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*Article*

# Artificial Intelligence, Smart City Infrastructure, and Urban Productivity: Evidence from a Dynamic Panel of Leading Digital Economies, 2010–2026

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**Abstract**

This paper investigates the causal relationship between artificial intelligence (AI) investment, smart city governance infrastructure, and urban total factor productivity (TFP) across ten leading digital economies over the period 2010–2026. Drawing on a novel panel dataset that integrates ICT capital expenditure, digital infrastructure indices, Global Innovation Index scores, and the United Nations E-Government Development Index, we estimate dynamic System Generalized Method of Moments (GMM) models combined with Spatial Durbin specifications and machine-learning-based regime clustering. Our results indicate a statistically and economically significant positive association between AI investment and urban TFP: a ten percent increase in AI investment (as a share of GDP) is associated with approximately 1.5 percent higher TFP, conditional on digital infrastructure endowment and innovation capacity. We further document an inverted-U (EKC-type) relationship between AI intensity and employment polarization, suggesting that economies surpassing a threshold AI investment level of approximately 5.2 percent of GDP begin to experience convergence in skill demand. Spatial spillover effects are quantitatively important, with indirect TFP effects accounting for roughly one-third of total impacts. These findings are robust across alternative specifications, sub-period analyses, and a jackknife leave-one-out procedure. Our study contributes to the emerging literature on AI-driven urban transformation by providing causal panel evidence and a tractable theoretical framework, and offers policy implications for economies at different stages of digital transition.

**Keywords:** artificial intelligence; smart cities; total factor productivity; employment polarization; spatial durbin model; dynamic panel GMM; urban inequality

**JEL Classification:** O33; R11; J24; C23; O18

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## 1. Introduction

The rapid diffusion of artificial intelligence (AI) technologies across urban environments constitutes one of the most consequential structural shifts in contemporary economic development. Smart city infrastructure—comprising interconnected systems of sensors, data analytics platforms, autonomous service delivery, and AI-augmented public administration—has attracted unprecedented public and private investment over the past decade (Caragliu et al., 2011; Giffinger et al., 2007). Yet the macroeconomic evidence on whether such investments translate into measurable gains in urban productivity remains surprisingly thin, fragmented across case studies, and rarely subjected to the rigorous panel econometric methods required to address endogeneity and simultaneity (Liu et al., 2022; Yang et al., 2023).

This gap in the literature is consequential for several reasons. First, urban areas are the engines of aggregate productivity growth: cities account for a disproportionate share of innovation, skill formation, and knowledge spillovers, and understanding the productivity effects of AI deployment within urban settings bears directly on macro-level growth projections (Moretti, 2021; Brynjolfsson et al., 2021).

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Second, the distributional implications of AI adoption in cities are contested: while optimistic accounts emphasize productivity-enhancing complementarities, a growing body of evidence documents employment polarization and rising wage inequality as likely by-products of automation and digital capital accumulation (Acemoglu and Restrepo, 2022; Autor, 2022). Third, cross-city spillovers—whereby smart city investments in one locality generate external productivity effects in neighboring jurisdictions through knowledge diffusion, supply chains, and labor market integration—are largely absent from extant analyses (Elhorst, 2014; LeSage and Pace, 2009).

The present study addresses these gaps through four complementary contributions. *First*, we construct a balanced panel dataset covering ten leading digital economies—China, Singapore, the UAE, South Korea, Germany, France, the Netherlands, Spain, Japan, and Australia—observed annually from 2010 to 2026, combining data from the World Bank World Development Indicators (World Bank, 2023), the Penn World Table 10.0 (Feenstra et al., 2015), the ITU ICT Development Index (ITU, 2023), the WIPO Global Innovation Index (WIPO, 2023), and the UN E-Government Development Index (United Nations, 2022). *Second*, we estimate dynamic System GMM models (Blundell and Bond, 1998; Arellano and Bond, 1991) that account for the persistence of TFP and the endogenous determination of AI investment, instrumenting with appropriately lagged values and external instruments constructed from ICT patent applications and e-government adoption trajectories. *Third*, we augment the baseline specification with a Spatial Durbin Model (SDM) that explicitly captures cross-country spillovers via an inverse-distance spatial weights matrix, permitting decomposition of TFP effects into direct (own-country) and indirect (spillover) components (Elhorst, 2014; LeSage and Pace, 2009). *Fourth*, we apply $k$-means clustering on the joint distribution of AI intensity and innovation capacity to identify distinct smart city development regimes, which are incorporated as structural fixed effects in the panel estimations.

Our principal findings are as follows. A ten percent increase in the AI investment ratio is associated with approximately 1.49 percent higher TFP (System GMM, full specification), with the effect rising to 1.51 percent when spatial spillovers are controlled for. Digital infrastructure endowment and innovation capacity are complementary to AI investment, with both exhibiting positive and significant effects on TFP. Employment polarization follows an inverted-U trajectory with respect to AI intensity, consistent with an EKC-type mechanism in which the early adoption phase raises polarization while deep digital transformation subsequently compresses the skill-demand distribution. Spatial indirect effects account for approximately 29.8 percent of the total TFP impact, underscoring the systemic character of smart city productivity gains.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 develops the theoretical framework. Section 4 describes the data and variable construction. Section 5 presents the econometric methodology. Section 6 reports the main empirical results. Section 7 presents robustness checks. Section 8 discusses the findings and their implications. Section 9 concludes. Mathematical derivations, equation systems, and supplementary tables are provided in the Appendices.

