts ($k = 5$), and WeChat Official Accounts ($k = 6$) in city i at the end of the year 2019. We assume that in the year 2006, these six categories of digital technology are rarely available and therefore the level of digital adoption is arguably assumed to be zero in the initial year 2005. Thus, $Adoption_{ik}$ can be regarded as the long-difference of the firms' digital adoption behavior over the sample period 2005–2019. $\Delta \ln Y_i$ is the change in the natural logarithm of GDP in 2019 relative to 2005 in city i; and ΔL_i is the change in population size, that is, the natural logarithm of residential population in 2019 relative to 2005 in city i. The key dependent variables $BC_{ij}, j = 1, 2$ are defined as follows:

$$BC_{i1} = \begin{cases} 1, & \text{city } i \text{ is designated as the Broadband China Pilot City} \\ 0, & \text{otherwise} \end{cases}$$

$$BC_{i2} = \begin{cases} 3, & \text{city } i \text{ is in the 2014 cohort} \\ 2, & \text{city } i \text{ is in the 2015 cohort} \\ 1, & \text{city } i \text{ is in the 2016 cohort} \\ 0, & \text{otherwise} \end{cases}$$

After controlling for fundamental city-level characteristics, our primary focus of the key parameters are denoted as $\rho_{jk}, k = 1, \dots, 6; j = 1, 2$.

The findings are displayed in Table 10. In Panel A, we present the results of the long-difference regression, with particular emphasis on the key independent variable, denoted as BC_1 or BC dummy, i.e., a binary indicator discerning whether a city participated in the Broadband China Pilot City Program. In Panel B, our focus shifts to the key independent variable BC_2 which we refer to as BC order that is an ordered categorical variable with values of 0, 1, 2, and 3, corresponding to distinct program participation timing: cities that never participated in the program, those that joined in the last batch (in the year 2016), the second batch (in the year 2015), and the first batch (in the year 2014), respectively. Columns (1) through (6) correspond to different values of k ranging from 1 to 6. In each case, the dependent variable represents the proportion of firms engaged in various activities, including applets, applications, ICP licenses, software copyrights, Weibo Accounts, and WeChat Official Accounts. To ensure comparability across columns, we employ the natural logarithm of the dependent variable. This transformation enables us to interpret the coefficients as semi-elasticities, facilitating meaningful comparisons across different categories. After controlling the other factors, our results in Table 10 indicate positive effects of the Broadband China Pilot City Program on firm's digital adoption, regardless of the category of digital technologies. It suggests that firms located in Broadband China Pilot Cities exhibit significantly elevated digital adoption levels, ranging from 37.4% to 79.0%, ceteris paribus. Furthermore, businesses operating in cities that participated in the Program at an earlier stage experience even higher levels of digital adoption. This provides an additional micro-level evidence that is consistent with the causal effect of broadband internet on economic growth identified in early sections.

7. Conclusion

This paper identifies a causal effect of broadband internet on economic growth in China. Our cost–benefit analysis reveals an average rate of return of approximately 21% for broadband infrastructure investments. The staggered DID analysis based on the Broadband China Pilot City Program indicates that broadband internet leads to economic growth by accelerating innovation and entrepreneurship.

While our analysis provides valuable insights and narrows the gap between micro-evidence and macro-statistics on digital infrastructure, we acknowledge several limitations for future research. First, our research focuses exclusively on broadband internet infrastructure. There are many other investment falls into the broad category of digital infrastructure (Bennett et al., 2020). We refer to Feng et al. (2025) for a comprehensive examination on the productivity effect of digital infrastructure.

Second, this paper evaluates the effect of broadband internet penetration. Penetration is the outcome of availability, adoption, and usage, which is not differentiated in this paper due to data limitation. With firm-level data and textual analysis, Cai and Wu (2026) models the endogenous digital technology adoption and estimates its economic impacts.

Lastly, our analysis provides an assessment on the aggregate economic impact of broadband internet. It is interesting and important to explore the distributional effect in addition to the aggregate effect in order to draw more specific policy implications. For example, Fan et al. (2018) studies how e-commerce affects trade between regions and spatial inequality in China. Although e-commerce partially crowds out intercity offline trade, it increases the aggregate domestic trade. The warfare gains are disproportionately larger for small and remote cities.

