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# Smart City Pilot Policy and the Socioeconomic Dimensions of Sustainable Urban Development: Evidence from China

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**Abstract**

Does China's smart city pilot policy (SCPP) do more than raise economic output? This paper asks whether it also spreads development gains across regions and between urban and rural areas, treating the policy as a lens on selected socioeconomic dimensions of sustainable urban development. We study the 2012 SCPP on a panel of 167 prefecture-level cities from 2007 to 2022. A common prosperity index, constructed with entropy-weighted TOPSIS, measures overall prosperity, urban–rural integration, and regional coordination; the policy effect is estimated with PSM-DID. The SCPP raises the index by 0.0328 points in the fixed-effects model and 0.0304 points in the PSM-DID model with controls. The gains are uneven across dimensions: they concentrate in overall prosperity, appear weakly in urban–rural integration, and are not statistically detectable in regional coordination. Digital economy development and new-type urbanization both moderate the policy effect upward. Location matters as well: the effects concentrate in eastern cities and in cities with higher human capital and better informatization infrastructure. Local development conditions, in short, shape where the benefits of smart-city investment land.

**Keywords:** smart city pilot policy; sustainable urban development; common prosperity; digital economy development; new-type urbanization; China

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**Correction Statement:** This article has been republished with a minor change. The change does not affect the scientific content of the article and further details are available within the backmatter of the website version of this article.

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## 1. Introduction

Urban social sustainability research treats social well-being as a dimension of sustainable development in its own right [1]. Smart technologies, however, do not deliver it automatically. Information and communication technologies (ICTs) can improve urban operations and governance, yet their contribution depends on how they address broader socioeconomic challenges [2,3]. Smart city initiatives should therefore be judged on two counts: technological and economic performance, and the implications for social justice and residents' quality of life [4,5].

International research has mapped smart city concepts, technological applications, urban performance, and governance models [6]. Work on the relationship between smart city development and SUD has grown, and it documents potential synergies as well as trade-offs [7,8]. Studies of SDG 11 and related policy frameworks make a similar demand: urban development should be evaluated against broader sustainability objectives [9,10]. Holding smart-city performance and the wider outcomes of urban sustainability apart follows from that standard [11].

In China, the question is bound up with common prosperity, a goal that national strategic documents emphasize [12]. Policy initiatives in the same spirit describe the digital

economy as a way to expand development opportunities, strengthen urban–rural integration, and promote regional coordination [13,14]. Meanwhile, China's smart city pilot policy (SCPP) has promoted investment in information infrastructure, digital urban management, and intelligent public services [15,16]. Prior research finds the SCPP conducive to economic growth and to green, high-quality development [17,18], although its effects on urban inequality and income distribution are more complex [19,20]. Whether the policy contributes to common prosperity therefore has to be assessed along three dimensions at once: overall prosperity, urban–rural integration, and regional coordination. These dimensions anchor the empirical analysis in this study; common prosperity is not treated as equivalent to SUD as a whole.

Two contextual factors may shape the socioeconomic effects of the SCPP. The first is digital economy development (DED), which has been linked to industrial upgrading [21] and urban–rural integration [22]. The second is new-type urbanization (NTU), which stresses people-centered development, urban–rural coordination, and equitable access to basic public services [23]; research on China's NTU pilot initiative examines its effects on public-service provision [24]. This study asks whether DED and NTU moderate the effect of the SCPP on the socioeconomic dimensions of SUD, as measured by a common prosperity index.

The effects may also differ across cities with different socioeconomic and institutional characteristics. Digital inequality extends beyond internet access to differences in digital skills, usage patterns, and the ability to turn technology into tangible benefits [25]. European evidence links greater urban smartness to a narrower digital divide [26], yet the distribution of digital capabilities and benefits may still vary considerably across Chinese cities. We therefore examine heterogeneity by region, innovation and entrepreneurship capacity, digital financial inclusion, human capital, informatization infrastructure, and economic development.

Despite this growing literature, evidence remains limited on two points: how the SCPP affects multiple socioeconomic dimensions of SUD at once, and which contextual factors shape those effects. Two questions follow. First, does the SCPP improve selected socioeconomic dimensions of SUD, as captured by the city-level common prosperity index? Second, do DED and NTU moderate the estimated policy effect, and how does the effect vary across cities with different characteristics?

To address these questions, we construct a common prosperity index using entropy-weighted TOPSIS and assess the 2012 SCPP's effect with a PSM-DID design. The index covers overall prosperity, urban–rural integration, and regional coordination, and serves as an operational measure of selected socioeconomic dimensions of SUD. Because it does not measure environmental quality, resource use, or carbon emissions, the findings should not be read as a comprehensive assessment of urban sustainability. We then examine whether DED and NTU shape the policy effect, and test heterogeneity across regions and across cities differing in innovation and entrepreneurship capacity, digital financial inclusion, human capital, informatization infrastructure, and economic development.

## 2. Policy Context and Hypotheses

### *2.1. China's Smart City Initiative: Policy Evolution*

China's SCPP has developed in parallel with the expansion of digital technologies and their growing application in urban management. The key institutional step came in 2012, when the government introduced the Notice on Carrying out the National Smart City Pilot Work and established the framework for pilot implementation [15]. The first batch of 90 localities followed in January 2013; the second batch added 103 localities in August 2013 [27]; and the third batch, announced in April 2015, brought in 84 new

pilots and 13 expanded-scope pilots, for a total of 290 pilot localities [28]. The initiative subsequently gained prominence in national development strategies: it was incorporated into the National NTU Plan (2014–2020) in 2014 [29], addressed in the 2015 Government Work Report [30], and further reinforced through subsequent national strategies for digital and urban development [12]. This study uses the first batch only, so that all treated cities share a common adoption year; cities designated in later batches are excluded from the analytical sample.

Smart city development continued to feature in China's digital transformation agenda during the 14th Five-Year Plan period. National strategies pushed to integrate digital technologies into urban development, improving infrastructure while aligning smart-city and digital-village development [12,13]. The 14th Five-Year Plan for the Implementation of New-Type Urbanization also promoted smart infrastructure, urban data sharing, and the digital delivery of public services [23]. Subsequent policy efforts have further encouraged the integration of digital applications across urban systems and the broader transformation of city governance. Against a backdrop of continuing urbanization, Digital China initiatives, and new infrastructure investment, the SCPP has become part of China's urban transformation, with effects that may reach beyond urban management into socioeconomic development, regional coordination, and urban–rural integration.

### *2.2. Prior Research and Hypothesis Formulation*

#### 2.2.1. Conceptual Foundations: Smart Cities and Sustainable Urban Development

The SCPP applies digital technologies to urban infrastructure, public administration, and public services within a specific policy framework [15,31]; SUD spans broader economic, social, and environmental objectives [32]. The wider smart-city concept adds the integration of physical infrastructure, knowledge networks, and social capital [33]. What smart-city initiatives contribute to SUD therefore depends on how digital capabilities enter economic activities, public institutions, and urban services, not on technology adoption alone [31,34].

Social inclusion offers a second lens on the SCPP-SUD association. Digital infrastructure, digital skills, and public services are unevenly available across social groups and places. Research on social justice and the urban digital divide separates unequal access from differences in users' skills and technology-use practices [25,26], and both shape whether individuals and communities can convert digital access into tangible benefits [35]. Social inclusion thus belongs to the broader social dimension of SUD, but this study does not measure it as a separate outcome. The common prosperity index captures selected aggregate socioeconomic dimensions but does not directly measure marginalized groups' access to public services and development opportunities or adequately capture inequalities within cities.

#### 2.2.2. Smart City Pilot Policy and the Socioeconomic Dimensions of Sustainable Urban Development

Building on this conceptual framework, we examine three interrelated aspects of the potential socioeconomic effects of the SCPP: expanding productivity and earning opportunities, which bear most directly on overall prosperity; improving public-service provision, which speaks to urban–rural integration; and reducing spatial barriers to development, which connects to regional coordination. These connections provide a theoretical basis for examining the SCPP's effect on the composite common prosperity index and its three component dimensions.

First, the SCPP may strengthen the economic base of urban development by improving information flows, reducing coordination costs, and facilitating the application of digital technologies in economic activities. Digital economics research suggests that

digitalization can reshape information exchange and the organization of economic activities [36]. Evidence on broadband development also indicates that improved connectivity can generate local economic growth and productivity gains [37,38]. These changes may expand employment opportunities, support household income growth, and reinforce the material foundations of urban prosperity [39]. They bear directly on the overall prosperity dimension.

Second, the SCPP may improve the accessibility and efficiency of public services. Research on smart cities commonly identifies governance, public services, and citizen-oriented applications as central components of smart urbanism [31,34]. Evidence from China suggests that the SCPP contributes to high-quality economic development and improves public-service delivery [16,17], and has been associated with greater urban convenience, potentially improving residents' everyday living conditions [40]. When digital systems make essential services easier to access and more efficient to deliver, they may advance residents' well-being and strengthen the social dimension of urban development [41]. These benefits speak to urban–rural integration, because differences in service accessibility and development opportunities affect the relationship between urban and rural communities. Public-service accessibility, however, is not measured as a separate dimension in the common prosperity index.

Third, the SCPP may enhance spatial coordination by improving connections among central urban areas, peripheral areas, and rural communities. Digital infrastructure can facilitate information exchange and extend access to economic opportunities across geographical areas, potentially helping to reduce urban–rural disparities [42]. Such benefits may vary spatially, since neither the availability of digital resources nor the ability to use them is evenly distributed [43]. The SCPP may therefore support more balanced spatial development, with implications for both regional coordination and urban–rural integration, two related but distinct dimensions of the common prosperity index.

Taken together, these arguments suggest that the SCPP may positively affect the composite common prosperity index. Examining its three components separately allows us to test whether the policy effect extends beyond overall prosperity to urban–rural integration and regional coordination.

**H1.** *The smart city pilot policy positively affects the city-level common prosperity index, which captures selected socioeconomic dimensions of sustainable urban development in Chinese cities.*

#### 2.2.3. Interactions with Digital Economy Development and New-Type Urbanization

This section examines whether the estimated effect of smart city pilot policy on the socioeconomic dimensions of sustainable urban development varies with the levels of DED and NTU. These two city-level contextual factors may shape the extent to which smart city initiatives are associated with socioeconomic outcomes, although they may also be partly influenced by policy implementation.