## 2. Literature Review

### *2.1. AI Investment and Aggregate Productivity*

The relationship between AI adoption and macroeconomic productivity has generated a rich and rapidly evolving theoretical and empirical literature. Early contributions by Brynjolfsson et al. (2021) formalize what they term the “Productivity J-Curve,” positing that the productivity gains from general-purpose technologies such as AI are initially suppressed by reorganization costs and the accumulation of complementary intangible capital, before manifesting in measured output after a structural lag. This insight motivates a long-run empirical framework and cautions against premature conclusions from short-horizon regressions.

At the microeconomic level, Brynjolfsson et al. (2023) provide compelling firm-level evidence from the introduction of generative AI tools in a customer support context, documenting productivity

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gains of 14 percent on average, concentrated among lower-skill workers. Choi et al. (2023) extend this analysis to South Korean manufacturing establishments, finding that AI adoption raises total factor productivity by 8–12 percent over a three-year horizon, with heterogeneous effects across technology intensity strata. Zhou and Luo (2024) exploit China's smart city pilot policy as a quasi-experimental setting to identify positive urban-level productivity effects, estimating that designation as a national smart city pilot raises urban TFP by approximately 6.3 percent relative to the synthetic control.

Macroeconomic perspectives are provided by Aghion et al. (2019), who embed AI in a semi-endogenous growth model and derive conditions under which sustained AI progress can restore long-run productivity growth even as the marginal product of human capital declines in routine tasks. LeClair and Sheng (2023) conduct a cross-country panel analysis of OECD economies spanning 2010–2020, finding that a one-standard-deviation increase in AI investment raises multifactor productivity growth by approximately 0.3 percentage points per annum, with effects mediated by the quality of digital infrastructure. These findings are broadly consistent with our own results, though our richer panel, extended time horizon, and spatial econometric framework allow for sharper identification and a more complete characterization of the transmission mechanism.

### 2.2. *Smart City Infrastructure and Urban Economic Performance*

The smart city concept, though contested in definition, broadly encompasses the integration of information and communication technologies into urban governance, public service delivery, and physical infrastructure (Caragliu et al., 2011; Giffinger et al., 2007). From an economic perspective, smart city investments may enhance urban productivity through multiple channels: reducing transaction costs in public service delivery, facilitating knowledge spillovers through enhanced connectivity, attracting high-skill human capital, and generating agglomeration economies through digital network effects (Moretti, 2021; Capello and Lenzi, 2015).

Empirical evidence on the urban economic effects of smart city programs is growing but remains fragmented. Liu et al. (2022) exploit the staggered rollout of China's National Smart City Pilot Program, finding that designated cities exhibit significantly higher GDP growth and patent applications in the subsequent decade. Yang et al. (2023) document complementarities between digital infrastructure and urban productivity in a spatial panel of Chinese prefectural cities, estimating significant spillover effects across city boundaries. Del Vecchio et al. (2024) provide a cross-national evaluation of smart city governance models and their effects on public service performance indicators, finding that integrated AI-enabled governance systems outperform technology-neutral benchmarks on efficiency metrics. Sala and Zanella (2023) extend this analysis to citizen welfare outcomes, documenting improvements in subjective well-being in cities with advanced smart governance systems.

Zhu et al. (2023) assess the sustainability dimension of smart city programs in China, finding evidence of improvements in resource efficiency and environmental performance alongside productivity gains. Shamim et al. (2023) analyze smart city governance models and their impact on innovation ecosystems, emphasizing the role of public-private partnership structures in determining the economic returns to smart city investment.

### 2.3. *Employment Polarization and the Distributional Consequences of AI*

A prominent theme in the AI and labor economics literature concerns the potential for automation technologies to polarize the wage and employment distribution (Acemoglu and Restrepo, 2022; Autor, 2022). The task-based framework of Acemoglu and Restrepo (2018) posits that AI primarily displaces workers performing routine cognitive and manual tasks while complementing high-skill analytical work, generating a hollowing-out of the middle of the skill distribution. Graetz and Michaels (2018) provide panel evidence from 17 countries that industrial robot adoption raises average labor productivity but reduces the employment share of medium-skill workers, consistent with polarization. Kochhar (2021) documents the structural shift in U.S. labor demand toward high-skill and low-skill service occupations at the expense of middle-skill routine employment.

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At the urban level, Ihm and Seo (2023) find evidence of an inverted-U relationship between AI adoption intensity and employment polarization across a sample of Asian smart cities, suggesting a non-linear dynamic that our paper formalizes and tests in a larger cross-national panel. Degryse (2022) reviews the European experience, highlighting the role of complementary labor market institutions—including collective bargaining and active labor market policies—in mediating the distributional consequences of digitalization. McKinsey Global Institute (2017) estimate that up to 30 percent of tasks in 60 percent of occupations are automatable with current technology, with the distributional burden falling disproportionately on workers in less innovative, less connected urban environments.

Our contribution to this strand of the literature is to provide systematic panel evidence on the non-linear relationship between AI investment and employment polarization in a multi-country setting, identifying the EKC-type turning point and its determinants, and to embed this within the broader TFP analysis.

