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Broadband China and Household Cultural Consumption

Ruitong Sun

University of California, Davis, USA
rtsun@ucdavis.edu

Abstract. Access to broadband may change household spending by making information about goods and services easier to obtain. This study examines that relationship through China's "Broadband China" demonstration program, with attention to cultural, educational, and recreational expenditure. The analysis combines household observations from the China Family Panel Studies with city-level information and program designation dates. Because participation was not randomly assigned, propensity score matching is used to identify candidate comparison cities. Stable balancing weights then improve comparability on eight principal components selected for their ability to predict participation. A difference-in-differences model with city and survey-year fixed effects estimates expenditure changes associated with the program. The pre-policy coefficients reveal no statistically detectable divergence between the groups. The estimated effect develops gradually: the coefficient is 0.1820 in the first survey wave after treatment and rises to 0.7043 in the second, when it is significant at the 1 percent level. The findings suggest that broadband development can support household spending on cultural, educational, and recreational activities. Reduced information frictions offer a possible explanation for this pattern, rather than a mechanism established separately by the analysis.

Keywords: household consumption, digital infrastructure, difference-in-differences, propensity score matching

1. Introduction

Prices and the availability of substitutes are familiar determinants of household consumption. Access to information may also shape what households purchase. The question examined here is whether broader broadband coverage changes spending on cultural, educational, and recreational goods and services by making relevant information easier to obtain.

China's "Broadband China" demonstration program provides the setting for this analysis. Designed to improve public broadband infrastructure, the program designated participating cities in three annual rounds from 2014 to 2016. The study includes 15 cities from each round. Admission depended on an existing broadband foundation, a development plan, provincial government support, and expert review. These requirements matter for the empirical comparison: cities outside the program cannot simply be assumed to resemble those selected. Propensity score matching therefore identifies a candidate comparison sample, and stable balancing weights improve its balance before the difference-in-differences (DID) estimation.

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The estimates show a positive expenditure response that becomes statistically significant after a delay. Before designation, the data do not reveal a statistically significant difference in trends between the two groups. The analysis thus extends the discussion of broadband infrastructure beyond aggregate growth and employment to a specific area of household consumption.

Section 2 sets out the literature and hypothesis, followed by the policy background in Section 3. Sections 4–6 explain the data, comparison-group construction, and estimation method. Section 7 presents the findings, and Section 8 concludes.

2. Literature review and hypothesis

Research on information and markets provides a starting point for the analysis. Easier access to information can reduce the difficulties consumers face when searching for products or comparing alternatives. A wider range of available goods may also increase consumer utility [1-3].

A related literature considers broadband as an input into economic activity. Previous studies examine its relationship with economic growth [4], employment [5], and productivity [6]. These contributions establish the broader relevance of broadband access, but household cultural, educational, and recreational expenditure receives less attention in the literature reviewed here.

This expenditure category offers a useful setting in which to connect the two arguments. Online learning and digital entertainment rely on Internet connectivity, so improvements in access may expand households' consumption options. The relationship need not be confined to services delivered online. Information found through the Internet can also help households compare courses, locate cultural events, or choose recreational activities that take place offline.

The proposed link is therefore between broadband access, the information available to consumers, and their spending decisions. When relevant goods and services become easier to find and assess, households may have more opportunities to consume them. This reasoning motivates the following hypothesis:

Hypothesis 1. The "Broadband China" demonstration program increases household cultural, educational, and recreational expenditure.

3. Policy background

The State Council introduced the "Broadband China" strategy in 2013 [7]. The Ministry of Industry and Information Technology (MIIT) and the National Development and Reform Commission (NDRC) subsequently announced lists of demonstration cities and city clusters in 2014, 2015, and 2016 [8-10]. The estimation sample contains 45 policy-designated cities, with 15 from each announcement year.

