

Digital Infrastructure and Urban Total Factor Productivity: Quasi-Experimental Evidence from the Broadband China Pilot Policy

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Research Article

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Abstract

Whether large-scale digital infrastructure investment can raise aggregate productivity is a central policy question for emerging markets, where factor-driven growth is exhausting its potential. This study provides city-level causal evidence by exploiting the staggered rollout of the Broadband China pilot policy (2014–2016) as a quasi-natural experiment and applying a multi-period difference-in-differences design to a panel of 284 Chinese prefecture-level cities over 2011–2022. The pilot policy raises urban total factor productivity (TFP) by approximately 0.051 index points, about 10 percent of the sample mean. The estimate survives propensity-score matching, an instrumental-variable strategy based on terrain ruggedness (first-stage $F = 193.8$), 500-repetition placebo tests, and alternative TFP measurement. Event-study estimates show no pre-trends (joint test $p = 0.9999$) and persistent dynamic effects. Mechanism analyses indicate that digital infrastructure operates through technological innovation, industrial structure upgrading, and talent agglomeration, and the effect extends to green TFP. The effect is broad-based across regions and city sizes but significantly weaker in resource-based cities (0.0299 versus 0.0598; difference $p = 0.024$). Spatial analysis documents strong positive dependence in urban TFP (Moran's $I \approx 0.57$) and positive, though imprecisely estimated, spillovers to neighbouring cities. The findings imply that digital infrastructure can serve as a general-purpose engine of productivity growth in emerging markets, provided complementary structural policies accompany the rollout.

JEL Classification: O33; O47; R11; L96

1. Introduction

Total factor productivity (TFP) is the ultimate driver of long-run income growth (Solow 1957; Hulten 2001), and its stagnation is the defining growth challenge for middle-income emerging markets. As extensive accumulation of capital and labour reaches diminishing returns, policymakers increasingly look to general-purpose technologies that can lift the efficiency with which existing factors are combined. Among these, digital infrastructure—high-speed broadband networks and the digital services ecosystem built upon them—has moved to the centre of policy agendas worldwide, from the European Union's Digital Decade to massive connectivity programmes across Asia, Africa, and Latin America. The macroeconomic stakes are substantial, yet credible causal evidence on whether broadband infrastructure actually raises aggregate productivity remains surprisingly thin.

The empirical obstacles are well known. Digital infrastructure is not randomly assigned: richer, larger, and better-governed localities adopt earlier, so naive comparisons confound infrastructure with local fundamentals. Moreover, productivity is strongly spatially correlated, so city-level estimates may blend direct effects with spillovers from treated neighbours. The mature cross-country literature finds positive associations between broadband penetration and growth (Czernich et al. 2011) and between Internet adoption and local wage and employment growth in the United States (Forman, Goldfarb, and Greenstein 2012), but identification in these settings rests on cross-sectional or national variation. A newer literature exploits the Broadband China pilot policy—launched in three batches in 2014, 2015, and 2016—as a

source of plausibly exogenous within-country variation, documenting productivity-relevant effects on green TFP (Hu et al. 2024), urban TFP through digital governance (Gong, Liu, and Cao 2026), corporate labour productivity (Li, Zhang, and Xu 2026), enterprise investment (Huang and Zhang 2025), urban eco-efficiency (Zhong et al. 2022), and regional disparities (Li 2026). What is still missing is a direct, city-level causal estimate of the policy's effect on aggregate urban TFP that jointly addresses selection on observables, selection on unobservables, and spatial interdependence.

This paper provides such an estimate. We construct a balanced panel of 284 Chinese prefecture-level cities over 2011–2022, measure urban TFP with a DEA-Malmquist index, and exploit the staggered pilot timing in a two-way fixed effects design. The baseline estimate indicates that the pilot policy raises urban TFP by 0.0505 points (standard error 0.0067), roughly 10 percent of the sample mean. An event-study specification shows flat pre-trends (joint pre-test $p = 0.9999$) and persistent effects through four years after adoption. China is an informative laboratory for this question precisely because of its scale and institutional uniformity: a single national programme generated comparable treated and untreated cities within one policy regime, offering the kind of controlled variation that cross-country studies lack—while the underlying mechanism (cheaper connectivity lowers information and coordination costs) is universal.