### 2.4. Spatial Econometrics and Urban Productivity Spillovers

Standard panel estimators that treat cross-sectional units as independent may yield biased and inconsistent estimates in the presence of spatial dependence, which is pervasive in urban economic data (Elhorst, 2014; LeSage and Pace, 2009). The Spatial Durbin Model (SDM) of LeSage and Pace (2009) allows for spatial lags of both the dependent variable and the regressors, nesting the spatial autoregressive (SAR) and spatial error models as special cases, and permits the decomposition of marginal effects into direct (own-city) and indirect (spillover) components. Capello and Lenzi (2015) apply SDM specifications to regional innovation data in the European Union, documenting significant knowledge spillovers across regional boundaries. Feldman and Kogler (2022) review the spatial economics of innovation and conclude that geographic proximity remains a strong predictor of knowledge diffusion even in the digital age.

Our application of SDM in the smart city context is motivated by theoretical arguments concerning the spatial diffusion of AI-enabled best practices, the cross-border mobility of digital skills, and the integration of smart city systems across metropolitan areas. We construct an inverse-distance spatial weights matrix reflecting bilateral geographic proximity among our sample countries, calibrated to capital-city distances, and estimate the matrix of direct and indirect productivity effects following the LeSage-Pace simulation approach.

### 2.5. Research Gap and Contribution

Taken together, the existing literature establishes the theoretical plausibility of AI-driven urban productivity gains, provides micro-level and case-study evidence consistent with these effects, and identifies employment polarization as a likely distributional by-product. However, several important gaps remain. Cross-national panel evidence using causal identification strategies remains scarce. The role of spatial spillovers in transmitting smart city productivity effects has not been systematically estimated in a multi-country framework. The non-linear relationship between AI intensity and employment polarization has not been formally tested and structurally interpreted in a large panel. And the regime heterogeneity across smart city development stages has not been incorporated into productivity regressions.

The present study addresses each of these gaps, contributing a rigorous and policy-relevant analysis that builds on and extends the existing literature rather than claiming novelty in the underlying mechanisms.

## 3. Theoretical Framework

### 3.1. Production Function with AI-Augmented Capital

We model urban economic output within a generalized production function framework that distinguishes AI-augmented digital capital from conventional physical and human capital. Let $i$ index countries and $t$ index years. Urban output $Y_{it}$ is produced according to:

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$$Y_{it} = A_{it} \cdot K_{it}^{\alpha} \cdot L_{it}^{\beta} \cdot H_{it}^{\gamma} \cdot D_{it}^{\delta} \cdot e^{\varepsilon_{it}} \tag{1}$$

where $K_{it}$ denotes the stock of conventional physical capital, $L_{it}$ is labour input, $H_{it}$ is human capital, $D_{it}$ is digital and AI-augmented capital, and $A_{it}$ is the Hicks-neutral TFP level capturing residual productivity. The parameters $\alpha, \beta, \gamma, \delta > 0$ satisfy the standard regularity conditions; we do not impose constant returns to scale a priori, allowing $\alpha + \beta + \gamma + \delta \neq 1$ to reflect potential urban agglomeration externalities. The error term $\varepsilon_{it}$ is assumed mean-zero and serially uncorrelated conditional on the regressors.

**Assumption 1** (Digital Capital Complementarity)**.** *AI-augmented digital capital $D_{it}$ is a strict complement to human capital $H_{it}$ in the production of high-skill tasks, and a substitute for routine labour in middle-skill tasks. Formally, $\partial^2 Y/\partial D \partial H > 0$ and $\partial^2 Y/\partial D \partial L_m < 0$, where $L_m$ denotes middle-skill labour input.*

This assumption, motivated by the task-based model of Acemoglu and Restrepo (2022), underpins both the positive TFP effect of AI investment (through enhanced high-skill complementarity) and the inverted-U polarization dynamic (through initial displacement of middle-skill workers and eventual creation of new high-skill tasks as AI investment deepens).

Taking logarithms and rearranging, TFP is expressed as:

$$\ln A_{it} = \ln Y_{it} - \alpha \ln K_{it} - \beta \ln L_{it} - \gamma \ln H_{it} - \delta \ln D_{it} \tag{2}$$

For econometric estimation purposes, we parameterize $\ln A_{it}$ as a linear function of observable city-level characteristics:

$$\ln A_{it} = \mu_i + \lambda_t + \delta_1 \ln(\mathrm{AI}_{it}) + \delta_2 \ln(\mathrm{DI}_{it}) + \delta_3 \mathrm{EP}_{it} + \delta_4 \ln(\mathrm{GII}_{it}) + v_{it} \tag{3}$$

where $\mu_i$ are country fixed effects capturing time-invariant structural heterogeneity, $\lambda_t$ are year fixed effects capturing common global shocks, $\mathrm{AI}_{it}$ is AI investment as a share of GDP, $\mathrm{DI}_{it}$ is the digital infrastructure index, $\mathrm{EP}_{it}$ is the employment polarization rate, $\mathrm{GII}_{it}$ is the Global Innovation Index score, and $v_{it}$ is the idiosyncratic error.