##### Digital Economy Development as a Contextual Factor

The socioeconomic effects of the SCPP may depend partly on DED. From a complementary-assets perspective, digital infrastructure generates greater socioeconomic benefits when organizational and workforce capabilities and practical applications support it [44]. At the city level, a more developed digital economy may provide a broader environment for digital technology adoption and more extensive economic applications. Evidence from Chinese cities links DED to entrepreneurial activity and high-quality economic development [36,45], as well as industrial upgrading [21], and connects it to urban–rural integration [22]. These developments may expand economic opportunities and support

overall prosperity. We therefore expect DED to positively moderate the effect of the SCPP on the socioeconomic dimensions of SUD.

New-Type Urbanization as a Contextual Factor

NTU provides an important urban context for smart-city investment. By shaping population distribution, built-up areas, and economic activity, it may influence the deployment and accessibility of digital capabilities. China's New-Type Urbanization Plan emphasizes coordinated improvements in urban infrastructure and public services [29]. Previous studies suggest that urbanization does not necessarily coincide with industrialization and that its socioeconomic benefits depend partly on the broader development context [46]. Digital infrastructure can facilitate information flows and market engagement [47], while coordinated public-service provision may improve access across urban and rural areas [16,48]. Accordingly, cities with more advanced NTU may be better positioned to translate smart-city investment into socioeconomic gains. We therefore expect NTU to positively moderate the effect of the SCPP on the selected socioeconomic dimensions of SUD.

**H2.** *Digital economy development and new-type urbanization positively moderate the effects of smart city pilot policy on the socioeconomic dimensions of sustainable urban development.*

2.2.4. Heterogeneous Effects Across City Characteristics

The uneven development of Chinese cities suggests that the relationship between the SCPP and SUD may depend on local conditions. Innovation and entrepreneurship capacity, digital financial inclusion, locational characteristics, and resource endowments can shape the ability of cities to absorb and translate digital technologies into broader socioeconomic benefits. Existing studies show that smart-city policies can promote urban innovation and entrepreneurial activity, with effects varying across regions and city characteristics [49,50]. Cities with stronger innovation ecosystems may be better positioned to develop and apply new digital solutions, while complementary workforce and organizational capabilities may influence how effectively digital technologies are integrated into economic activities [44].

Digital financial inclusion and human capital may also shape the extent to which cities can translate digital development into broader socioeconomic benefits. Digital financial inclusion may broaden access to financial resources and support entrepreneurship and self-employment, particularly among groups facing financial constraints [51]. Access to digital technologies alone, however, does not ensure equal benefits: users' digital skills and socioeconomic circumstances affect their ability to use these technologies effectively [35].

Finally, informatization infrastructure, economic development, and geographic location may influence cities' capacity to benefit from smart-city investment. Research suggests that broadband and digital infrastructure may yield greater returns where demand from IT-intensive industries and supportive local economic and educational conditions are stronger [39,47]. Studies of smart-city policies and related place-based innovation policies also document heterogeneous effects across cities and regions [50,52]. We therefore expect the estimated policy effects to vary across cities with different geographic locations, innovation and entrepreneurship capacity, levels of digital financial inclusion and human capital, informatization infrastructure, and economic development.

**H3.** *The estimated effect of smart city pilot policy on the socioeconomic dimensions of sustainable urban development varies across cities with different levels of innovation and entrepreneurship, digital financial inclusion, locational characteristics, and resource endowments.*

## 3. Data and Methods

### *3.1. Model Specification*

We treat the introduction of China's SCPP as a quasi-natural experiment and use a 2007–2022 panel of 167 prefecture-level cities. The policy year is 2012, when the national pilot notice was issued; the first batch of pilot localities was announced in January 2013. All treated cities are assigned to 2012 so that they share a common adoption year. The treatment group comprises the 32 prefecture-level cities designated in the first batch, which are listed with their six-digit administrative division codes in Appendix A (Table A1). Cities designated in subsequent pilot rounds are excluded from the sample, because they were exposed to the policy at different times and a common adoption year cannot be assigned to them.

Several first-batch designations covered only a county-level unit within a prefecture-level city, such as a municipal district, a county-level city, or a county. Our classification of prefecture-level pilot cities follows the official first-batch list released by MOHURD in January 2013. Two entries in this list, Jiyuan and Pingtan, are not standard prefecture-level cities under China's administrative division system; Jiyuan is a province-administered county-level city and Pingtan is a county-level administrative unit within Fuzhou. We therefore exclude them from our prefecture-level city sample. Three further first-batch cities, namely Tongren, Liupanshui and Lhasa, are dropped because city-level indicators are incomplete over the sample period. This restriction ensures a consistent analytical unit across treated and comparison cities. The resulting analytical sample comprises 167 prefecture-level cities, of which 32 are treated and 135 form the comparison group.

We start with a two-way fixed-effects DID specification to evaluate how the SCPP affects the city-level common prosperity index, which captures selected socioeconomic dimensions of SUD. Next, we match observations on pre-policy characteristics, re-estimate the DID model on the matched sample, and derive the PSM-DID estimates. Finally, we perform a battery of robustness tests to examine whether the identification strategy is valid and to evaluate the sensitivity of the estimated policy effect to alternative specifications and sample restrictions.

To estimate the effect of the SCPP on the selected socioeconomic dimensions of SUD, we specify the following baseline model:

$$Com_Pros_{i,t} = \alpha + \beta Smart_City_{i,t} + \gamma Control_Var_{i,t} + CityFE + YearFE + \varepsilon_{i,t} \quad (1)$$

where $i$ and $t$ denote city and year, respectively. Com_Pros denotes the city-level common prosperity index, which serves as an empirical measure of selected socioeconomic dimensions of SUD. Smart_City represents exposure to the SCPP, and Control_Var denotes a vector of control variables including government expenditure (Fiscal), science and technology expenditure (Sic), infrastructure development (Infra), foreign investment (Fore), registered urban unemployment (Unemploy), financial development (Finance), and human capital (Human). CityFE and YearFE denote city and year fixed effects, respectively. $\varepsilon_{it}$ is the disturbance term. The coefficient $\beta$ captures the effect of the SCPP on urban common prosperity by comparing pre-post changes in pilot cities with those in control cities.

### *3.2. Variable Measurement*

#### 3.2.1. Dependent Variable: Common Prosperity Index

To measure selected socioeconomic dimensions of SUD, we construct a city-level common prosperity index (Com_Pros), drawing on the literature on common prosperity measurement. The index is constructed to capture both development levels and the distribution of development outcomes across space. As shown in Table 1, it comprises

three dimensions: overall prosperity, urban–rural integration, and regional coordination. Accordingly, Com_Pros serves as an empirical measure of selected socioeconomic aspects of urban development in the Chinese context; it is not intended to represent a comprehensive measure of SUD.

**Table 1.** Measurement of the Socioeconomic Dimensions of Sustainable Urban Development Using the City-Level Common Prosperity Index.

| Dimension | Indicator | Measurement |
| --- | --- | --- |
| Overall prosperity | Urban income | Urban per capita disposable income |
| Overall prosperity | Rural income | Rural per capita disposable income |
| Overall prosperity | Income share | Disposable income per capita as a share of per capita GDP |
| Urban–rural integration | Urban–rural income coordination | Rural-urban ratio of per capita income |
| Urban–rural integration | Urban–rural consumption coordination | Rural-urban ratio of per capita consumption expenditure |
| Urban–rural integration | Theil index | Urban–rural income Theil index |
| Regional coordination | Regional income performance | Per capita rural income relative to the national rural average; per capita urban income relative to the national urban average |
| Regional coordination | Regional education performance | Per-student education expenditure relative to the national average; public library books per capita relative to the national average |
| Regional coordination | Regional healthcare performance | Hospital beds per capita relative to the national average; licensed physicians/assistant physicians per 1000 people relative to the national average |
| Regional coordination | Regional public amenity performance | Green space per capita relative to the national average; public transport vehicles per capita relative to the national average |

Note: The Theil index is treated as a negative indicator in the entropy-weighted TOPSIS construction because a lower value represents a more balanced urban–rural income distribution. All other indicators in the common prosperity index are treated as positive indicators, for which higher values indicate more favorable inclusive development outcomes.

We construct the common prosperity index (Com_Pros) via entropy-weighted TOPSIS. First, all indicators undergo range normalization; their information entropy and difference coefficients are calculated to determine the indicator weights. A weighted normalized decision matrix is then constructed, and the relative closeness to the ideal solution is calculated for each city-year observation. The resulting index is scaled from 0 to 1, and larger values indicate higher levels of Com_Pros, reflecting better performance in the selected socioeconomic dimensions of SUD captured by the index.

#### 3.2.2. Key Explanatory Variable: Smart City Pilot Policy

The key explanatory variable, Smart_City, is defined as the interaction between the treatment dummy (Treat) and the post-policy indicator (Post). Treat takes the value of one for the 32 cities retained as smart city pilot cities and zero for the 135 control cities. Although the first group of pilot localities was announced in January 2013, the national smart city pilot program was initiated by a policy notice in November 2012 [15]. Accordingly, we designate 2012 as the policy year in the baseline specification and set Post to one from 2012

onward and zero before 2012. Thus, Smart_City thus equals one for treated cities from the policy year onward and zero otherwise.

#### 3.2.3. Control Variables

Government expenditure (Fiscal) is measured by per capita general public budget spending. Infrastructure development (Infra) enters as the logarithm of road area per capita. Foreign direct investment (Fore) is captured using the logarithm of realized foreign investment, converted into RMB using the annual average exchange rate. Science and technology expenditure (Sic) is taken as the natural log of fiscal spending on science and technology. Financial development (Finance) is defined as the ratio of RMB-denominated loan balances to deposit balances at financial institutions. Registered urban unemployment (Unemploy) is measured by the logarithm of the number of registered unemployed persons in urban areas. Human capital (Human) equals the natural log of higher-education enrollment.

### *3.3. Sample and Data Sources*

The sample draws on panel data for 167 Chinese prefecture-level cities from 2007 to 2022. As shown in Table 2, cities selected for the 2012 SCPP form the treated group, while eligible non-pilot cities act as the comparison group. The empirical data are compiled from the EPS and WIND databases, supplemented by the China City Statistical Yearbook, provincial statistical yearbooks, and municipal statistical bulletins.