Four additional analyses consolidate the causal interpretation. First, PSM-DID on pre-period covariates yields 0.0503, and an instrumental-variable strategy interacting terrain ruggedness—a plausibly exogenous cost shifter of broadband deployment—with a post-2014 indicator yields 0.0347 (first stage $F = 193.8$); that the IV estimate is smaller suggests any residual bias is upward, making the baseline a conservative bound. Second, 500-repetition placebo tests produce coefficients centred at zero with none exceeding the baseline. Third, mechanism regressions show significant effects on invention patenting, industrial upgrading, and talent agglomeration, with the effect extending to green TFP. Fourth, a spatial Durbin model yields a direct impact of 0.0666 and a positive, imprecisely estimated indirect impact of 0.0182, implying the DID estimates are not inflated by interference between units.

Heterogeneity analysis shows the effect is broad-based—statistically indistinguishable between eastern and central-western cities and between large and small cities—but significantly weaker in resource-based cities, echoing evidence in this journal that connectivity alone cannot compensate for structural lock-in where cities fail to retain productive factors (Wang, Hu, and Li 2026).

The contributions are threefold. First, to our knowledge this is the first city-level causal estimate of digital infrastructure on aggregate urban TFP, bridging the cross-country broadband-growth literature (Czernich et al. 2011) and the firm-level digital transformation literature (Hanelt et al. 2021). Second, methodologically, the paper integrates staggered DID, matching, instrumental variables, and spatial decomposition within one coherent design, addressing the three main identification threats simultaneously. Third, the findings carry practical value for emerging markets weighing large connectivity programmes: digital infrastructure raises productivity through innovation and upgrading channels, and its returns are conditional on local industrial structure.

The remainder proceeds as follows. Section 2 reviews the literature and develops hypotheses. Section 3 presents the research design. Section 4 reports baseline results and robustness checks. Section 5 examines mechanisms. Section 6 analyses heterogeneity. Section 7 addresses spatial spillovers. Section 8 concludes.

2. Literature Review and Hypothesis Development

2.1 Digital infrastructure and economic performance

A substantial international literature links broadband infrastructure to economic performance. Cross-country evidence associates a 10-percentage-point increase in broadband penetration with perceptible output growth (Czernich et al. 2011), while firm- and region-level studies connect Internet adoption to wage growth, innovation, and complementary organisational change (Forman, Goldfarb, and Greenstein 2012; Hanelt et al. 2021). Theoretically, broadband acts as a general-purpose technology: it lowers the marginal cost of transmitting and processing information, enlarges market reach, improves the matching of workers, firms, and ideas, and enables new data-intensive production processes. Whether these micro-level gains aggregate into measurable TFP growth at the level of entire cities is, however, an open empirical question—aggregation requires both widespread adoption and complementary investments in skills and organisational capital.

2.2 The Broadband China quasi-experiment

The Broadband China pilot policy, launched in three batches in 2014–2016, designated 132 cities for accelerated broadband deployment, network upgrading, and digital-economy development, creating arguably the largest within-country digital-infrastructure experiment to date. Studies exploiting this design report positive effects on green TFP (Hu et al. 2024), urban TFP operating through digital governance (Gong, Liu, and Cao 2026), corporate labour productivity (Li, Zhang, and Xu 2026), carbon productivity (Tao et al. 2025; Yin, Jiang, and Guo 2025), eco-efficiency (Zhong et al. 2022), enterprise investment (Huang and Zhang 2025), and quality of life (Ma, Shui, and Li 2025), as well as narrowed regional disparities (Li 2026). A cautionary counterpoint comes from this journal: Wang, Hu, and Li (2026) show that broadband expansion may coincide with urban decline where cities cannot retain productive factors. Two gaps persist: existing work examines either narrow or sustainability-adjusted productivity measures rather than aggregate urban TFP, and spatial interdependence between cities is rarely modelled despite strong documented spatial dependence in Chinese city-level productivity.