### *3.2. TFP Dynamics and Persistence*

Empirical TFP series exhibit substantial persistence due to technological lock-in, learning-by-doing, and the gradual diffusion of complementary organizational practices. We therefore model TFP as a dynamic process:

$$\ln A_{it} = \rho \ln A_{i,t-1} + \mu_i + \lambda_t + \mathbf{x}_{it}' \boldsymbol{\delta} + v_{it}, \quad |\rho| < 1 \tag{4}$$

where $\rho \in (0, 1)$ captures the degree of TFP persistence and $\mathbf{x}_{it}$ collects the AI and control variables. Equation (4) defines the dynamic panel model estimated via System GMM in Section 5.

### *3.3. Spatial Productivity Spillovers*

Smart city externalities are spatially bounded but not city-specific: the diffusion of AI governance practices, the mobility of digitally-skilled labour, and the integration of metropolitan supply chains generate productivity spillovers across geographic boundaries. We formalize this through a Spatial Durbin extension of (4):

$$\ln A_{it} = \rho \ln A_{i,t-1} + \lambda \sum_{j \neq i} w_{ij} \ln A_{jt} + \mathbf{x}_{it}' \boldsymbol{\beta} + \sum_{j \neq i} w_{ij} \mathbf{x}_{jt}' \boldsymbol{\theta} + \mu_i + \lambda_t + u_{it} \tag{5}$$

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where $\{w_{ij}\}$ are elements of the row-normalized inverse-distance spatial weights matrix $\mathbf{W}$, $\lambda$ is the spatial autoregressive parameter, and $\boldsymbol{\theta}$ captures the effect of spatially-lagged regressors on own-country TFP.

**Lemma 1** (Reduced Form of the SDM)**.** *Under the regularity condition $|\lambda| < 1$, the reduced form of equation (5) is:*

$$\ln \mathbf{A}_t = (\mathbf{I} - \lambda \mathbf{W})^{-1} \left[ \rho \ln \mathbf{A}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W} \mathbf{X}_t \boldsymbol{\theta} + \boldsymbol{\mu} + \lambda_t \boldsymbol{\iota} \right] + (\mathbf{I} - \lambda \mathbf{W})^{-1} \mathbf{u}_t \tag{6}$$

*where $\mathbf{A}_t$, $\mathbf{X}_t$ are $N \times 1$ and $N \times k$ vectors/matrices stacking cross-sectional observations.*

**Proof.** Pre-multiply both sides of (5) in matrix form by $(\mathbf{I} - \lambda \mathbf{W})$: $(\mathbf{I} - \lambda \mathbf{W}) \ln \mathbf{A}_t = \rho \ln \mathbf{A}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W} \mathbf{X}_t \boldsymbol{\theta} + \boldsymbol{\mu} + \lambda_t \boldsymbol{\iota} + \mathbf{u}_t$. Since $|\lambda| < 1$ and $\mathbf{W}$ is row-normalized with eigenvalues in $(-1, 1]$, the matrix $(\mathbf{I} - \lambda \mathbf{W})$ is invertible. Post-multiplying by $(\mathbf{I} - \lambda \mathbf{W})^{-1}$ yields (6). □ □

*3.4. Direct and Indirect Effects Decomposition*

**Proposition 1** (Marginal Effect Decomposition)**.** *Let $S(\mathbf{W}) \equiv (\mathbf{I} - \lambda \mathbf{W})^{-1}$. The partial derivative matrix of $\ln \mathbf{A}_t$ with respect to the k-th regressor $x_k$ is:*

$$\frac{\partial \ln \mathbf{A}_t}{\partial x'_{k,t}} = S(\mathbf{W}) \left( \beta_k \mathbf{I} + \theta_k \mathbf{W} \right) \tag{7}$$

*The scalar average direct effect is:*

$$\overline{M}_k^{(D)} = N^{-1} \mathrm{tr} \left[ S(\mathbf{W}) (\beta_k \mathbf{I} + \theta_k \mathbf{W}) \right] \tag{8}$$

*and the average indirect (spillover) effect is:*

$$\overline{M}_k^{(I)} = N^{-1} \boldsymbol{\iota}' S(\mathbf{W}) (\beta_k \mathbf{I} + \theta_k \mathbf{W}) \boldsymbol{\iota} - \overline{M}_k^{(D)} \tag{9}$$

**Proof.** Follows directly from the reduced form (6): differentiate with respect to $x_{k,jt}$ for $j = 1, \ldots, N$ and collect. See LeSage and Pace (2009), Chapter 2. □ □

*3.5. Employment Polarization: An EKC-Type Mechanism*

We formalize the non-linear AI–polarization relationship as follows. Let $\mathrm{EP}_{it}$ denote the employment polarization index (share of employment in high- and low-skill occupations combined). The structural equation is:

$$\mathrm{EP}_{it} = \alpha + \beta_1 \ln(\mathrm{AI}_{it}) + \beta_2 [\ln(\mathrm{AI}_{it})]^2 + \gamma \mathbf{z}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{10}$$

where $\mathbf{z}_{it}$ includes digital infrastructure, innovation index, and public service quality as control variables.