The designation process was selective. Eligibility reflected existing broadband infrastructure and local development conditions [11], as set out in the January 8, 2014 notice on creating demonstration cities and city clusters. Consequently, participating and nonparticipating cities may have differed before the policy began. Those initial differences are the reason for constructing a weighted comparison group rather than treating all other cities as equivalent controls.

Propensity score matching uses observed pre-policy city characteristics to identify the candidate control sample. Stable balancing weights are then calculated from eight principal components associated with treatment assignment. The subsequent DID analysis compares household expenditure across the resulting groups.

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4. Data

The empirical dataset links city-level policy designations to household records from the China Family Panel Studies (CFPS) and covariates from the China City Statistical Yearbook. Program status is defined at the city level, while the outcome is household cultural, educational, and recreational expenditure.

4.1. Treated cities and treatment timing

The sample comprises 45 treated cities and 26 control cities. The treated group includes three designation cohorts, each containing 15 cities, announced in 2014, 2015, and 2016. At each treatment date, cities that have not yet entered the program form the pool of potential controls.

Administrative designation years must be mapped to the biennial CFPS observations. The 2014 cohort is assigned a first treated survey wave of 2014. For cities designated in 2015, the next available survey is in 2016; cities designated in 2016 are assigned to that same wave. The analysis therefore distinguishes two first-treatment waves, 2014 and 2016, rather than three separate administrative dates.

4.2. Data sources

Household expenditure is drawn from the CFPS, a nationally representative longitudinal survey conducted by Peking University. Its consistent identifiers allow individuals, households, and communities to be linked across survey rounds, making changes in consumption observable over time. The analysis uses five waves: 2010, 2012, 2014, 2016, and 2018.

The China City Statistical Yearbook supplies the city-level covariates. Their pre-policy information contributes to comparison-group construction and the balancing procedure described below.

5. Control-group construction

The comparison group is constructed to address observable differences associated with nonrandom designation. Principal component analysis (PCA) summarizes the pre-policy covariates. A treatment-prediction model then selects eight components, and stable balancing weights bring the control group closer to the treated group on those measures.

5.1. Principal component analysis and covariate selection

The source data contain 124 CFPS variables and 520 city-yearbook variables. Many are correlated, and their number is large relative to the city sample. PCA reduces this information to a more manageable set of components. All inputs are standardized to remove differences in measurement units. Separate PCA procedures are applied to the household and city-yearbook blocks so that the larger city-level block does not dominate the household information.

A regularized model predicts program participation from the candidate components. Components are ranked by the absolute size of their coefficients, and the eight highest-ranked are retained. Six come from the CFPS block and describe household assets and wealth; land, agriculture, and fixed assets; industrial structure and education; health, social security, business, and assets; local economic scale and growth; and housing assets and household debt. The remaining two come from

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the city-yearbook block. One summarizes wages, consumption, and urban development; the other summarizes foreign investment, mining, gas, and freight.

5.2. Stable balancing weights

Minimum-dispersion stable balancing weights are used to reweight the comparison group [12]. Each of the 26 potential control cities receives a nonnegative weight. The weighted means of the eight selected PCA components are constrained to approximate the corresponding means for the 45 treated cities. In the preferred specification, no absolute standardized mean difference may exceed 0.03, and the effective sample size of the control cities must remain at least 10.

5.3. Covariate balance

Figure 1 shows how balance changes for the eight selected PCA components. Before weighting, the largest absolute standardized mean difference is 0.777. Under the preferred weights, the largest difference falls to 0.030 and the mean difference is 0.024. All eight components therefore meet the specified 0.03 threshold.