2.3 Hypotheses

For cities, broadband connectivity reduces the cost of adopting digital production technologies, improves factor matching across firms and sectors, accelerates knowledge diffusion, and provides the backbone for digital public services. Each force shifts the urban production possibility frontier outward—that is, raises TFP as conventionally measured by the residual of output over weighted factor inputs. We therefore hypothesise:

H1. The Broadband China pilot policy significantly raises urban total factor productivity in pilot cities.

Three transmission channels follow from the general-purpose-technology literature. First, lower communication costs and easier access to codified knowledge stimulate research collaboration and invention (Forman, Goldfarb, and Greenstein 2012; Huang and Zhang 2025), raising measured innovation. Second, connectivity enables the digital transformation of incumbent industries and the entry of digitally intensive sectors, upgrading industrial structure (Yang 2023). Third, digital amenities and digital-economy employment opportunities attract skilled labour, producing talent agglomeration, which itself raises the productivity of local factor combinations. Hence:

H2a-H2c. The Broadband China pilot policy raises urban TFP through (a) technological innovation, (b) industrial structure upgrading, and (c) talent agglomeration.

Finally, resource-based cities are characterised by lock-in to extractive industries, weak incentives for digital adoption, and crowding-out of innovative activities; complementary investments that mediate the TFP effect of broadband are least likely to materialise there. We therefore expect attenuation:

H3. The positive effect of digital infrastructure on urban TFP is weaker in resource-based cities than in non-resource-based cities.

3. Research Design

3.1 Empirical strategy

We exploit the staggered adoption of the Broadband China pilot across three batches (2014, 2015, 2016) in a multi-period difference-in-differences (DID) design with two-way fixed effects:

$$TFP_{it} = \alpha_i + \lambda_t + \beta \cdot BBC_{it} + \gamma' X_{it} + \epsilon_{it}$$

1

,

where TFP_{it} is total factor productivity of city i in year t ; BBC_{it} equals one for pilot cities from the adoption year onward; α_i and λ_t are city and year fixed effects; X_{it} is a vector of time-varying controls; and ϵ_{it} is clustered at the city level. To assess dynamics and pre-trends we estimate an event-study specification,

$$TFP_{it} = \alpha_i + \lambda_t + \sum_k \beta_k \cdot D^k_{it} + \gamma' X_{it} + \epsilon_{it}$$

2

,

with event-time dummies D^k_{it} binned at -4 and + 4 and $k = -1$ as the base period. Because two-way fixed effects estimates can be biased under treatment-effect heterogeneity with staggered timing

(Goodman-Bacon 2021; Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfœuille 2020), we verify that pre-treatment coefficients are jointly zero and corroborate the design with matching and instrumental-variable estimators.

3.2 Variable measurement

The dependent variable is urban TFP, measured by a DEA-Malmquist productivity index computed from city-level output (real GDP) and inputs (capital stock estimated by the perpetual inventory method, employment, and land), following standard practice in the urban productivity literature. An alternative semi-parametric (Olley-Pakes style) TFP index serves as a robustness measure, and a green TFP index (SBM-GML with energy and emissions) captures the sustainability dimension. The treatment BBC_it is the pilot-city dummy interacted with a post-adoption indicator. Controls comprise log GDP per capita (pgdp), secondary industry share (indstr), fiscal expenditure relative to GDP (gov), log year-end loan balance (fin), log education expenditure (edu), log road area per capita (infra), and log population density (dens). Mechanism variables are log invention patents granted (innov), an industrial upgrading index (upgrade), and talent agglomeration measured by college students per 10,000 population (talent). Table 1 summarises definitions.