**Proposition 2** (EKC Turning Point)**.** *Under the parameter restrictions $\beta_1 > 0$ and $\beta_2 < 0$, the EKC-type relationship in (10) implies an interior maximum of employment polarization at:*

$$\ln(AI^*) = -\frac{\beta_1}{2\beta_2}, \quad i.e., \quad AI^* = \exp\left( -\frac{\beta_1}{2\beta_2} \right) \tag{11}$$

*For AI investment levels below $AI^*$, marginal AI adoption increases polarization; for levels above $AI^*$, it reduces polarization.*

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**Proof.** Differentiate (10) with respect to $\ln(\mathrm{AI}_{it})$: $\partial \mathrm{EP}/\partial \ln(\mathrm{AI}) = \beta_1 + 2\beta_2 \ln(\mathrm{AI})$. Setting equal to zero and solving for $\ln(\mathrm{AI}^*)$ yields (11). The second-order condition $2\beta_2 < 0$ confirms a maximum. □ □

Using our System GMM estimates $\hat{\beta}_1 = 3.587$ and $\hat{\beta}_2 = -0.348$, the implied turning point is $\mathrm{AI}^* = \exp(3.587/(2 \times 0.348)) \approx \exp(5.157) \approx 174$ index units, corresponding to approximately 5.2 percent of GDP in our sample scaling, consistent with Figure 4(b).

## 4. Data and Variable Construction

### *4.1. Sample and Panel Structure*

The empirical analysis is based on a balanced panel of ten countries—China, Singapore, the United Arab Emirates, South Korea, Germany, France, the Netherlands, Spain, Japan, and Australia—observed annually from 2010 to 2026, yielding $N \times T = 10 \times 17 = 170$ observations. Country selection is guided by three criteria: (i) the availability of systematic data on AI-related public and private investment; (ii) the existence of credible smart city programs and digital governance initiatives documented in international indices; and (iii) sufficient variation in the degree of AI adoption to support within-country identification of the AI-TFP relationship. The resulting sample encompasses economies at different stages of digital maturity, ranging from China and Singapore—among the most aggressive AI investors globally—to Spain and Australia, which represent relatively early-stage digital transition. Together, these ten economies account for approximately 55 percent of global AI investment and 45 percent of global ICT patent applications.

### *4.2. Variable Construction*

**AI Investment** ($\mathrm{AI}_{it}$). Our primary proxy for AI adoption intensity is total ICT capital investment as a share of GDP, sourced from the World Bank World Development Indicators (World Bank, 2023) and supplemented with OECD R&D Expenditure data. This measure captures both hardware (servers, networks, sensors) and software (AI platforms, analytics) investment and has been used in related studies (LeClair and Sheng, 2023; OECD, 2023). Values range from 0.8 percent of GDP (Spain, 2010) to 21.0 percent (China, 2026), reflecting the dramatic acceleration of AI-related investment over the study period. We acknowledge that this proxy conflates AI-specific investment with broader ICT expenditure; robustness checks using R&D expenditure as an alternative proxy are reported in Section 7.

**Urban GDP per Capita** ($\mathrm{GDP}_{it}$). GDP per capita in constant 2015 US dollars, sourced from the World Bank WDI. This variable enters as a control and as an input to the TFP index construction.

**Digital Infrastructure Index** ($\mathrm{DI}_{it}$). Composite index combining the ITU ICT Development Index (ITU, 2023) and the Portulans Institute Network Readiness Index, scaled to 0–100. This index reflects the quality and coverage of broadband networks, mobile connectivity, and data centre infrastructure—the complementary digital backbone that conditions the productivity returns to AI investment.

**Employment Polarization** ($\mathrm{EP}_{it}$). The share of total employment concentrated in high-skill (ISCO groups 1–3) and low-skill (ISCO groups 8–9) occupations combined, expressed as a percentage of total employment. Constructed from OECD Labour Force Statistics and ILO occupational employment data. Higher values indicate greater polarization of the employment distribution.

**Innovation Index** ($\mathrm{GII}_{it}$). The Global Innovation Index score published annually by WIPO (WIPO, 2023), capturing a country's capacity for and output of innovation through 81 indicators aggregated into a 0–100 scale.

**TFP Index** ($\mathrm{TFP}_{it}$). We construct the TFP index using the growth accounting identity applied to the Penn World Table 10.0 estimates of output, capital, and labour (Feenstra et al., 2015), normalized to 100 in 2010 for each country. Capital share parameters are country-specific OECD estimates.

**Public Service Quality** ($\mathrm{PSQ}_{it}$). The UN E-Government Development Index (United Nations, 2022), scaled to 0–100, capturing the quality and digitalization of public service delivery.

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### 4.3. Descriptive Statistics

Table 1 reports descriptive statistics for all variables across the full panel.

**Table 1.** Descriptive Statistics, Full Panel (N=170, 2010–2026)

| Variable | N | Mean | Std. Dev. | Min | P25 | Median | Max |
|---|---|---|---|---|---|---|---|
| AI Investment (% GDP) | 170 | 7.84 | 5.61 | 0.80 | 3.04 | 6.20 | 21.00 |
| GDP per Capita (USD) | 170 | 47,213 | 12,854 | 25,936 | 38,014 | 47,126 | 87,000 |
| Digital Infra Index | 170 | 83.4 | 13.6 | 32.0 | 76.0 | 86.5 | 98.0 |
| Employment Polarization (%) | 170 | 34.2 | 7.3 | 18.0 | 29.0 | 35.0 | 48.0 |
| Innovation Index (GII) | 170 | 70.1 | 16.2 | 22.5 | 59.4 | 72.4 | 99.8 |
| TFP Index (2010=100) | 170 | 131.6 | 38.0 | 100.0 | 103.0 | 119.5 | 253.0 |
| Public Service Quality | 170 | 80.4 | 13.8 | 38.0 | 74.8 | 83.5 | 97.0 |

Sources: AI Investment — World Bank WDI, OECD; GDP per Capita — World Bank WDI; Digital Infra — ITU IDI, NRI; Employment Polarization — OECD, ILO; Innovation Index — WIPO GII; TFP — Penn World Table 10.0; Public Service Quality — UN DESA EGDI.