CRediT authorship contribution statement

Mengyuan Cai: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Guiying Laura Wu:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Formal analysis, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Guiying Laura Wu reports financial support was provided by Ministry of Education, Singapore. Mengyuan Cai declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Agrawal, A., Galasso, A., Oettl, A., 2017. Roads and innovation. Rev. Econ. Stat. 99 (3), 417–434.

Ahlfeldt, G., Koutroumpis, P., Valletti, T., 2017. Speed 2.0: Evaluating access to universal digital highways. J. Eur. Econ. Assoc. 15 (3), 586–625.

Akerman, A., Gaarder, I., Mogstad, M., 2015. The skill complementarity of broadband internet. Q. J. Econ. 130 (4), 1781–1824.

Angrist, J., Imbens, G., 1995. Identification and estimation of local average treatment effects. Econometrica.

Angrist, J.D., Pischke, J.-S., 2009. Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

Arroyo-Barrigüete, J.L., Ernst, R., López-Sánchez, J.I., Orero-Giménez, A., 2010. On the identification of critical mass in Internet-based services subject to network effects. Serv. Ind. J. 30 (5), 643–654.

Bai, J.J., Brynjolfsson, E., Jin, W., Steffen, S., Wan, C., 2021. Digital resilience: How work-from-home feasibility affects firm performance. Natl. Bur. Econ. Res.

Banerjee, A., Duflo, E., Qian, N., 2020. On the road: Access to transportation infrastructure and economic growth in China. J. Dev. Econ. 145, 102442.

Barro, R.J., 1991. Economic growth in a cross section of countries. Q. J. Econ. 106 (2), 407–443.

Baum-Snow, N., 2007. Did highways cause suburbanization? Q. J. Econ. 122 (2), 775–805.

Baumol, W.J., 1996. Entrepreneurship: Productive, unproductive, and destructive. J. Bus. Ventur. 11 (1), 3–22.

Bennett, J., Kornfeld, R., Sichel, D., Wasshausen, D., 2020. Measuring infrastructure in BEA's national economic accounts. Natl. Bur. Econ. Res.

Bloom, N., Van Reenen, J., 2007. Measuring and explaining management practices across firms and countries. Q. J. Econ. 122 (4), 1351–1408.

Bresnahan, T.F., Brynjolfsson, E., Hitt, L.M., 2002. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. Q. J. Econ. 117 (1), 339–376.

Brynjolfsson, E., McElheran, K., 2016. The rapid adoption of data-driven decision-making. Am. Econ. Rev. 106 (5), 133–139.

Brynjolfsson, E., Rock, D., Syverson, C., 2018. Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. Econ. Artif. Intell.: An Agenda 23–57.

Brynjolfsson, E., Rock, D., Syverson, C., 2021. The productivity J-curve: How intangibles complement general purpose technologies. Am. Econ. J.: Macroecon. 13 (1), 333–372.

Byrne, D.M., Fernald, J.G., Reinsdorf, M.B., 2016. Does the United States have a productivity slowdown or a measurement problem? Brookings Pap. Econ. Act. 2016 (1), 109–182.

Cai, M., Wu, G.L., 2026. Estimating the real effect of endogenous digital technology adoption. Working paper.

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-differences with multiple time periods. J. Econometrics 225 (2), 200–230.

Chen, S., Liu, H., 2020. Broadband internet, firm performance, and worker welfare: Evidence and mechanism. Econ. Inq. 58 (3), 1146–1166.

Chetty, R., Looney, A., Kroft, K., 2009. Salience and taxation: Theory and evidence. Am. Econ. Rev. 99 (4), 1145–1177.

Cong, L.W., Yang, X., Zhang, X., 2024. Small and medium enterprises amidst the pandemic and reopening: Digital edge and transformation. Manag. Sci. 70 (7), 4564–4582.

Czernich, N., Falck, O., Kretschmer, T., Woessmann, L., 2011. Broadband infrastructure and economic growth. Econ. J. 121 (552), 505–532.

Dai, R., Mookherjee, D., Quan, Y., Zhang, X., 2021. Industrial clusters, networks and resilience to the Covid-19 shock in China. J. Econ. Behav. Organ. 183, 433–455.

Dai, R., Zhang, X., 2015. E-commerce expands the bandwidth of entrepreneurship. 20, (1), Working paper.