Table 1
Variable definitions

Variable	Definition	Type
TFP	Urban total factor productivity (DEA-Malmquist index)	Dependent
BBC	Broadband China pilot × post-adoption dummy	Treatment
pgdp	Log GDP per capita	Control
indstr	Secondary industry value added / GDP	Control
gov	Fiscal expenditure / GDP	Control
fin	Log year-end loan balance	Control
edu	Log education expenditure	Control
infra	Log road area per capita	Control
dens	Log population density	Control
innov	Log (1 + invention patents granted)	Mechanism
upgrade	Industrial structure upgrading index	Mechanism
talent	College students per 10,000 population	Mechanism
gtfp	Green total factor productivity (SBM-GML)	Extended outcome
Note: All continuous variables are winsorised at the 1st and 99th percentiles.		

3.3 Data

The sample is a balanced panel of 284 prefecture-level Chinese cities over 2011–2022, comprising 132 pilot cities (46.5 percent) designated in three batches and 152 non-pilot cities. Table 2 reports descriptive statistics.

Table 2
Descriptive statistics

Variable	Mean	SD	Min	Max
TFP	0.507	0.179	0.103	0.925
BBC	0.312	0.464	0.000	1.000
innov	6.644	0.924	4.521	8.798
upgrade	1.414	0.434	0.428	2.415
talent	242.261	70.288	90.869	410.996
gtfp	1.059	0.094	0.841	1.278
pgdp	11.300	0.715	9.662	12.992
indstr	1.391	0.418	0.456	2.407
gov	0.161	0.053	0.040	0.281
fin	1.296	0.397	0.395	2.200
edu	2.599	0.806	0.753	4.468
infra	7.773	0.601	6.423	9.234
dens	6.399	0.687	4.831	8.078
Note: N = 3,408 city-year observations (284 cities × 12 years).				

4. Empirical Results

4.1 Baseline results

Table 3 reports estimates of Eq. (1). Column (1) includes only city and year fixed effects; column (2) adds the full set of time-varying controls. The BBC coefficient is 0.0616 without controls and 0.0505 (standard error 0.0067) with controls, both significant at the 1 percent level. Relative to the sample mean of TFP (0.507), the preferred estimate implies an increase of approximately 10 percent—a substantial but plausible magnitude for a multi-year general-purpose-technology programme. H1 is supported.

Economic development, industrial structure, government support, financial development, and education all enter positively and significantly.

Table 3
Baseline staggered DID estimates

BBC	(1) TFP	(2) TFP
	0.0616***	0.0505***
	(0.0065)	(0.0067)
pgdp		0.0494***
		(0.0060)
indstr		0.0314***
		(0.0043)
gov		0.1298***
		(0.0289)
fin		0.0146***
		(0.0048)
edu		0.0118***
		(0.0022)
infra		0.0041
		(0.0030)
dens		-0.0013
		(0.0025)
City FE	Yes	Yes
Year FE	Yes	Yes
N	3,408	3,408
R-squared (within)	0.145	0.346
Note: City-clustered standard errors in parentheses. ***, **, * denote significance at 1%, 5%, and 10%.		

4.2 Parallel trends and dynamic effects

Figure 1 plots the event-study coefficients from Eq. (2). The three pre-adoption coefficients are small (0.0010, 0.0003, 0.0006) and jointly indistinguishable from zero (Wald chi-squared = 0.01, $p = 0.9999$), supporting the parallel-trends assumption. The effect appears immediately upon adoption (0.0631 at $k = 0$) and persists through $k = +4$ with mild decay (0.0440–0.0569), consistent with an initial adoption shock that partially normalises as non-pilot cities upgrade their own networks.