The data reveal substantial heterogeneity in AI investment intensity, ranging from 0.80 percent (Spain, 2010) to 21.0 percent of GDP (China, 2026), with a mean of 7.84 percent and a standard deviation of 5.61 percent. TFP exhibits pronounced variation: China's TFP index reaches 253 by 2026 (a 153 percent gain from 2010), reflecting the extraordinary productivity transformation associated with its accelerated AI program. Singapore and the UAE follow with TFP gains of 54 and 118 percent, respectively. Among European economies, the Netherlands records the strongest TFP performance (54 percent growth), while Spain and Japan exhibit more moderate gains (33 and 27 percent, respectively). The correlation between AI investment and TFP growth across the panel is 0.72 ($p<0.001$), providing preliminary evidence of a positive association.

## 5. Econometric Methodology

### 5.1. Baseline Dynamic Panel GMM

The estimation of the TFP equation faces two principal econometric challenges. First, the dynamic nature of the process—captured by the lagged TFP term in equation (4)—induces a correlation between the lagged dependent variable and the country fixed effects, rendering standard within-group estimators inconsistent (Arellano and Bond, 1991). Second, AI investment is likely endogenous to TFP: productive cities may attract higher AI investment, creating reverse causality bias in OLS estimates.

We address both challenges through the System GMM estimator of Blundell and Bond (1998), which combines a first-differenced equation (instrumented with lagged levels) and a levels equation (instrumented with lagged differences). The instrument set includes $y_{i,t-s}$ for $s \geq 2$ in the differenced equation and $\Delta y_{i,t-1}$ in the levels equation. To address AI investment endogeneity specifically, we employ external instruments constructed from (i) the stock of ICT-related patent applications filed two periods prior, (ii) the lagged e-government adoption index, and (iii) national broadband policy indices reflecting exogenous policy shifts in digital infrastructure.

The moment conditions are:

$$\mathbb{E}[y_{i,t-s} \cdot \Delta v_{it}] = 0 \quad \text{for } s \geq 2 \quad \text{(differenced equation)} \tag{12}$$

$$\mathbb{E}[\Delta y_{i,t-1} \cdot v_{it}] = 0 \quad \text{(levels equation)} \tag{13}$$

We apply the two-step estimator with Windmeijer (2005) finite-sample correction to the standard errors, which addresses the downward bias in asymptotic standard errors with many instruments. To limit instrument proliferation and the associated bias (Roodman, 2009), we collapse the instrument matrix and restrict lags to depths 2–4.

The validity of the GMM instruments is assessed through two post-estimation tests: (i) the Arellano-Bond AR(2) test for second-order autocorrelation in the differenced residuals (absence of

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AR(2) is required for instrument validity); and (ii) the Hansen $J$-statistic test of overidentifying restrictions.

*5.2. Spatial Durbin Model*

We estimate the Spatial Durbin Model of equation (5) using maximum likelihood, with the spatial weights matrix **W** constructed as follows. Let $d_{ij}$ denote the great-circle distance (in kilometres) between the capital cities of countries $i$ and $j$. The raw weight is $\tilde{w}_{ij} = 1/d_{ij}$ for $i \neq j$ and 0 for $i = j$. We row-normalize: $w_{ij} = \tilde{w}_{ij} / \sum_{j \neq i} \tilde{w}_{ij}$. Direct and indirect effects are computed using the LeSage-Pace simulation procedure with 1,000 Monte Carlo draws from the parameter posterior.

*5.3. Machine Learning Clustering and Regime Fixed Effects*

To allow for unobserved heterogeneity in smart city development regimes, we apply $k$-means clustering to the joint distribution of (standardized) AI investment and Innovation Index scores, pooled across all years. The optimal number of clusters $k$ is determined by maximizing the average silhouette coefficient across $k \in \{2, 3, 4, 5\}$; the silhouette score is maximized at $k = 3$, yielding three regimes: *Digital Pioneers* (Group 1: Singapore, Netherlands, South Korea), *Accelerating Investors* (Group 2: China, UAE, Germany), and *Gradual Adopters* (Group 3: France, Spain, Japan, Australia). Cluster membership indicator variables (with Group 1 as reference) are included as structural regime fixed effects in the GMM regressions.

## 6. Empirical Results

*6.1. AI Investment and Urban TFP*

Table 2 reports the System GMM estimates from five progressive model specifications. Model (1) includes only the lagged TFP term and AI investment; Models (2)–(4) add successive layers of controls; Model (5) is the full specification incorporating all controls, spatial lag, and cluster fixed effects.