**Table 2.** Descriptive Statistics.

| Variable | Symbol | Full Sample Mean (SD) | Control Mean (SD) | Treatment Mean (SD) | Min | Max |
|---|---|---|---|---|---|---|
| Common Prosperity Index | Com_Pros | 0.2973 (0.0899) | 0.2819 (0.0808) | 0.3623 (0.0973) | 0.1318 | 0.6968 |
| Science and technology expenditure | Sic | 4.0713 (0.7231) | 3.9864 (0.6867) | 4.4293 (0.7628) | 0.6028 | 6.2466 |
| Government expenditure | Fiscal | 0.6348 (0.4978) | 0.6375 (0.5182) | 0.6235 (0.4004) | 0.0441 | 1.3090 |
| Human capital | Human | 4.3983 (0.5264) | 4.3154 (0.4717) | 4.7479 (0.5973) | 2.3600 | 6.1300 |
| Registered urban unemployment | Unemploy | 4.1930 (0.2921) | 4.1784 (0.2827) | 4.2540 (0.3220) | 2.9823 | 5.1335 |
| Infrastructure | Infra | 1.1517 (0.2030) | 1.1374 (0.2044) | 1.2117 (0.1850) | 0.1903 | 1.9144 |
| Foreign investment | Fore | 4.8201 (0.9257) | 4.6948 (0.9113) | 5.3488 (0.7899) | 0.1332 | 7.0748 |
| Financial development | Finance | 0.6626 (0.2868) | 0.6495 (0.3098) | 0.7180 (0.1437) | 0.2070 | 6.3405 |
| Observations | | 2672 | 2160 | 512 | | |

## 4. Results

### *4.1. Testing the Parallel Trends Assumption*

We conduct an event-study analysis to trace how the SCPP's effects evolve over time, defining event time relative to the 2012 implementation year. We include event-time indicators for years −5 through −2, the implementation year (event time 0), and post-policy years 1 through 7, while grouping event times of 8 or later into a single terminal category. We omit 2011 (event time −1) and use it as the baseline category, so the coefficients for

the pre-policy years are estimated relative to 2011. Table 3 shows that the estimated pre-policy coefficients are statistically insignificant, suggesting no significant divergence in pre-treatment trends between the two groups. The dynamic pattern of these event-study estimates is visualized in Figure 1.

**Table 3.** Event-Study Estimates of the Smart City Pilot Policy Effect on the Common Prosperity Index.

| Variable | Com_Pros | Variable | Com_Pros | Variable | Com_Pros |
|---|---|---|---|---|---|
| Admico_−5 | 0.0061<br>(1.56) | Admico_1 | 0.0045 **<br>(2.23) | Admico_6 | 0.0343 ***<br>(10.31) |
| Admico_−4 | −0.0032<br>(−1.02) | Admico_2 | 0.0091 ***<br>(5.03) | Admico_7 | 0.0403 ***<br>(10.98) |
| Admico_−3 | 0.0006<br>(0.18) | Admico_3 | 0.0165 ***<br>(6.46) | Admico_8+ | 0.0496 ***<br>(12.78) |
| Admico_−2 | 0.0039<br>(1.10) | Admico_4 | 0.0215 ***<br>(7.71) | Constant | 0.1865 ***<br>(5.00) |
| Admico_0 | 0.0080 *<br>(1.85) | Admico_5 | 0.0274 ***<br>(8.83) | Observations | 2672 |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Parentheses contain t-statistics calculated using standard errors clustered at the city level. All specifications control for covariates as well as city and year fixed effects. Same as below. The adjusted $R^2$ is 0.3347. Admico_8+ represents the terminal category grouping all periods from 2020 onward.

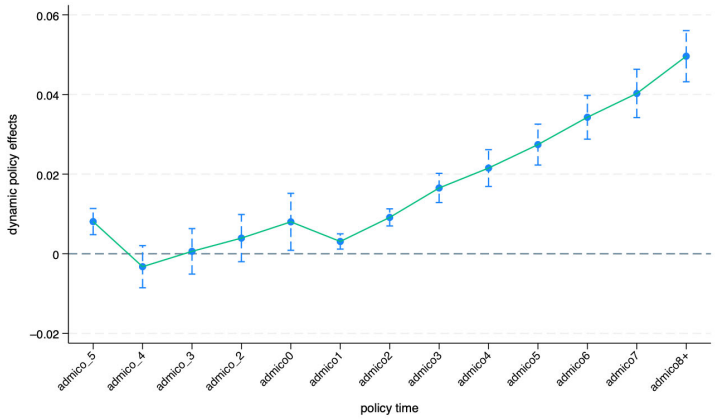


**Figure 1.** Dynamic Effects of Smart City Pilot Policy on Common Prosperity Index. Note: Event time −1 (2011) is the omitted reference period. All reported event-study coefficients are estimated relative to 2011. Error bars represent 95% confidence intervals. The figure corresponds to the dynamic-effect specification reported in Table 3.

Following policy implementation, the estimated coefficients remain positive and generally increase in magnitude, with statistical significance strengthening over time. This gradual increase may reflect the time needed for digital infrastructure and information platforms to be integrated into production activities, public services, and urban governance, alongside the adaptation of local governments, businesses, and residents. As these complementary processes develop, the socioeconomic benefits of smart city investment may become more fully realized, consistent with the expectation that the effects of the SCPP emerge gradually.

### *4.2. Propensity Score Matching and Covariate Balance*

To improve the comparability of treatment and control cities, we employ propensity score matching (PSM) based on the observed covariates in the original, unmatched sample.

A logit model is used to estimate each city's propensity to belong to the treated group, incorporating the control variables Fiscal, Sic, Infra, Human, Fore, Unemploy, and Finance. The logit model is statistically significant (LR chi2(7) = 463.38, $p < 0.001$), with a pseudo-$R^2$ of 0.1775. We then apply 1:5 nearest-neighbor matching to construct a matched sample.

Table 4 reports covariate balance before and after matching. After matching, all covariate mean differences become statistically insignificant, and the absolute standardized biases fall below the commonly used 10% threshold. The mean and median absolute standardized biases decrease from 44.6% to 3.4% and from 38.1% to 3.2%, respectively. Meanwhile, the balance-assessment pseudo-$R^2$ declines from 0.170 to 0.002, and the post-matching LR test is insignificant ($\chi^2 = 3.49$, $p = 0.837$). These results indicate substantial improvements in covariate mean balance following matching.

**Table 4.** Changes in Covariate Balance Following Propensity Score Matching.

| Variable | Matching | Treatment Mean | Control Mean | Standardized Bias (%) | t | *p* |
|---|---|---|---|---|---|---|
| Sic | Before | 4.4293 | 3.9864 | 61.0 | 12.84 | 0.000 |
| | After | 4.4293 | 4.3946 | 4.8 | 0.78 | 0.438 |
| Fiscal | Before | 0.6235 | 0.6375 | −3.0 | −0.57 | 0.567 |
| | After | 0.6235 | 0.6102 | 2.9 | 0.54 | 0.587 |
| Human | Before | 4.7479 | 4.3155 | 80.3 | 17.66 | 0.000 |
| | After | 4.7479 | 4.7544 | −1.2 | −0.18 | 0.853 |
| Unemploy | Before | 4.2540 | 4.1785 | 24.9 | 5.29 | 0.000 |
| | After | 4.2540 | 4.2654 | −3.8 | −0.54 | 0.592 |
| Infra | Before | 1.2117 | 1.1374 | 38.1 | 7.52 | 0.000 |
| | After | 1.2117 | 1.1979 | 7.1 | 1.28 | 0.202 |
| Fore | Before | 5.3488 | 4.6948 | 76.7 | 14.96 | 0.000 |
| | After | 5.3488 | 5.3655 | −2.0 | −0.33 | 0.739 |
| Finance | Before | 0.7180 | 0.6495 | 28.3 | 4.88 | 0.000 |
| | After | 0.7180 | 0.7205 | −1.1 | −0.16 | 0.874 |

Note: Standardized bias is calculated as the percentage difference in the means of each covariate between the treatment and control groups, standardized by the pooled standard deviation. An absolute standardized bias below 10% is commonly used as a benchmark for acceptable covariate balance.

### *4.3. Baseline Results*

We first estimate a two-way fixed-effects DID model and then apply propensity score matching before re-estimating the model (PSM-DID), so as to assess how sensitive the estimated policy effect is to comparability between the full and matched samples. Table 5 reports the baseline estimates in Models (1) and (2) and the matched-sample estimates in Models (3) and (4); Models (1) and (3) exclude control variables, whereas Models (2) and (4) include the full set of controls.

In the baseline regressions, the estimated Smart_City coefficients range from 0.0281 to 0.0328, and both estimates are statistically distinguishable from zero at conventional significance levels. The PSM-DID estimates are similar in magnitude, indicating that the findings remain stable after matching on observable characteristics. With control variables included, the coefficient in the matched-sample model is 0.0304, corresponding to a 0.0304-unit increase in Com_Pros associated with the SCPP. Given the index's 0–1 scale and a full-sample mean of 0.2973, the baseline estimate of 0.0328 amounts to approximately 11.0% of the sample mean.

**Table 5.** Baseline Fixed-Effects and PSM-DID Results for Common Prosperity Index.

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Smart_City | 0.0328 *** | 0.0281 *** | 0.0325 *** | 0.0304 *** |
| | (8.78) | (7.46) | (7.69) | (7.57) |
| Sic | | 0.0278 *** | | 0.0201 *** |
| | | (5.98) | | (3.70) |
| Fiscal | | −0.0006 | | −0.0103 |
| | | (−0.22) | | (−1.18) |
| Human | | 0.0056 | | 0.0035 |
| | | (0.65) | | (0.14) |
| Unemploy | | 0.0027 | | −0.0148 * |
| | | (0.40) | | (−1.74) |
| Infra | | −0.0039 | | −0.0139 |
| | | (−0.48) | | (−1.55) |
| Fore | | 0.0041 ** | | −0.0004 |
| | | (2.01) | | (−0.14) |
| Finance | | 0.0021 | | 0.0032 |
| | | (0.82) | | (1.31) |
| Constant | 0.2709 *** | 0.1394 *** | 0.2812 *** | 0.2823 *** |
| | (146.99) | (2.93) | (101.16) | (5.91) |
| City-fixed | Y | Y | Y | Y |
| Year-fixed | Y | Y | Y | Y |
| Observations | 2672 | 2672 | 1540 | 1540 |
| Adj. $R^2$ | 0.4234 | 0.4684 | 0.5000 | 0.5243 |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is Com_Pros. The estimated treatment effect is expressed in index points. All specifications include city and year fixed effects. Parentheses contain t-statistics based on standard errors clustered at the city level.