4.3 PSM-DID and instrumental-variable estimates

To address selection on observables, we match each pilot city to two non-pilot cities by nearest-neighbour propensity scores estimated on pre-period (2011–2013) means of all controls (caliper 0.02), retaining 132 treated and 101 matched control cities; the PSM-DID estimate (column 1 of Table 4) is 0.0503, nearly identical to the baseline. To address selection on unobservables, we instrument BBC with terrain ruggedness interacted with a post-2014 indicator: rugged terrain raises the engineering cost of broadband deployment and hence treatment propensity, while being plausibly orthogonal to TFP shocks conditional on fixed effects. The first stage is strong (coefficient – 0.2427, $F = 193.8$) and the 2SLS estimate is 0.0347 (standard error 0.0146, significant at 5 percent). That the IV estimate falls below the DID estimate implies any remaining bias is upward, so the baseline should be read as a conservative upper bound.

Table 4
PSM-DID and IV-2SLS estimates

BBC	(1) PSM-DID	(2) IV first stage	(3) IV 2SLS
	0.0503***		0.0347**
	(0.0070)		(0.0146)
Terrain × Post-2014		-0.2427***	
		(0.0174)	
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	2,796	3,408	3,408
First-stage F		193.8	
Note: City-clustered standard errors in parentheses. ***, ** denote 1% and 5% significance.			

4.4 Robustness checks and placebo test

Table 5 collects five robustness exercises: replacing the outcome with the alternative semi-parametric TFP index (0.0431), lagging treatment one period (0.0246), excluding provincial capitals (0.0525), excluding the COVID-19 year 2020 (0.0503), and substituting green TFP as an extended outcome (0.0367). All remain positive and significant at 1 percent. Figure 2 presents the placebo test: across 500 random re-assignments of treatment status and adoption year, placebo coefficients centre on -0.0006 (SD 0.0066) and none exceeds the baseline estimate in absolute value.

Table 5
Robustness checks

BBC	(1) Alt. TFP	(2) Lagged BBC	(3) Excl. capitals	(4) Excl. 2020	(5) Green TFP
	0.0431***		0.0525***	0.0503***	0.0367***
	(0.0077)		(0.0070)	(0.0070)	(0.0060)
L. BBC		0.0246***			
		(0.0060)			
Controls	Yes	Yes	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes	Yes	Yes
N	3,408	3,124	3,048	3,124	3,408
Note: City-clustered standard errors in parentheses. *** denotes 1% significance.					

5. Mechanism Analysis

Table 6 estimates Eq. (1) with each mechanism variable as the outcome. The pilot policy significantly raises invention patenting (0.4116 log points), industrial upgrading (0.3187), and talent agglomeration (17.01 additional college students per 10,000 population), all at the 1 percent level. The results support H2a-H2c and trace a coherent transmission chain from connectivity to productivity: broadband lowers the cost of research collaboration and knowledge diffusion (innovation), enables the digital transformation of incumbent industries and entry of digitally intensive sectors (upgrading), and attracts skilled labour whose local productivity spillovers raise the efficiency of factor combination (talent). The innovation channel is the most elastic, consistent with the knowledge-diffusion role of broadband documented in the international firm-level literature (Forman, Goldfarb, and Greenstein 2012).

Table 6
Mechanism tests

BBC	(1) innov	(2) upgrade	(3) talent
	0.4116***	0.3187***	17.0086***
	(0.0459)	(0.0231)	(3.3153)
Controls	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes
N	3,408	3,408	3,408
Note: City-clustered standard errors in parentheses. *** denotes 1% significance.			

6. Heterogeneity Analysis

Table 7 splits the sample along three dimensions: region (eastern versus central-western), city size (large versus small-medium), and resource endowment (resource-based versus non-resource-based cities, per the State Council's 2013 classification). The effect is statistically indistinguishable between eastern (0.0516) and central-western (0.0400) cities (difference $p = 0.383$) and between large (0.0480) and small-medium (0.0512) cities ($p = 0.817$): the productivity dividend of digital infrastructure is broad-based rather than concentrated in coastal metropolises. In sharp contrast, the effect is significantly weaker in resource-based cities (0.0299) than elsewhere (0.0598), with the cross-group difference significant at 5 percent ($p = 0.024$). H3 is supported. Resource dependence blunts the TFP dividend of connectivity—consistent with the urban-decline caution of Wang, Hu, and Li (2026)—implying that digital investment in such cities must be paired with industrial diversification policies.