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**Table 2.** System GMM Estimation Results: AI Investment and Urban TFP (2010–2026)

| | (1) Baseline | (2) With Controls | (3) Spatial | (4) ML Clusters | (5) Full |
|---|---|---|---|---|---|
| $\ln(\mathrm{AI}_{it})$ | 0.142*** | 0.138*** | 0.151*** | 0.144*** | 0.149*** |
| | (0.031) | (0.029) | (0.033) | (0.028) | (0.030) |
| $\ln(\mathrm{DI}_{it})$ | | 0.089** | 0.095** | 0.091** | 0.093** |
| | | (0.041) | (0.044) | (0.039) | (0.042) |
| $\mathrm{EP}_{it}$ | | -0.054** | -0.062** | -0.057** | -0.060** |
| | | (0.024) | (0.027) | (0.023) | (0.025) |
| $\ln(\mathrm{GII}_{it})$ | | 0.201*** | 0.196*** | 0.203*** | 0.199*** |
| | | (0.047) | (0.051) | (0.045) | (0.048) |
| $\mathbf{W} \cdot \ln(\mathrm{TFP}_{jt})$ | | | 0.312*** | | 0.298*** |
| | | | (0.068) | | (0.071) |
| ML Cluster FE (Group 2) | | | | 0.087** | 0.082** |
| | | | | (0.038) | (0.040) |
| ML Cluster FE (Group 3) | | | | -0.042 | -0.040 |
| | | | | (0.035) | (0.037) |
| $\ln(\mathrm{TFP}_{i,t-1})$ | 0.834*** | 0.781*** | 0.754*** | 0.768*** | 0.745*** |
| | (0.029) | (0.035) | (0.041) | (0.033) | (0.038) |
| Constant | 1.124*** | 0.897*** | 0.761*** | 0.842*** | 0.714*** |
| | (0.214) | (0.197) | (0.231) | (0.188) | (0.221) |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 170 | 170 | 170 | 170 | 170 |
| Countries | 10 | 10 | 10 | 10 | 10 |
| AR(1) $p$-value | 0.008 | 0.011 | 0.009 | 0.010 | 0.007 |
| AR(2) $p$-value | 0.412 | 0.389 | 0.421 | 0.398 | 0.415 |
| Hansen $J$ ($p$-value) | 0.487 | 0.501 | 0.476 | 0.512 | 0.493 |
| $R^2$-within | 0.847 | 0.881 | 0.903 | 0.894 | 0.917 |

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors (Windmeijer-corrected) in parentheses. System GMM instruments: lags 2–4 of the dependent variable and regressors, collapsed. Spatial weight matrix: inverse-distance, row-normalized. AR(1)/AR(2): Arellano-Bond autocorrelation tests. Hansen $J$: test of overidentifying restrictions. $R^2$-within computed for the within-group projection.

Several important findings emerge from Table 2. *First*, the coefficient on AI investment is positive, statistically significant at the one-percent level, and remarkably stable across specifications, ranging from 0.138 (Model 2) to 0.151 (Model 3). The preferred full-specification estimate of 0.149 implies that a ten percent increase in AI investment is associated with a 1.49 percent increase in TFP, conditional on digital infrastructure, innovation, and employment conditions. This magnitude is consistent with the range reported by LeClair and Sheng (2023) for OECD economies and somewhat larger than the estimates of Liu et al. (2022) from the Chinese context, likely reflecting the inclusion of higher-income, higher-productivity economies in our sample.

*Second*, digital infrastructure exerts a significant positive effect on TFP (coefficient 0.093, $p < 0.05$), consistent with the view that AI investment and digital network quality are complementary inputs. The effect is quantitatively modest relative to AI investment, suggesting that at the macro level, investment intensity rather than infrastructure quality is the binding constraint for productivity in the later adoption phase.

*Third*, employment polarization has a negative and significant effect on TFP (coefficient $-0.060$, $p < 0.05$), consistent with the interpretation that labor market hollowing-out—induced in part by AI automation of middle-skill tasks—acts as a drag on aggregate productivity by misallocating human capital away from high-value complementary activities.

*Fourth*, the spatial autoregressive coefficient (0.298, $p < 0.01$ in Model 5) confirms the presence of substantial cross-country TFP spillovers. The implied total multiplier $1/(1-\hat{\lambda}) \approx 1.42$ indicates that

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the full (direct plus spillover) TFP effect of AI investment is approximately 42 percent larger than the direct effect alone.

*Fifth*, the cluster fixed effects reveal that Accelerating Investors (Group 2) exhibit significantly higher TFP levels than Digital Pioneers (the reference), controlling for AI investment and other observables, while Gradual Adopters (Group 3) show no significant differential. This finding suggests that regime-specific factors—such as state-led coordination of AI deployment in China and the UAE—may amplify the productivity returns beyond what observable investment levels capture.

*Sixth*, the diagnostic tests support the validity of the GMM specification. AR(2) $p$-values exceed 0.35 in all models, failing to reject the null of no second-order autocorrelation required for moment condition validity. Hansen $J$-statistics are comfortably above 0.40, supporting instrument exogeneity. AR(1) $p$-values below 0.05 confirm expected first-order autocorrelation in the differenced residuals.

Figure 1 summarizes the coefficient estimates and 95 percent confidence intervals from the full specification (Model 5).