In practical terms, this estimate indicates an improvement in cities' overall socioeconomic performance as captured by the common prosperity index, which combines indicators of income levels, urban–rural income and consumption relationships, and the relative provision of education, healthcare, and public amenities. However, because these indicators are normalized and aggregated using entropy-derived weights, a 0.03-point increase cannot be translated directly into a specific change in any single underlying indicator. It instead reflects an improvement in the weighted composite measure, potentially arising from changes in several components. The consistency of the positive and statistically significant estimates across specifications lends support to H1.

### *4.4. Effects on the Three Dimensions of Common Prosperity*

To further examine how the estimated effects of Smart_City vary across the socioeconomic dimensions captured by Com_Pros, we estimate fixed-effects and PSM-DID models using overall prosperity (Ove_Pro), urban–rural integration (Ur_Score), and regional coordination (Re_Score) as dependent variables. The results are reported in Table 6, with descriptive statistics provided in Appendix A Table A2.

**Table 6.** Estimated Effects of the Smart City Pilot Policy on the Three Dimensions of Common Prosperity.

| Variable | Ove_Pro | | Ur_Score | | Re_Score | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Smart_City | 0.0645 *** (15.00) | 0.0601 *** (12.83) | 0.0127 ** (2.52) | 0.0084 * (1.76) | −0.0214 (−1.57) | −0.0135 (−1.41) |
| Constant | 0.4080 *** (8.19) | 0.4708 *** (8.58) | 0.1981 *** (4.41) | 0.2247 *** (4.17) | 0.0148 (0.23) | 0.1249 (1.61) |
| Controls | Y | Y | Y | Y | Y | Y |
| City-fixed | Y | Y | Y | Y | Y | Y |
| Year-fixed | Y | Y | Y | Y | Y | Y |
| Observations | 2672 | 1540 | 2672 | 1540 | 2672 | 1540 |
| Adj. $R^2$ | 0.2751 | 0.3181 | 0.2621 | 0.2912 | 0.1537 | 0.1781 |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Ove_Pro denotes overall prosperity, Ur_Score denotes urban–rural integration, and Re_Score denotes regional coordination. Columns report fixed-effects and PSM-DID estimates.

Table 6 reveals distinct patterns across the three dimensions. For Ove_Pro, the estimated coefficients are positive and significant at the 1% level in both the fixed-effects and PSM-DID models (0.0645 and 0.0601, respectively). For Ur_Score, the coefficients are also positive and statistically significant (0.0127, $p < 0.05$; 0.0084, $p < 0.10$), although the evidence is weaker in the matched sample. Regional coordination is the exception: the coefficients for Re_Score are negative in both specifications (−0.0214 and −0.0135), but neither is statistically significant. Taken together, the results reveal a dimension-specific pattern: the positive effect of the SCPP is consistently supported for overall prosperity, positive but less strongly supported for urban–rural integration, and not statistically distinguishable from zero for regional coordination. These findings suggest that the socioeconomic benefits of the SCPP are not uniform across the three dimensions of common prosperity.

### *4.5. Robustness Checks*

#### 4.5.1. Placebo Test

To rule out the possibility that the estimated policy impact is attributable to chance, we randomly select 32 of the 167 sample cities as pseudo-treatment cities and repeat the estimation 500 times. Figure 2 shows that the placebo coefficients cluster near zero. By comparison, the benchmark estimate of 0.0328 lies apart from the bulk of the placebo distribution, suggesting that the estimated policy effect is not readily reproduced by randomly assigning treatment status. Nevertheless, the placebo exercise cannot exclude every possible source of unobserved confounding.

#### 4.5.2. Alternative Outcome Measures and Weighting Scheme

We conduct robustness checks using an alternative outcome measure and an alternative weighting scheme for the common prosperity index. First, we replace the dependent variable with the logarithm of regional GDP to examine whether the estimated policy effect extends to aggregate economic performance. Second, we reconstruct the common prosperity index by assigning equal weights to its component indicators rather than using entropy weights and re-estimate the baseline model. As reported in Table 7, the coefficient on Smart_City remains positive and statistically significant in both specifications, indicating that the estimated policy effect is robust in direction and statistical significance to the use of an alternative economic outcome and an alternative weighting scheme. However, the

coefficient obtained using the equal-weighted index is smaller than that obtained using the entropy-weighted index. This difference suggests that the estimated magnitude may be sensitive to the weighting scheme and the resulting construction of the composite index. Accordingly, the robustness of the estimated effect is reflected in its direction and statistical significance, rather than in the invariance of its magnitude.

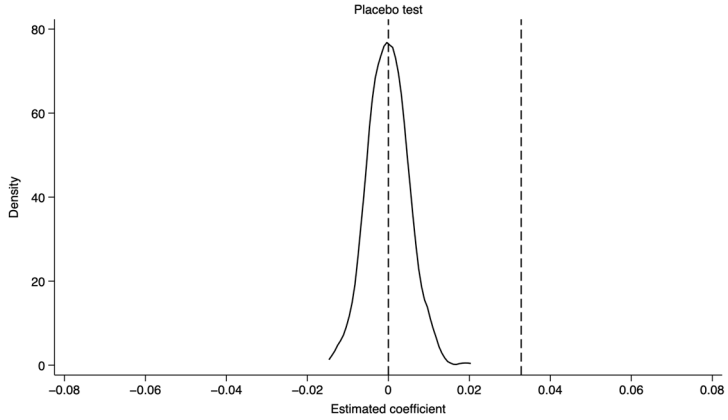


**Figure 2.** Placebo Test Results for Common Prosperity Index. Note: The horizontal axis reports coefficients estimated from 500 randomized placebo assignments, and the *y*-axis represents their kernel density. The two vertical dashed lines indicate zero and the baseline estimate, respectively.

**Table 7.** Robustness Checks Using Alternative Outcome Measures, Weighting Schemes, and Sample Adjustments.

| Variable | (1) Alternative Outcome: lnGDP | (2) Equal-Weighted Com_Pros | (3) Lagged Dependent Variable | (4) Exclude Zhejiang | (5) Winsorization at 1% | (6) Trimming at 1% |
|---|---|---|---|---|---|---|
| Smart_City | 0.0901 ** | 0.0142 *** | 0.0110 *** | 0.0290 *** | 0.0277 *** | 0.0262 *** |
| | (2.35) | (3.22) | (8.01) | (7.40) | (7.77) | (7.47) |
| L.Com_Pros | | | 0.7051 *** | | | |
| | | | (33.66) | | | |
| Constant | 10.7519 *** | 0.0311 | 0.0497 ** | 0.1367 *** | 0.1318 *** | 0.1282 *** |
| | (18.61) | (0.61) | (1.97) | (2.88) | (2.68) | (2.42) |
| Controls | Y | Y | Y | Y | Y | Y |
| City-fixed | Y | Y | Y | Y | Y | Y |
| Year-fixed | Y | Y | Y | Y | Y | Y |
| Observations | 2672 | 2672 | 2505 | 2528 | 2672 | 2384 |
| Adj. $R^2$ | 0.8651 | 0.6499 | 0.6881 | 0.4583 | 0.4657 | 0.4731 |

Note: *** $p < 0.01$, ** $p < 0.05$. Column (3) additionally includes the one-period lagged dependent variable, L.Com_Pros.

#### 4.5.3. Lagged Dependent Variable

Current Com_Pros may simply inherit the development base of the previous year. We therefore re-estimate the model while accounting for the prior year's common prosperity score. As reported in Table 7, the Smart_City estimate retains a positive sign and remains highly statistically significant. This result lends further support to the baseline finding, although potential dynamic-panel bias cannot be entirely ruled out.

#### 4.5.4. Sample Restrictions and Treatment of Extreme Values

To account for Zhejiang Province's distinct policy environment, we exclude it from the sample because its designation as a common prosperity demonstration zone may introduce additional policy effects. We further test how far the results are robust to outliers. We winsorize continuous variables at the 1st and 99th percentiles; in a separate specification, observations in the bottom and top 1% tails are dropped. Across the corresponding specifications in Table 7, the estimated Smart_City effect remains positive and statistically significant, indicating that neither the inclusion of Zhejiang nor outlier observations drives the findings.

#### 4.5.5. Robustness Check Using the Callaway–Sant'Anna Estimator

As an additional robustness check, we re-estimate the dynamic treatment effects using the approach proposed by Callaway and Sant'Anna (2021) [53]. Figure 3 reports the estimated event-time effects. The average pre-treatment effect is close to zero and statistically insignificant (−0.0006, $p = 0.640$). Although the estimate for event time −5 is negative and statistically significant ($p = 0.010$), the estimates for the other four pre-treatment periods are statistically insignificant. Moreover, the joint test fails to reject the null hypothesis that the pre-treatment effects are jointly zero ($p = 0.1125$). Taken together, the average and joint pre-treatment estimates are broadly consistent with the absence of systematic pre-treatment effects.

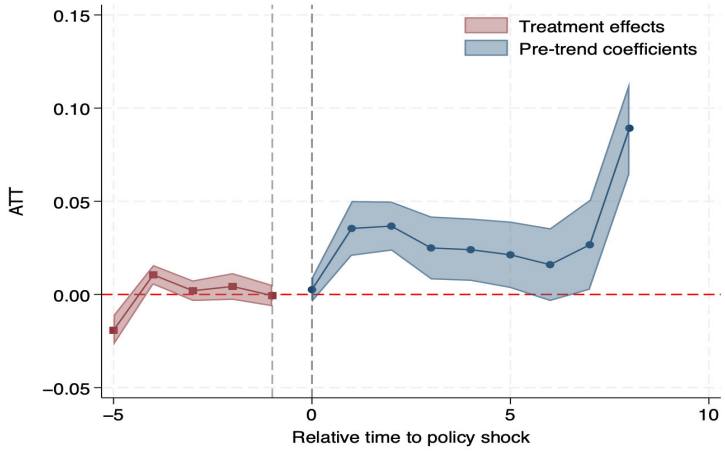


**Figure 3.** Dynamic Treatment Effects Estimated Using the Callaway–Sant'Anna Method.

Following policy implementation, the estimated treatment effects are generally positive, although their magnitude and statistical significance vary across periods. The effect in the implementation year is positive but statistically insignificant (0.0026, $p = 0.453$), suggesting that the policy did not produce an immediate measurable improvement in the common prosperity index. Positive and statistically significant effects emerge from the first post-treatment year and remain statistically significant in most subsequent periods. The estimates for event times 1–5 and 7 are positive and statistically significant, whereas the estimate for event time 6 is positive but statistically insignificant. The average post-treatment effect is 0.0308 (SE = 0.0081, $p < 0.001$), indicating a significant positive effect of the SCPP on the common prosperity index. This estimate is close to the baseline PSM-DID estimate of 0.0304, providing additional evidence that the main finding is robust to the alternative DID estimation approach.