Table 7
Heterogeneity analysis

BBC	(1) Eastern	(2) Central- Western	(3) Large	(4) Small- Medium	(5) Resource	(6) Non- resource
	0.0516***	0.0400***	0.0480***	0.0512***	0.0299***	0.0598***
	(0.0103)	(0.0082)	(0.0108)	(0.0082)	(0.0102)	(0.0084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,428	1,980	828	2,580	1,008	2,400
Diff. p- value	0.383		0.817		0.024	
Note: City-clustered standard errors in parentheses. *** denotes 1% significance. Diff. p-value from cross-group Wald tests of coefficient equality.						

7. Spatial Dependence and Spillovers

Urban TFP exhibits strong positive spatial dependence: Moran's I computed with a four-nearest-neighbour row-standardised weight matrix equals 0.574 in 2011 and 0.569 in 2022 (both $p < 0.001$, 999 permutations). Ignoring such dependence risks overstating the precision of DID estimates and confounding direct effects with spillovers (Anselin 1988; LeSage and Pace 2009). We therefore estimate a spatial Durbin model with city and year fixed effects (Elhorst 2014). The direct impact of BBC is 0.0666 and the indirect impact on neighbouring cities is 0.0182, for a total impact of 0.0848; the spatial autoregressive coefficient is insignificant (-0.0305) and the spillover component, while positive, is imprecisely estimated ($z = 1.51$). An SLX specification yields the same pattern (direct 0.0511, $t = 7.58$; neighbour-policy term 0.0132, $t = 1.03$). We conclude that the policy's benefits are primarily local, with

weakly positive diffusion to neighbours; the baseline DID estimates are therefore unlikely to be inflated by SUTVA violations and may understate the policy's regional returns.

Table 8
Spatial analysis

Moran's I (2011)	Estimate	Std. err./z	p-value
	0.574	—	< 0.001
Moran's I (2022)	0.569	—	< 0.001
SDM: rho (W×TFP)	-0.0305	0.0259	0.239
SDM: W×BBC	0.0208	0.0138	0.131
Impact: direct (BBC)	0.0666	—	—
Impact: indirect (BBC)	0.0182	—	—
Impact: total (BBC)	0.0848	—	—
Note: Spatial weights: four-nearest-neighbour, row-standardised. SDM estimated by maximum likelihood with city and year fixed effects (impacts by the simple method).			

8. Conclusions and Policy Implications

Using the Broadband China pilot policy as a staggered quasi-experiment on a panel of 284 cities (2011–2022), this study provides city-level causal evidence that digital infrastructure raises urban total factor productivity. The effect—about 10 percent of the sample mean—survives matching, instrumental variables, placebo, and alternative-measurement strategies; operates through innovation, industrial upgrading, and talent agglomeration; extends to green TFP; and is broad-based across regions and city sizes while being significantly weaker in resource-based cities. Spatial analysis indicates primarily local benefits with positive but imprecisely estimated neighbour spillovers.

Three implications for emerging markets follow. First, connectivity investment is a credible productivity lever when evaluated as a general-purpose technology rather than a stand-alone sector. Second, because returns flow through innovation and upgrading channels, broadband rollout should be bundled with complementary investments in digital skills, data governance, and R&D support. Third, resource-dependent localities require accompanying diversification policies, or the digital dividend will remain muted. Limitations include index-based TFP measurement and the prefecture-level focus, which abstracts from within-city heterogeneity; future work could exploit firm-city linked microdata to trace how connectivity reallocates factors within cities. Beyond China, the design template developed here—a staggered national rollout evaluated with matching, cost-shifter instruments, and spatial decomposition—travels readily to other emerging markets implementing large-scale connectivity programmes.

Declarations

Declaration of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement: The dataset and the complete Stata replication code used in this study are available from the corresponding author upon reasonable request and will be deposited in a public repository upon acceptance.