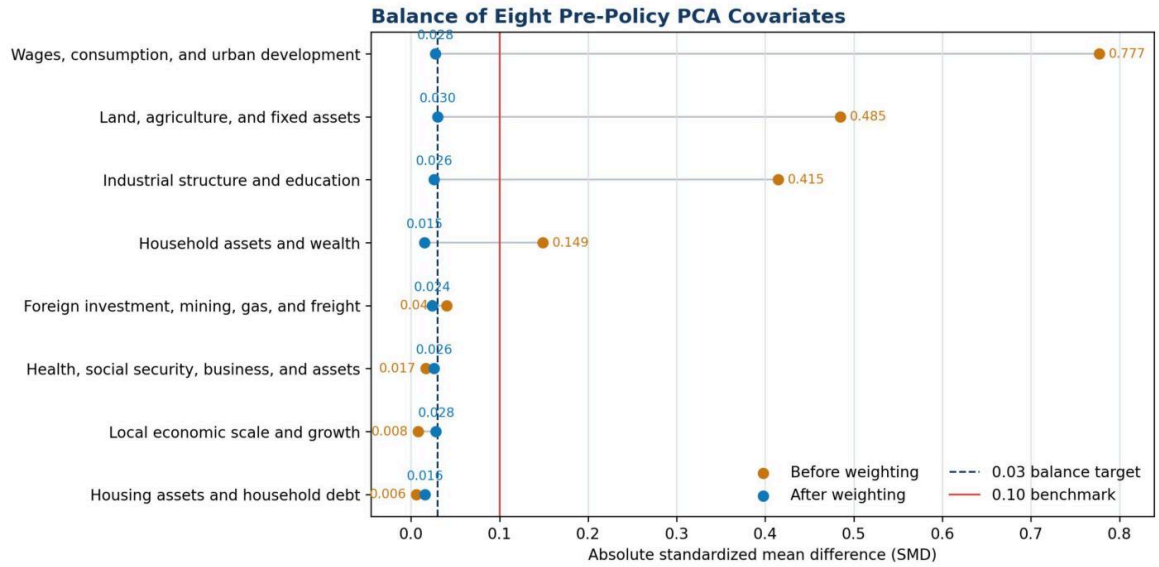


Figure 1. Balance of the eight selected pre-policy components

Notes: The red solid line indicates the 0.10 benchmark, while the dashed line marks the 0.03 target. Blue markers represent weighted absolute standardized mean differences. These balance results concern only the eight PCA components displayed.

6. Difference-in-differences method

The DID analysis follows changes in household expenditure around designation. Equation (1) gives the event-study specification used to examine both pre-policy trends and the timing of the expenditure response:

$$Y_{hct} = \sum_{k \neq -1} \beta_k 1\{D_c = 1, Event_{ct} = k\} + \mu_c + \lambda_t + \varepsilon_{hct} \quad (1)$$

Here, h indexes households, c cities, and t CFPS survey years. Y_{hct} denotes household cultural, educational, and recreational expenditure on a logarithmic scale. The indicator D_c equals one for

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treated cities and zero for controls. $Event_{ct}$ records survey-wave distance from the first treated wave, and k denotes a particular event time. The term $1\{D_c = 1, Event_{ct} = \mathrm{k}\}$ selects treated-city observations at that event time. Each β_k coefficient is measured relative to the omitted wave, $k = -1$. City fixed effects are denoted by μ_c, survey-year fixed effects by λ_t, and the error term by ε_{hct}. Standard errors are clustered by city.

Event time is measured in survey waves, not individual calendar years: one unit corresponds to two years. The first treated wave is 2014 for the earliest designation cohort and 2016 for the other two cohorts. As Table 1 shows, the reference wave is 2012 for the former group and 2014 for the latter.

Table 1. Mapping CFPS survey years to event time

Treatment cohort	2010	2012	2014	2016	2018
2014 cohort	−2	−1 (reference)	0	1	2
2015–2016 cohorts	−3	−2	−1 (reference)	0	1

7. Results

The results distinguish the overall DID estimate from the expenditure response observed at different times around designation.