### *4.6. Moderating Effects of Digital Economy Development and New-Type Urbanization*

To investigate whether the estimated effect of Smart_City on Com_Pros varies with digital economy development (DED) and new-type urbanization (NTU), we construct interaction terms between Smart_City and each moderating variable. The empirical specification is:

$$Com_Pros_{i,t} = \alpha + \beta Smart_City_{i,t} + \delta Var_Set_{i,t} + \theta Smart_City_{i,t} \times Var_Set_{i,t} + \gamma Control_Var_{i,t} + CityFE + YearFE + \varepsilon_{i,t} \quad (2)$$

The DED index (Digi) is constructed as a city-level proxy for digital economy development. China's Statistical Classification of Digital Economy and Its Core Industries (2021) identifies information networks and the effective use of information and communication technologies as key elements of the digital economy [54]. Consistent with existing city-level studies [55], the index comprises four indicators: telecommunications revenue per capita, fixed-broadband penetration, mobile-phone penetration, and the proportion of total employment accounted for by computer services and software. Together, these indicators capture digital connectivity, telecommunications activity, and digital-sector employment. Digital financial inclusion is excluded because it is examined separately in the heterogeneity analysis. Digi captures observable aspects of DED rather than the digital economy as a whole.

The NTU index (Urb) covers four dimensions: population urbanization, gauged by the permanent-resident urbanization rate; spatial urbanization, measured as the share of built-up land within urban boundaries; economic urbanization, proxied by the non-agricultural contribution to GDP; and environmental urbanization, reflected in green coverage within built-up zones. Existing city-level studies commonly adopt multidimensional frameworks to measure NTU, although the specific dimensions and indicators vary across studies [56]. Our index captures these four observable dimensions but excludes a separate social dimension and therefore does not directly measure access to education, healthcare, or other public services.

These indicators provide a concise, data-consistent measure of the selected dimensions, although alternative frameworks may include additional indicators. Both indices are normalized and aggregated using entropy weights, with descriptive statistics reported in Appendix A Table A2.

Table 8 reports the interaction estimates using mean-centered Digi and Urb. Mean-centering makes the Smart_City coefficient represent the estimated policy effect at the sample mean of the corresponding moderator, without changing the interaction coefficients or their statistical significance. The Smart_City coefficients remain positive and significant at the 1% level, ranging from 0.0186 to 0.0232 in the DED models and from 0.0258 to 0.0289 in the NTU models. The interaction coefficients are also positive and significant at the 5% level or better, ranging from 0.0434 to 0.0653 for Smart_City × Digi and from 0.0284 to 0.0499 for Smart_City × Urb.

The positive interaction coefficients indicate that the estimated effect of Smart_City on Com_Pros is stronger at higher observed levels of Digi and Urb. This pattern is consistent with a conditional-complementarity interpretation, but the interaction estimates do not establish mediation or causal complementarity. The observed levels of Digi and Urb may themselves be endogenously related to policy rollout. Cities with stronger digital connectivity, a larger digital-sector base, more developed urban infrastructure, and greater fiscal or administrative capacity may be better positioned to participate in smart-city pilot selection and implement related projects. Conversely, SCPP-related investments in ICT infrastructure and digital public services may themselves affect DED and some components of NTU. Thus, the observed levels of these indices may reflect both pre-existing city

conditions and changes associated with policy implementation. Mean-centering facilitates the interpretation of interaction terms but does not resolve this potential endogeneity. The estimates should therefore be interpreted as conditional associations rather than definitive causal moderation effects.

**Table 8.** Moderating Effects of Digital Economy Development and New-type Urbanization on the Effect of Smart City Pilot Policy.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Digi | | | | Urb | | | |
| Smart_City | 0.0221 *** (5.91) | 0.0186 *** (5.03) | 0.0232 *** (5.57) | 0.0218 *** (5.50) | 0.0289 *** (7.75) | 0.0258 *** (6.58) | 0.0281 *** (6.84) | 0.0277 *** (6.80) |
| Smart_City × Digi | 0.0653 *** (3.57) | 0.0588 *** (2.74) | 0.0506 *** (2.91) | 0.0434 ** (2.23) | | | | |
| Digi | 0.0647 *** (2.70) | 0.0590 *** (2.62) | 0.0685 ** (2.42) | 0.0702 ** (2.57) | | | | |
| Smart_City × Urb | | | | | 0.0467 *** (3.70) | 0.0284 ** (1.99) | 0.0499 *** (3.66) | 0.0332 ** (2.34) |
| Urb | | | | | 0.0208 (0.58) | 0.0066 (0.19) | −0.0262 (−0.73) | −0.0226 (−0.63) |
| Constant | 0.2739 *** (125.42) | 0.1451 *** (3.10) | 0.2836 *** (96.08) | 0.2787 *** (5.95) | 0.2709 *** (147.68) | 0.1396 *** (2.95) | 0.2819 *** (92.76) | 0.2786 *** (5.80) |
| Controls | N | Y | N | Y | N | Y | N | Y |
| City-fixed | Y | Y | Y | Y | Y | Y | Y | Y |
| Year-fixed | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 2672 | 2672 | 1540 | 1540 | 2672 | 2672 | 1540 | 1540 |
| Adj. $R^2$ | 0.4400 | 0.4819 | 0.5188 | 0.5418 | 0.4262 | 0.4693 | 0.5050 | 0.5266 |

Note: *** $p < 0.01$, ** $p < 0.05$. Digi and Urb are mean-centered. Columns (1)–(4) report estimates using Digi, while columns (5)–(8) report estimates using Urb.

Both indices are proxies and may contain measurement error due to indicator limitations, cross-city data differences, and the sensitivity of entropy weights to the sample distribution. Classical measurement error in a moderator may attenuate the interaction estimate, whereas non-classical measurement error may bias it in either direction.

As a robustness check, we reconstruct Digi and Urb using equal weights. The interaction coefficients remain positive and statistically significant across all specifications, consistent with the results based on entropy-weighted indices. However, their magnitudes differ considerably between the two weighting schemes, suggesting that the estimated strength of the moderating effects is sensitive to index construction. Thus, the robustness of the results is primarily reflected in the direction and statistical significance of the interaction effects, rather than the stability of their estimated magnitudes. These results are reported in Appendix A Table A3.

## 5. Further Analysis: Heterogeneous Effects Across City Characteristics

### *5.1. Heterogeneity by Regional Location*

Following China's standard regional classification, the 167 cities are grouped into its eastern, central, and western regions. As shown in Table 9, subsample estimates show that the Smart_City coefficient reaches 0.0381 in the east and 0.0247 in the central region; both estimates are statistically significant. The western-region estimate is 0.0117 and does not reach conventional significance levels, so the coefficients decline numerically from

eastern to western China. A joint Wald test further rejects the null hypothesis that the three regional coefficients are equal (F(2, 144) = 3.82, $p$ = 0.0242). Unadjusted pairwise comparisons indicate statistically significant differences between eastern and central China ($p$ = 0.0238) and between eastern and western China ($p$ = 0.0183), whereas the difference between central and western China is not statistically significant ($p$ = 0.4981). Overall, the results indicate regional heterogeneity, although the differences are not significant for every pair of regions. These differences may reflect disparities in digital infrastructure, technological development, economic foundations, and local implementation capacity, which warrant further investigation.

**Table 9.** Regional Differences in the Estimated Smart City Pilot Policy Effect.

| Variable | Eastern China | Central China | Western China |
|---|---|---|---|
| Smart_City | 0.0381 *** (7.66) | 0.0247 *** (3.74) | 0.0117 (1.56) |
| Constant | 0.1645 ** (2.34) | 0.1124 (1.36) | 0.2972 *** (3.58) |
| Controls | Y | Y | Y |
| City-fixed | Y | Y | Y |
| Year-fixed | Y | Y | Y |
| Observations | 1024 | 928 | 720 |
| Adj. $R^2$ | 0.5336 | 0.4930 | 0.5779 |
| Formal Difference Test | F = 3.82; $p$ = 0.0242 | | |

Note: *** $p < 0.01$, ** $p < 0.05$. Subgroup estimates are obtained from separate fixed-effects regressions. Regional heterogeneity is assessed using a joint Wald test based on a pooled fully interacted specification (F(2, 144) = 3.82, $p$ = 0.0242). The $p$-values for pairwise comparisons are 0.0238 (eastern vs. central), 0.0183 (eastern vs. western), and 0.4981 (central vs. western).

### *5.2. Heterogeneity by Innovation and Digital Financial Inclusion*

To determine whether SCPP effects vary with cities' innovation environment and access to digital financial services, we conduct separate subgroup analyses using two indicators. Per capita scores on the China Regional Innovation and Entrepreneurship Index (IRIEC), produced by Peking University's Research Center for Enterprise Big Data, serve as a proxy for innovation and entrepreneurship capacity. Digital financial inclusion is captured by the coverage-breadth sub-index of Peking University's Digital Financial Inclusion Index. Because the SCPP starts in 2012 in the retained sample, the 2011 value of the digital financial inclusion index is employed to reflect pre-policy conditions. For each indicator, cities are split into high- and low-level groups at the respective sample median.

Table 10 shows that the estimated Smart_City coefficients are larger in the high-level groups for both innovation and entrepreneurship capacity and digital financial inclusion. Formal tests of coefficient differences, however, provide different levels of evidence for the two characteristics. For innovation and entrepreneurship capacity, the coefficient difference is 0.0209 but is not statistically significant ($p$ = 0.1419), suggesting that there is insufficient statistical evidence of a systematic difference in the estimated policy effects between the two groups. For digital financial inclusion, the coefficient difference is 0.0284 and is statistically significant at the 10% level ($p$ = 0.0825), providing modest evidence that the estimated policy effect is larger in cities with broader digital financial inclusion. One possible interpretation is that broader access to digital financial services may reduce financial access barriers for households and firms, potentially supporting their participation in economic activities. This

explanation remains tentative, as the subgroup analysis identifies differences in estimated policy effects but does not directly test the underlying channels.