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Figures

Figure 1. Dynamic effects (event-study estimates)

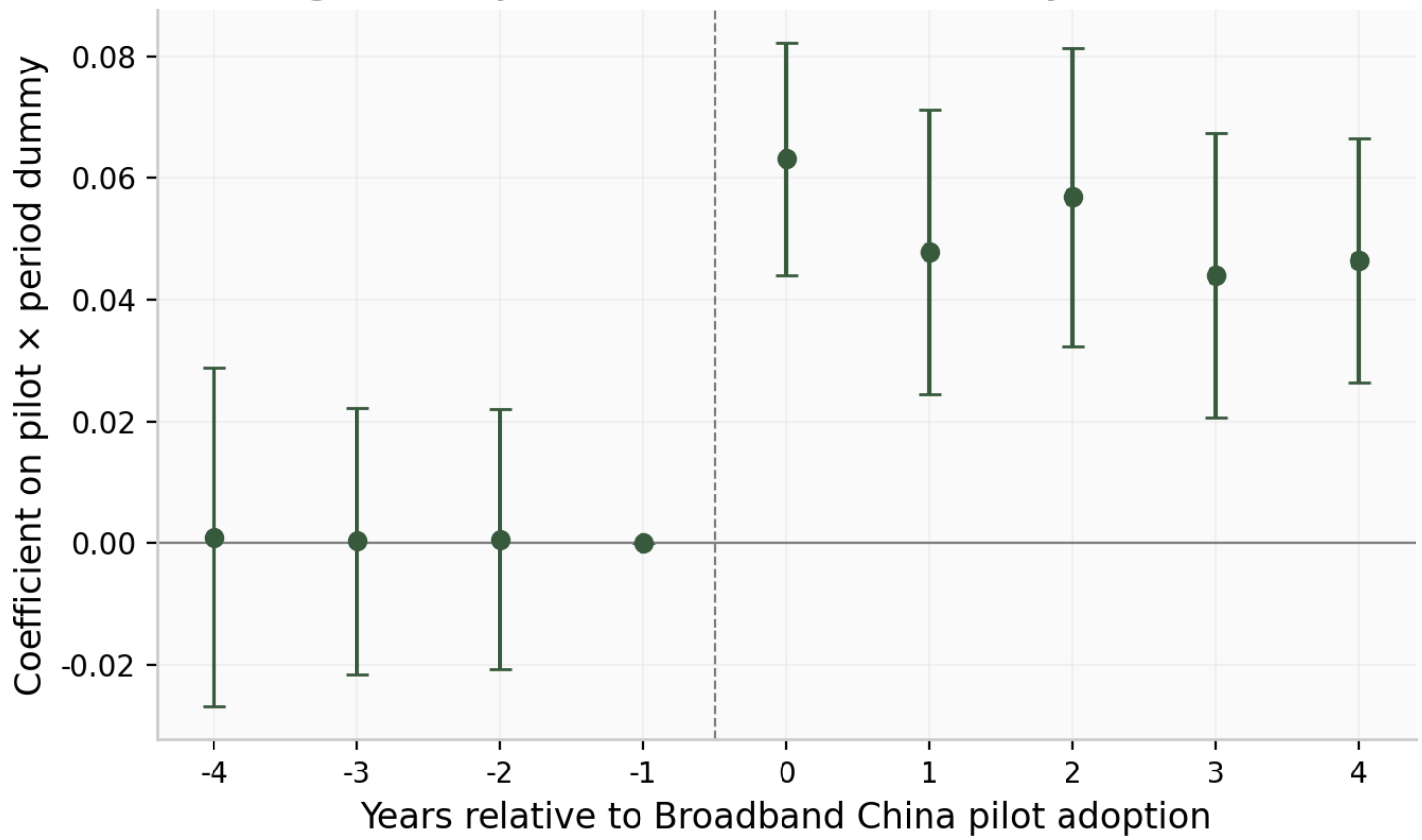