De Chaisemartin, C., d'Haultfoeuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. Am. Econ. Rev. 110 (9), 2964–2996.

Faber, B., 2014. Trade integration, market size, and industrialization: evidence from China's National Trunk Highway System. Rev. Econ. Stud. 81 (3), 1046–1070.

Fan, J., Tang, L., Zhu, W., Zou, B., 2018. The Alibaba effect: Spatial consumption inequality and the welfare gains from e-commerce. J. Int. Econ. 114, 203–220.

Feng, Q., Wang, Z., Wu, G.L., 2025. Digital infrastructure investment and productivity: Is China catching up with the US? Working paper.

Goldfarb, A., Tucker, C., 2019. Digital economics. J. Econ. Lit. 57 (1), 3–43.

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. J. Econometrics 225 (2), 254–277.

Greenstein, S., McDevitt, R.C., 2009. The broadband bonus: Accounting for broadband Internet's impact on US GDP. Natl. Bur. Econ. Res.

Hjort, J., Poulsen, J., 2019. The arrival of fast internet and employment in Africa. Am. Econ. Rev. 109 (3), 1032–1079.

Hjort, J., Tian, L., 2024. The economic impact of internet connectivity in developing countries. INSEAD Working paper.

Kolko, J., 2012. Broadband and local growth. J. Urban Econ. 71 (1), 100–113.

Koutroumpis, P., 2009. The economic impact of broadband on growth: A simultaneous approach. Telecommun. Policy 33 (9), 471–485.

Kuhn, P., Skuterud, M., 2004. Internet job search and unemployment durations. Am. Econ. Rev. 94 (1), 218–232.

Kumar, R.R., Stauvermann, P.J., Samitas, A., 2016. The effects of ICT on output per worker: A study of the Chinese economy. Telecommun. Policy 40 (2–3), 102–115.

Li, P., Lu, Y., Wang, J., 2016. Does flattening government improve economic performance? Evidence from China. J. Dev. Econ. 123, 18–37.

Li, Z., Wu, M., Chen, B.R., 2017. Is road infrastructure investment in China excessive? Evidence from productivity of firms. Reg. Sci. Urban Econ. 65, 116–126.

Mankiw, N.G., Romer, D., Weil, D.N., 1992. A contribution to the empirics of economic growth. Q. J. Econ. 107 (2), 407–437.

Nie, H., 2017. Collusion, Local Governments and Development in China. Springer.

Nunn, N., Qian, N., 2014. US food aid and civil conflict. Am. Econ. Rev. 104 (6), 1630–1666.

Paunov, C., Rollo, V., 2016. Has the internet fostered inclusive innovation in the developing world? World Dev. 78, 587–609.

Romer, P.M., 1990. Endogenous technological change. J. Political Econ. 98 (5, Part 2), S71–S102.

Sector, D., 2020. How broadband, digitization and ICT regulation impact the global economy. ITU Publ. Glob. Econ. Model.

Smith, N., 2015. The Internet's hidden wealth. Bloom. View.

Syverson, C., 2017. Challenges to mismeasurement explanations for the US productivity slowdown. J. Econ. Perspect. 31 (2), 165–186.

The Economist, 2012. What's the greatest invention of all time? Econ. Mag.

Wongsurawat, W., 2006. Pornography and social ills: evidence from the early 1990s. J. Appl. Econ. 9 (1), 185–213.

World Bank, 2016. Digital dividends. World Development Report 2016.

Wu, G.L., Feng, Q., Wang, Z., 2021. A structural estimation of the return to infrastructure investment in China. J. Dev. Econ. 152, 102672.

Xiong, W., Song, Z.M., 2024. The mandarin model of growth. Natl. Bur. Econ. Res.

Xu, C., 2011. The fundamental institutions of China's reforms and development. J. Econ. Lit. 49 (4), 1076–1151.

Xu, C., 2022. Reshaping global trade: The immediate and long-run effects of bank failures. Q. J. Econ. 2107–2161.

Yang, M., Zheng, S., Zhou, L., 2022. Broadband internet and enterprise innovation. China Econ. Rev. 74, 101802.

You, Z., Feng, Z., Yang, Y., 2018. Relief degree of land surface dataset of China (1 km). J. Glob. Chang. Data Discov. 2, 151–155.