7.1. Main estimates and pre-policy trends

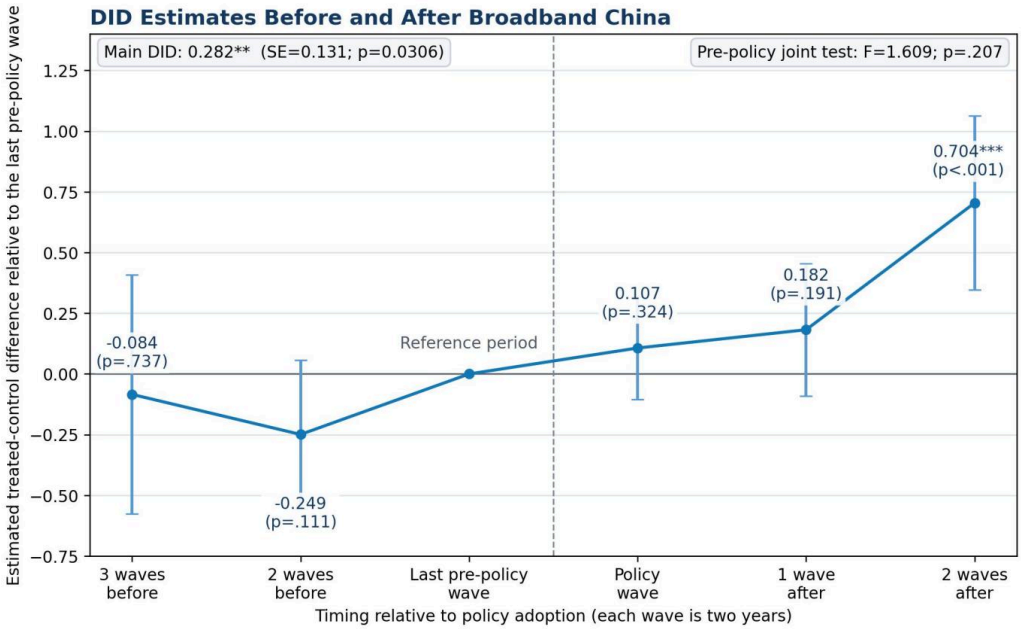


Figure 2. Estimated expenditure effects around policy designation

Notes: Point labels give coefficient estimates and p-values; vertical bars indicate 95 percent confidence intervals. The final pre-policy wave is omitted as the reference. Significance levels of 1, 5, and 10 percent are marked by ***, **, and *, respectively.

The outcome is the logarithm of household cultural, educational, and recreational expenditure. Figure 2 plots the event-study estimates from equation (1), using the final pre-policy wave as the

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reference. A point above zero represents a larger treated–control expenditure difference than in that reference wave. The vertical bars display 95 percent confidence intervals.

The main DID coefficient reported in Figure 2 is 0.282, with a standard error of 0.131 and a p-value of 0.0306. The individual pre-policy coefficients are not statistically distinguishable from zero, and their joint test yields a p-value of 0.207. Thus, the available observations do not show evidence of divergent pre-policy trends. This result is compatible with the parallel-trends assumption, but it does not establish that the assumption holds.

The response is clearer in the later survey waves. One wave after treatment, the coefficient is 0.1820 ($p = 0.191$), which is not statistically significant. Two waves after treatment, it reaches 0.7043 ($p < 0.001$). The pattern points to a delayed increase in expenditure rather than an immediate, statistically significant change. Within the study's design, the later estimate supports a positive effect of broadband development on the combined consumption category.

8. Conclusion

The staggered designation of cities under "Broadband China" offers evidence on how digital infrastructure relates to household cultural, educational, and recreational spending. Using CFPS household records, the analysis constructs stable balancing weights from eight treatment-predictive principal components and estimates DID models with city and year fixed effects. Inference accounts for clustering at the city level.

The estimates reveal no statistically significant difference in pre-policy trends, while the post-policy expenditure response becomes significant only after a delay. Broadband development is therefore associated with higher spending in this category over the observed post-policy horizon. Easier access to information is consistent with the findings, although the expenditure estimates alone do not identify that channel. The contribution is evidence on a household consumption outcome alongside the broader economic effects emphasized in earlier research.

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