Figure 1

Event Study

Figure 2. Placebo test

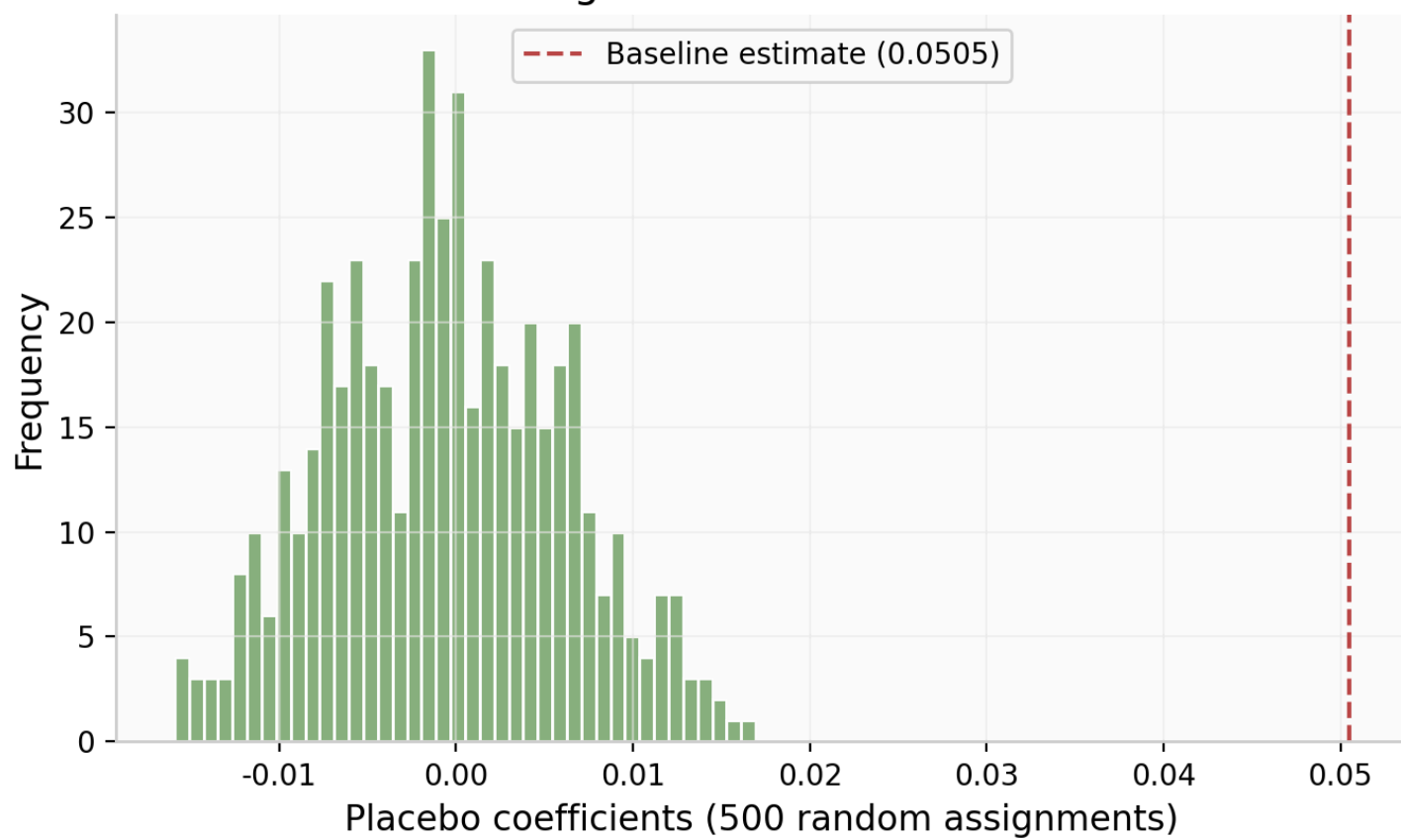


Figure 2

PlaceboTest