**Table 10.** Heterogeneity by Innovation and Digital Financial Inclusion.

| Characteristic | Innovation & Entrepreneurship: Low | Innovation & Entrepreneurship: High | Digital Financial Inclusion: Low | Digital Financial Inclusion: High |
|---|---|---|---|---|
| Smart_City | 0.0104<br>(1.39) | 0.0313 ***<br>(7.15) | 0.0084<br>(1.31) | 0.0368 ***<br>(7.21) |
| Constant | 0.1291 **<br>(2.07) | 0.1949 ***<br>(3.24) | 0.1586 ***<br>(2.85) | 0.2138 ***<br>(2.97) |
| Controls | Y | Y | Y | Y |
| City-fixed | Y | Y | Y | Y |
| Year-fixed | Y | Y | Y | Y |
| Observations | 1328 | 1344 | 1328 | 1344 |
| Adj. $R^2$ | 0.4899 | 0.5415 | 0.5178 | 0.5083 |
| Difference in coefficients | 0.0209 | | 0.0284 | |
| *p*-value for difference | 0.1419 | | 0.0825 | |

Note: *** $p < 0.01$, ** $p < 0.05$. Coefficient differences are calculated as the estimates for the high-level subgroups minus those for the low-level subgroups. The reported *p*-values correspond to tests of equality between subgroup coefficients. Same as below.

### *5.3. Heterogeneity by Resource Endowments*

Finally, we investigate differences in resource endowments. Informatization infrastructure is proxied by fixed-broadband subscriptions per 10,000 residents. Human capital is operationalized as the log of regular higher-education enrollment per 10,000 residents, whereas economic development enters as log per capita GDP. For each indicator, the sample median serves as the threshold for separating cities into high- and low-value subsamples.

The estimates in Table 11 show larger Smart_City coefficients in the high-level groups across all three characteristics. Formal coefficient-equality tests indicate that all three differences are statistically significant at the 10% level: 0.0189 for human capital ($p = 0.0473$), 0.0184 for economic development ($p = 0.0904$), and 0.0241 for informatization infrastructure ($p = 0.0209$). One possible explanation is that a more educated workforce may facilitate the adoption and productive use of digital technologies, while better-developed informatization infrastructure may improve cities' capacity to deploy smart-city applications. More advanced economic development may also provide a stronger economic base for realizing the associated socioeconomic benefits. These explanations remain tentative, as the subgroup analysis does not directly test the underlying mechanisms.

**Table 11.** Heterogeneity by Resource Endowments.

| Resource Endowments | Human Capital Level | | Economic Development | | Informatization Infrastructure | |
|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High |
| Smart_City | 0.0166<br>(1.57) | 0.0355 ***<br>(7.82) | 0.0185 *<br>(1.89) | 0.0369 ***<br>(7.60) | 0.0162<br>(1.62) | 0.0403 ***<br>(9.28) |
| Constant | 0.0997 *<br>(1.69) | 0.1656 *<br>(1.94) | 0.1467 ***<br>(2.73) | 0.1971 ***<br>(2.84) | 0.1353 **<br>(2.25) | 0.2379 ***<br>(3.80) |

**Table 11.** *Cont.*

| Resource Endowments | Human Capital Level | | Economic Development | | Informatization Infrastructure | |
|---|---|---|---|---|---|---|
| | **Low** | **High** | **Low** | **High** | **Low** | **High** |
| Controls | Y | Y | Y | Y | Y | Y |
| City-fixed | Y | Y | Y | Y | Y | Y |
| Year-fixed | Y | Y | Y | Y | Y | Y |
| Observations | 1328 | 1344 | 1328 | 1344 | 1328 | 1344 |
| Adj. $R^2$ | 0.4724 | 0.5005 | 0.5063 | 0.4791 | 0.5107 | 0.4912 |
| Difference in coefficients | 0.0189 | | 0.0184 | | 0.0241 | |
| *p*-value for difference | 0.0473 | | 0.0904 | | 0.0209 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## 6. Discussion

The findings reinforce the distinction between technological investment and broader sustainability outcomes, a distinction emphasized in research on the sustainable development of smart cities [57,58]. Critical studies go further and caution against equating technological or entrepreneurial development with broader urban and social progress [59,60].

Empirical studies of China's SCPP have examined its effects on various urban outcomes. Stronger effects on high-quality economic development and urban convenience have been identified in central and western cities [17,40], whereas the effects on urban innovation and entrepreneurship are more pronounced in eastern cities [49,50]. Public-service improvements are also found to be stronger in high-income regions [16]. Beyond the pilot policy itself, research on smart city construction has linked broader urban digitalization to green and high-quality development [18]. Our findings add a distributional angle: common-prosperity effects are stronger in eastern cities, and pairwise tests confirm significant differences between eastern cities and both central and western cities, whereas the difference between central and western cities is not statistically significant. Regional patterns in smart-city policy effects, in other words, depend on the socioeconomic outcome being examined.

Evidence on the distributional effects of smart-city development remains mixed: smart-city construction has been found to alleviate urban inequality [19], whereas the SCPP has been associated with a widening urban–rural income gap in the Yangtze River Delta [20]. Research on the digital economy identifies a nonlinear relationship between digital development and urban–rural income disparities [61], and studies of urban–rural digitalization stress the importance of digital inclusion [62]. The socioeconomic benefits of digital transformation, on this evidence, have to be weighed against their spatial and distributional consequences.

### *6.1. Theoretical Implications*

First, this study extends the evaluation of the SCPP by showing that its socioeconomic effects differ across dimensions of common prosperity. The estimates indicate greater improvements in overall prosperity, weaker positive effects on urban–rural integration, and no statistically significant effect on regional coordination. This disaggregated assessment complements previous studies that focus on high-quality economic development [17], urban inequality [19], and urban–rural income disparities [20]. The differences between our

findings and those of Li and Yu [20] may partly reflect differences in outcome measurement, geographical coverage, and sample periods.

Second, the analysis draws attention to local development conditions as moderators of smart-city policy effects. The positive interaction estimates indicate that the estimated effect of the SCPP is stronger in cities with higher levels of DED and NTU. Previous research has linked DED to urban–rural integration [22] and NTU pilot policies to public-service provision [24]. By examining these factors jointly as contextual moderators, this study extends the discussion from their direct associations with urban outcomes to their role in shaping the estimated effects of smart-city policies. These interaction estimates indicate conditional relationships and should not be interpreted as evidence of causal mediation or definitive complementarity between specific policy interventions.

Third, the findings contribute to the discussion of uneven benefits from digital transformation. Related studies identify the role of human capital in the relationship between digital infrastructure and common prosperity [63], as well as the contribution of digital inclusive finance to common prosperity [51]. Research on digital divides and smart-city inclusion further emphasizes disparities in digital access and capabilities [43]. These studies suggest that the benefits of digital transformation depend not only on technological investment but also on the local conditions supporting its adoption and effective use. Cities with stronger human-capital foundations, better informatization infrastructure, and greater implementation capacity may be better positioned to translate smart-city investments into socioeconomic gains, whereas cities with weaker initial conditions may face greater constraints. Such differences may generate cumulative advantages, or a potential "Matthew effect", whereby cities with stronger initial conditions are more likely to benefit from subsequent digital transformation. However, heterogeneous policy effects do not necessarily demonstrate that inter-city inequality has widened. Whether differences in local development capacity translate into persistent disparities in development outcomes requires further investigation using more direct measures of inter-city disparities and longitudinal data.

### *6.2. Limitations and Future Research*

Several limitations should be acknowledged. First, the study uses city-level data ending in 2022. The aggregated nature of these data limits our ability to identify household-level distributional outcomes, differences in individual digital skills, and disparities in access to development opportunities across population groups.

Second, the empirical analysis is restricted to the first-batch smart-city pilot cities, with 2012 designated as the policy year. Although the Callaway-Sant'Anna estimator is included as a supplementary check of dynamic treatment effects, the sample remains limited to a single adoption cohort and therefore cannot capture differences in policy effects across successive pilot batches. Moreover, DED and NTU may reflect pre-existing city characteristics that influence policy implementation and may themselves be affected by the SCPP. The interaction estimates are therefore interpreted as conditional policy effects rather than definitive evidence of causal mediation or complementarity.

Third, the common prosperity index captures three selected socioeconomic dimensions of SUD rather than urban sustainability as a whole. Its component indicators do not directly capture intra-city inequality or differences in access to public services across population groups. Although the index includes a green-space-related indicator, it does not systematically measure environmental quality, resource consumption, or carbon emissions. Moreover, entropy-weighted TOPSIS assigns weights according to the relative variation of component indicators, which may not fully reflect their substantive importance. The alter-

native equal-weighting specification provides a sensitivity check, although the differences in coefficient magnitudes indicate some sensitivity to the weighting method.

Future research could extend the analysis to cities admitted in later pilot rounds and employ cohort-specific estimators designed to account for staggered policy adoption, thereby examining variations in policy effects across adoption cohorts. It could also incorporate household surveys, firm-level records, and administrative microdata to investigate distributional effects more directly, while introducing more comprehensive environmental indicators to assess the broader sustainability implications of the SCPP.

## 7. Conclusions and Policy Implications

This study examines the effects of China's 2012 SCPP on common prosperity, which serves as an indicator of selected socioeconomic dimensions of SUD. Drawing on a 2007–2022 panel covering 167 Chinese prefecture-level cities, we construct a common prosperity index via entropy-weighted TOPSIS and assess the policy effect with a PSM-DID design. The results show that the SCPP significantly promotes common prosperity, with estimated coefficients of 0.0328 in the fixed-effects model and 0.0304 in the PSM-DID model with controls; this finding is robust to alternative measures, index constructions, and sample specifications. The effects are strongest for overall prosperity, weaker for urban–rural integration, and insignificant for regional coordination. DED and NTU positively moderate the policy effect. The estimated effects are largest in eastern cities, with significant differences between eastern and both central and western cities, but not between the latter two. Significant heterogeneity is also found across levels of human capital and informatization infrastructure, while differences by economic development and digital financial inclusion are significant only at the 10% level and those by innovation and entrepreneurship capacity are insignificant. Given the city-level nature of our data, the following policy implications focus on urban planning and local implementation capacity rather than household- or individual-level interventions.

Accordingly, we draw three policy considerations.

First, the evaluation of smart-city policies should extend beyond aggregate socioeconomic performance to consider different dimensions of common prosperity. The absence of a statistically significant effect on regional coordination suggests that improvements in overall prosperity do not necessarily translate into more balanced regional development. Policy assessment should therefore pay particular attention to the spatial distribution of development gains.

Second, smart-city initiatives should be considered alongside broader strategies for DED and NTU. The positive interaction estimates suggest that these urban development conditions are relevant to the effectiveness of smart-city policies. Policy planning should therefore account for the digital economic environment and urbanization context in which smart-city investments are implemented, rather than treating technological investment as an isolated intervention.

Third, greater attention should be paid to disparities in local development capacity. The stronger estimated effects in cities with higher human capital and better informatization infrastructure suggest that cities with weaker economic and digital foundations may face greater difficulties in translating smart-city investment into socioeconomic gains. To mitigate this risk, policy efforts should prioritize basic informatization infrastructure, human-capital development, and local implementation capacity in these cities. Inter-city cooperation and knowledge sharing may also facilitate the diffusion of effective practices. These policy measures are derived from the observed heterogeneity and require further evaluation.

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## Appendix A

**Table A1.** List of Treatment Cities in the Baseline Sample.

| City Code | City | Designated Unit in the First Batch | Type |
|---|---|---|---|
| 130100 | Shijiazhuang | Shijiazhuang City | City |
| 130300 | Qinhuangdao | Qinhuangdao City; Qinhuangdao Beidaihe New Area | City + additional unit |
| 130400 | Handan | Handan City | City |
| 131000 | Langfang | Langfang City | City |
| 140100 | Taiyuan | Taiyuan City | City |
| 140400 | Changzhi | Changzhi City | City |
| 150300 | Wuhai | Wuhai City | City |
| 220400 | Liaoyuan | Liaoyuan City | City |
| 320200 | Wuxi | Wuxi City | City |
| 320400 | Changzhou | Changzhou City | City |
| 321100 | Zhenjiang | Zhenjiang City | City |
| 321200 | Taizhou | Taizhou City | City |
| 330300 | Wenzhou | Wenzhou City | City |
| 330700 | Jinhua | Jinhua City | City |
| 340200 | Wuhu | Wuhu City | City |
| 340300 | Bengbu | Bengbu City | City |
| 340400 | Huainan | Huainan City | City |
| 340700 | Tongling | Tongling City | City |
| 350700 | Nanping | Nanping City | City |
| 360300 | Pingxiang | Pingxiang City | City |
| 370500 | Dongying | Dongying City | City |
| 371000 | Weihai | Weihai City | City |
| 371400 | Dezhou | Dezhou City | City |
| 410100 | Zhengzhou | Zhengzhou City; Xinzheng City | City + additional unit |
| 410600 | Hebi | Hebi City | City |
| 411100 | Luohe | Luohe City | City |
| 420100 | Wuhan | Wuhan City; Jiang'an District | City + additional unit |
| 430200 | Zhuzhou | Zhuzhou City; Zhuzhou Yunlong Demonstration Zone | City + additional unit |
| 440400 | Zhuhai | Zhuhai City | City |
| 511800 | Ya'an | Ya'an City | City |

**Table A1.** *Cont.*

| City Code | City | Designated Unit in the First Batch | Type |
|---|---|---|---|
| 610400 | Xianyang | Xianyang City | City |
| 640300 | Wuzhong | Wuzhong City | City |

Note: This table presents the 32 prefecture-level cities in the treatment group, with six-digit administrative division codes provided. The first batch of national smart city pilots was announced in January 2013. Jiyuan and Pingtan are excluded as they are not standard prefecture-level cities; Tongren, Liupanshui and Lhasa are dropped due to incomplete city-level indicators over the sample period. The remaining 32 cities form the treatment group.

**Table A2.** Descriptive Statistics of the Outcome Dimensions and Composite Moderators.

| Variable | Symbol | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| Overall prosperity | Ove_Pro | 2672 | 0.3678 | 0.0999 | 0.1400 | 0.7657 |
| Urban–rural integration | Ur_Score | 2672 | 0.2618 | 0.1090 | 0.1048 | 0.6825 |
| Regional coordination | Re_Score | 2672 | 0.1957 | 0.0996 | 0.0946 | 0.6194 |
| Digital economy development (DED) | Digi | 2672 | 0.2375 | 0.1140 | 0.0245 | 0.8894 |
| New-type urbanization (NTU) | Urb | 2672 | 0.1681 | 0.1163 | 0.0193 | 0.9855 |

**Table A3.** Robustness Check Using Equal-Weighted DED and NTU Indices.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Digi | | | | Urb | | | |
| Smart_City | 0.0237 *** | 0.0208 *** | 0.0246 *** | 0.0235 *** | 0.0216 *** | 0.0204 *** | 0.0230 *** | 0.0233 *** |
| | (6.67) | (6.01) | (5.95) | (6.03) | (4.68) | (4.27) | (4.64) | (4.78) |
| Smart_City × Digi | 0.1918 *** | 0.1623 *** | 0.1844 *** | 0.1678 *** | | | | |
| | (5.80) | (4.60) | (4.35) | (4.00) | | | | |
| Digi | −0.0447 | −0.0586 | −0.0788 | −0.0888 | | | | |
| | (−1.03) | (−1.39) | (−1.24) | (−1.43) | | | | |
| Smart_City × Urb | | | | | 0.1108 *** | 0.0809 *** | 0.0991 *** | 0.0777 *** |
| | | | | | (4.23) | (2.91) | (3.93) | (3.10) |
| Urb | | | | | 0.2013 *** | 0.1548 *** | 0.1169 ** | 0.1017 ** |
| | | | | | (5.14) | (4.50) | (2.56) | (2.43) |
| Constant | 0.2685 *** | 0.1304 *** | 0.2772 *** | 0.2522 *** | 0.2871 *** | 0.1807 *** | 0.2872 *** | 0.2899 *** |
| | (92.09) | (2.81) | (69.77) | (5.51) | (76.86) | (4.03) | (78.47) | (6.08) |
| Controls | N | Y | N | Y | N | Y | N | Y |
| City-fixed | Y | Y | Y | Y | Y | Y | Y | Y |
| Year-fixed | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 2672 | 2672 | 1540 | 1540 | 2672 | 2672 | 1540 | 1540 |
| Adj. $R^2$ | 0.4359 | 0.4771 | 0.5087 | 0.5229 | 0.4534 | 0.4849 | 0.5057 | 0.5256 |

Note: *** $p < 0.01$, ** $p < 0.05$.

## References


1. Dempsey, N.; Bramley, G.; Power, S.; Brown, C. The social dimension of sustainable development: Defining urban social sustainability. *Sustain. Dev.* **2011**, *19*, 289–300. [CrossRef]
2. Bibri, S.E.; Krogstie, J. Smart sustainable cities of the future: An extensive interdisciplinary literature review. *Sustain. Cities Soc.* **2017**, *31*, 183–212. [CrossRef]
3. Albino, V.; Berardi, U.; Dangelico, R.M. Smart cities: Definitions, dimensions, performance, and initiatives. *J. Urban Technol.* **2015**, *22*, 3–21. [CrossRef]
4. Alizadeh, H.; Sharifi, A. Toward a societal smart city: Clarifying the social justice dimension of smart cities. *Sustain. Cities Soc.* **2023**, *95*, 104612. [CrossRef]

5. Chang, K.; Smith, M.K. Residents' quality of life in smart cities: A systematic literature review. *Land* **2023**, *12*, 876. [CrossRef]
6. Mora, L.; Bolici, R.; Deakin, M. The first two decades of smart-city research: A bibliometric analysis. *J. Urban Technol.* **2017**, *24*, 3–27. [CrossRef]
7. Sharifi, A.; Allam, Z.; Bibri, S.E.; Khavarian-Garmsir, A.R. Smart cities and sustainable development goals (SDGs): A systematic literature review of co-benefits and trade-offs. *Cities* **2024**, *146*, 104659. [CrossRef]
8. Wang, M.M.; Zhou, T. Understanding the dynamic relationship between smart city implementation and urban sustainability. *Technol. Soc.* **2022**, *70*, 102018. [CrossRef]
9. Almulhim, A.I.; Sharifi, A.; Aina, Y.A.; Ahmad, S.; Mora, L.; Leal Filho, W.; Abubakar, I.R. Charting sustainable urban development through a systematic review of SDG11 research. *Nat. Cities* **2024**, *1*, 677–685. [CrossRef]
10. United Nations Department of Economic and Social Affairs. Goal 11: Make Cities and Human Settlements Inclusive, Safe, Resilient and Sustainable. Available online: https://sdgs.un.org/goals/goal11 (accessed on 19 October 2026).
11. Karal, F.S.; Soyer, A. A systematic literature review: Setting a basis for smart and sustainable city performance measurement. *Sustain. Dev.* **2024**, *32*, 555–573. [CrossRef]
12. National People's Congress of the People's Republic of China. Outline of the 14th Five-Year Plan for National Economic and Social Development and Long-Range Objectives for 2035. 2021. Available online: https://www.gov.cn/xinwen/2021-03/13/content_5592681.htm (accessed on 19 October 2026). (In Chinese)
13. National Development and Reform Commission; National Data Administration of China. Notice on Issuing the Implementation Plan for Promoting Common Prosperity Through the Digital Economy. Document No. Fa Gai Shu Ju [2023] No. 1770, 2023. Available online: https://www.ndrc.gov.cn/xxgk/zcfb/tz/202401/t20240105_1363120.html (accessed on 19 October 2026). (In Chinese)
14. State Council of the People's Republic of China. Notice on Issuing the "14th Five-Year Plan for the Development of the Digital Economy". State Council Document No. 29, 2021. Available online: https://www.gov.cn/zhengce/content/2022-01/12/content_5667817.htm (accessed on 19 October 2026). (In Chinese)
15. General Office of the Ministry of Housing and Urban-Rural Development of the People's Republic of China. Notice on Carrying out the National Smart City Pilot Work. Document No. Jian Ban Ke [2012] No. 42, 2012. Available online: https://zjt.fujian.gov.cn/xxgk/zfxxgkzl/xxgkml/dfxfgzfgzhgfxwj/jskj_3794/201212/t20121207_2865019.htm (accessed on 19 October 2026). (In Chinese)
16. Cai, Q.; Zhang, C. Does the smart city improve public service delivery? A quasi-natural experiment based on a smart city pilot program in China. *Public Perform. Manag. Rev.* **2023**, *46*, 752–769. [CrossRef]
17. Liu, S.; Jiang, G.; Chang, L.; Wang, L. Can the smart city pilot policy promote high-quality economic development? A quasi-natural experiment based on 239 cities in China. *Sustainability* **2022**, *14*, 16005. [CrossRef]
18. Li, S.; Wang, R. Can Smart City Construction Promote Urban Green and High-Quality Development?—Validation Analysis from 156 Cities in China. *Buildings* **2024**, *14*, 2500. [CrossRef]
19. Yang, Z.; Gao, W.; Han, Q.; Qi, L. Aggravating or alleviating? Smart city construction and urban inequality in China. *Technol. Soc.* **2024**, *77*, 102562. [CrossRef]
20. Li, M.; Yu, M. Does smart city policy widen the urban-rural income gap? Evidence from the Yangtze River Delta using a double machine learning approach. *Land* **2026**, *15*, 1575. [CrossRef]
21. Wu, T.; Shao, W. How does digital economy drive industrial structure upgrading: An empirical study based on 249 prefecture-level cities in China. *PLoS ONE* **2022**, *17*, e0277787. [CrossRef] [PubMed]
22. Zhang, X.; Fang, C.; Ma, H.; Hu, X. How does digital economy affect urban-rural integration? An empirical study from China. *Habitat Int.* **2024**, *154*, 103229. [CrossRef]
23. National Development and Reform Commission of the People's Republic of China. Notice on Issuing the 14th Five-Year Plan for the Implementation of New-Type Urbanization. Document No. Fa Gai Gui Hua [2022] No. 960, 2022. Available online: https://www.gov.cn/zhengce/zhengceku/2022-07/12/content_5700632.htm (accessed on 19 October 2026). (In Chinese)
24. Yuan, C.; Zhang, B.; Xu, J.; Lyu, D.; Liu, J.; Hu, Z.; Han, Y. Impact of new-type urbanization pilot policy on public service provision: Evidence from China. *Cities* **2025**, *161*, 105853. [CrossRef]
25. van Dijk, J. *The Digital Divide*; Polity Press: Cambridge, UK, 2020.
26. Kolotouchkina, O.; Ripoll González, L.; Belabas, W. Smart cities, digital inequalities, and the challenge of inclusion. *Smart Cities* **2024**, *7*, 3355–3370. [CrossRef]
27. General Office of the Ministry of Housing and Urban-Rural Development. Notice on Announcing the 2013 Annual National Smart City Pilot List. 2013. Available online: https://news.12371.cn/2013/08/05/ARTI1375709026254487.shtml (accessed on 31 October 2026). (In Chinese)
28. General Office of the Ministry of Housing and Urban-Rural Development; General Office of the Ministry of Science and Technology. Notice on Announcing the 2014 Annual National Smart City Pilot List. 2015. Available online: https://www.waizi.org.cn/law/4327.html (accessed on 31 October 2026). (In Chinese)

29. Central Committee of the Communist Party of China; State Council of the People's Republic of China. National New-Type Urbanization Plan (2014–2020). 2014. Available online: https://www.gov.cn/gongbao/content/2014/content_2644805.htm (accessed on 19 October 2026). (In Chinese)
30. State Council of the People's Republic of China. 2015 Government Work Report. 2015. Available online: https://www.gov.cn/guowuyuan/2015-03/16/content_2835101.htm (accessed on 19 October 2026). (In Chinese)
31. Meijer, A.; Rodríguez Bolívar, M.P. Governing the smart city: A review of the literature on smart urban governance. *Int. Rev. Adm. Sci.* **2016**, *82*, 392–408. [CrossRef]
32. Merino-Saum, A.; Halla, P.; Superti, V.; Boesch, A.; Binder, C.R. Indicators for urban sustainability: Key lessons from a systematic analysis of 67 measurement initiatives. *Ecol. Indic.* **2020**, *119*, 106879. [CrossRef]
33. Caragliu, A.; Del Bo, C.; Nijkamp, P. Smart cities in Europe. *J. Urban Technol.* **2011**, *18*, 65–82. [CrossRef]
34. McFarlane, C.; Söderström, O. On alternative smart cities: From a technology-intensive to a knowledge-intensive smart urbanism. *City* **2017**, *21*, 312–328. [CrossRef]
35. Lythreatis, S.; Singh, S.K.; El-Kassar, A.-N. The digital divide: A review and future research agenda. *Technol. Forecast. Soc. Change* **2022**, *175*, 121359. [CrossRef]
36. Zhao, T.; Zhang, Z.; Liang, S. Digital economy, entrepreneurship, and high-quality economic development: Empirical evidence from urban China. *Front. Econ. China* **2022**, *17*, 393–426. [CrossRef]
37. Czernich, N.; Falck, O.; Kretschmer, T.; Woessmann, L. Broadband infrastructure and economic growth. *Econ. J.* **2011**, *121*, 505–532. [CrossRef]
38. Shahnazi, R. Do information and communications technology spillovers affect labor productivity? *Struct. Change Econ. Dyn.* **2021**, *59*, 342–359. [CrossRef]
39. Forman, C.; Goldfarb, A.; Greenstein, S. The internet and local wages: A puzzle. *Am. Econ. Rev.* **2012**, *102*, 556–575. [CrossRef]
40. Chen, X.; Wang, Q.; Zhou, J. Construction of smart city and enhancement of urban convenience: A quasi-natural experiment based on a smart city pilot. *Int. Rev. Econ. Finance* **2025**, *98*, 103875. [CrossRef]
41. Haque, M.N.; Beckers, D.; Costales, E.; Aad, S.; Sharifi, A.; Mora, L. A systematic review of research on just, equitable, responsible, and inclusive smart cities. *Technol. Soc.* **2025**, *83*, 103050. [CrossRef]
42. Duanmu, X.; Yu, J.; Yuan, X.; Zhang, X. How does digital infrastructure mitigate urban-rural disparities? *Sustainability* **2025**, *17*, 1561. [CrossRef]
43. Scheerder, A.; van Deursen, A.; van Dijk, J. Determinants of internet skills, uses and outcomes: A systematic review of the second- and third-level digital divide. *Telemat. Inform.* **2017**, *34*, 1607–1624. [CrossRef]
44. Bresnahan, T.F.; Brynjolfsson, E.; Hitt, L.M. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *Q. J. Econ.* **2002**, *117*, 339–376. [CrossRef]
45. Wang, S.; Song, Y.; Du, A.M.; Liang, J. The digital economy and entrepreneurial dynamics: An empirical analysis of urban regions in China. *Res. Int. Bus. Finance* **2024**, *71*, 102459. [CrossRef]
46. Gollin, D.; Jedwab, R.; Vollrath, D. Urbanization with and without industrialization. *J. Econ. Growth* **2016**, *21*, 35–70. [CrossRef]
47. Kolko, J. Broadband and local growth. *J. Urban Econ.* **2012**, *71*, 100–113. [CrossRef]
48. Yang, Y. Heterogeneous effects of e-government on urban and rural public services: The perspective of the digital divide. *Appl. Econ.* **2026**, *58*, 3989–4004. [CrossRef]
49. Wang, J.; Deng, K. Impact and mechanism analysis of smart city policy on urban innovation: Evidence from China. *Econ. Anal. Policy* **2022**, *73*, 574–587. [CrossRef]
50. Li, C.; Zhang, X.; Dong, X.; Yan, Q.; Zeng, L.; Wang, Z. The impact of smart cities on entrepreneurial activity: Evidence from a quasi-natural experiment in China. *Resour. Policy* **2023**, *81*, 103333. [CrossRef]
51. Zou, J.; Yao, L.; Wang, B.; Zhang, Y.; Deng, X. How does digital inclusive finance promote the journey of common prosperity in China? *Cities* **2024**, *150*, 105083. [CrossRef]
52. Yang, H.; Wang, C.; Wang, G. Convergence or dispersion? The impact of China's innovative city pilot policy on regional innovation differences. *PLoS ONE* **2023**, *18*, e0281685. [CrossRef] [PubMed]
53. Callaway, B.; Sant'Anna, P.H.C. Difference-in-Differences with Multiple Time Periods. *J. Econom.* **2021**, *225*, 200–230. [CrossRef]
54. National Bureau of Statistics of China. Statistical Classification of Digital Economy and Its Core Industries (2021). National Bureau of Statistics Order No. 33, 2021. Available online: https://www.gov.cn/gongbao/content/2021/content_5625996.htm (accessed on 26 October 2026). (In Chinese)
55. Zhao, X.; Dong, Y.; Gong, X. The Digital Economy and Carbon Productivity: Evidence at China's City Level. *Sustainability* **2022**, *14*, 10642. [CrossRef]
56. He, B.; Du, X.; Lu, Y.; Chen, Q.; Lan, R. An Improved Approach for Measuring the Coupling Relationship between New Type Urbanization and Low Carbon Development in China. *Ecol. Indic.* **2024**, *158*, 111383. [CrossRef]
57. Trindade, E.P.; Hinnig, M.P.F.; da Costa, E.M.; Marques, J.S.; Bastos, R.C.; Yigitcanlar, T. Sustainable development of smart cities: A systematic review of the literature. *J. Open Innov. Technol. Mark. Complex.* **2017**, *3*, 11. [CrossRef]

58. Yigitcanlar, T.; Kamruzzaman, M.; Foth, M.; Sabatini-Marques, J.; da Costa, E.; Ioppolo, G. Can cities become smart without being sustainable? A systematic review of the literature. *Sustain. Cities Soc.* **2019**, *45*, 348–365. [CrossRef]
59. Hollands, R.G. Will the real smart city please stand up? Intelligent, progressive or entrepreneurial? *City* **2008**, *12*, 303–320. [CrossRef]
60. Yigitcanlar, T.; Kamruzzaman, M.; Buys, L.; Ioppolo, G.; Sabatini-Marques, J.; da Costa, E.M.; Yun, J.J. Understanding "smart cities": Intertwining development drivers with desired outcomes in a multidimensional framework. *Cities* **2018**, *81*, 145–160. [CrossRef]
61. Shen, C.; Wu, X.; Shi, L.; Wan, Y.; Hao, Z.; Ding, J.; Wen, Q. How does the digital economy affect the urban-rural income gap? Evidence from Chinese cities. *Habitat Int.* **2025**, *157*, 103327. [CrossRef]
62. Fang, C.; Chen, Z.; Liao, X.; Sun, B.; Meng, L. Urban-rural digitalization evolves from divide to inclusion: Empirical evidence from China. *npj Urban Sustain.* **2024**, *4*, 51. [CrossRef]
63. Cao, B.; Zhang, K.; Liu, Y.; Wang, Y. The impact of digital infrastructure on the common prosperity of Chinese cities. *Econ. Anal. Policy* **2026**, *93*, 900–918. [CrossRef]

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