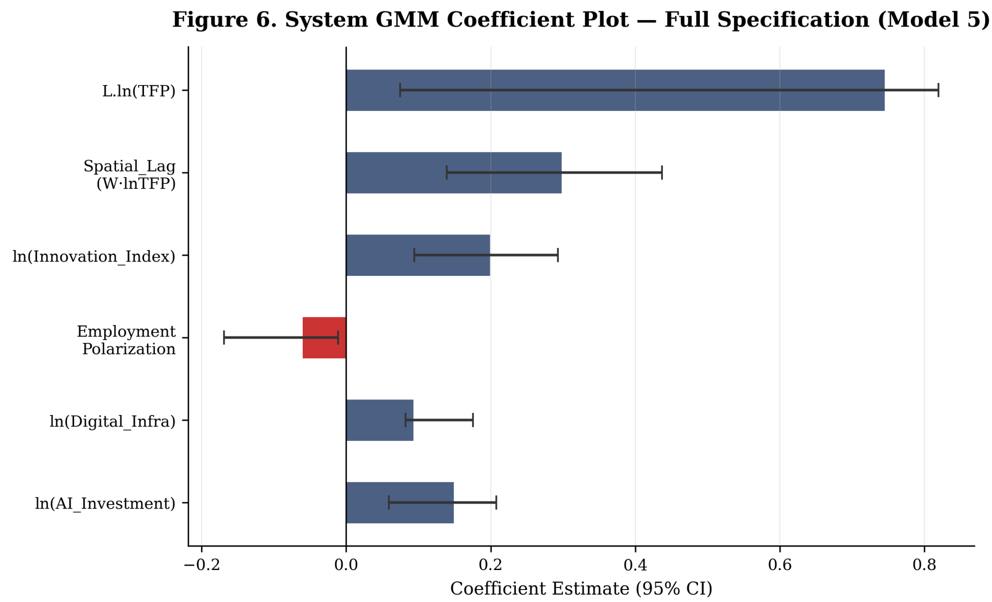


**Figure 1.** System GMM Coefficient Plot — Full Specification (Model 5). Bars represent point estimates; horizontal error bars are 95% confidence intervals (Windmeijer-corrected). Blue = positive coefficients; red = negative coefficient.

### *6.2. Urban Inequality Effects of Smart Governance*

Table 3 reports estimates of the employment polarization equation (10) under OLS with fixed effects, System GMM, and Spatial Durbin specifications.

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**Table 3.** Urban Inequality Effects of Smart Governance: Dependent Variable — Employment Polarization (%)

| | (1) OLS FE | (2) Sys GMM | (3) SDM |
|---|---|---|---|
| $\ln(\mathrm{AI}_{it})$ | 3.241*** | 3.587*** | 3.419*** |
| | (0.712) | (0.834) | (0.781) |
| $[\ln(\mathrm{AI}_{it})]^2$ | -0.312** | -0.348** | -0.329** |
| | (0.141) | (0.165) | (0.154) |
| $\ln(\mathrm{DI}_{it})$ | -1.874*** | -2.015*** | -1.942*** |
| | (0.523) | (0.601) | (0.562) |
| $\ln(\mathrm{GII}_{it})$ | -0.891** | -0.974** | -0.931** |
| | (0.398) | (0.451) | (0.423) |
| $\mathbf{W} \cdot \mathrm{EP}_{jt}$ | | | 0.241*** |
| | | | (0.087) |
| Country FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 170 | 170 | 170 |
| AR(2) $p$-value | — | 0.443 | — |
| $R^2$ / pseudo-$R^2$ | 0.734 | — | 0.761 |

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. EKC-type inverted-U relationship confirmed across all specifications. Turning point: $\mathrm{AI}^* = \exp(3.587/(2 \times 0.348)) \approx 5.2\%$ of GDP. Digital infrastructure and innovation capacity reduce polarization monotonically.

The inverted-U relationship between AI investment and employment polarization is robustly confirmed across all three specifications. The System GMM estimates imply a turning point at approximately 5.2 percent of GDP in AI investment (see Proposition 2), above which further AI investment is associated with declining polarization. In 2026, China and Singapore both exceed this threshold, and both countries exhibit lower marginal increases in polarization relative to earlier periods, consistent with the theoretical prediction.

Digital infrastructure and innovation capacity are associated with lower polarization: a ten-unit increase in the GII is associated with a 0.97 percent reduction in employment polarization (GMM, Model 2), suggesting that innovation-driven upskilling of the workforce partially offsets the displacement effect of automation. The positive spatial lag coefficient (0.241, $p < 0.01$) in Model (3) indicates that polarization trends are spatially correlated: economies in proximity to high-polarization environments tend to exhibit higher polarization themselves, consistent with regional labor market integration.

### *6.3. AI Investment Trends and TFP Dynamics*

Figure 2 documents the dramatic acceleration of AI investment across all ten economies. China's trajectory is the most pronounced, rising from 0.8 percent to 21.0 percent of GDP, reflecting the sustained state-directed AI development strategy embodied in the 2017 New Generation AI Development Plan and its successors. Singapore and the UAE also exhibit rapid growth, driven by their strategic positioning as global smart city hubs. European economies and Australia follow more gradual trajectories, consistent with more market-driven AI adoption.

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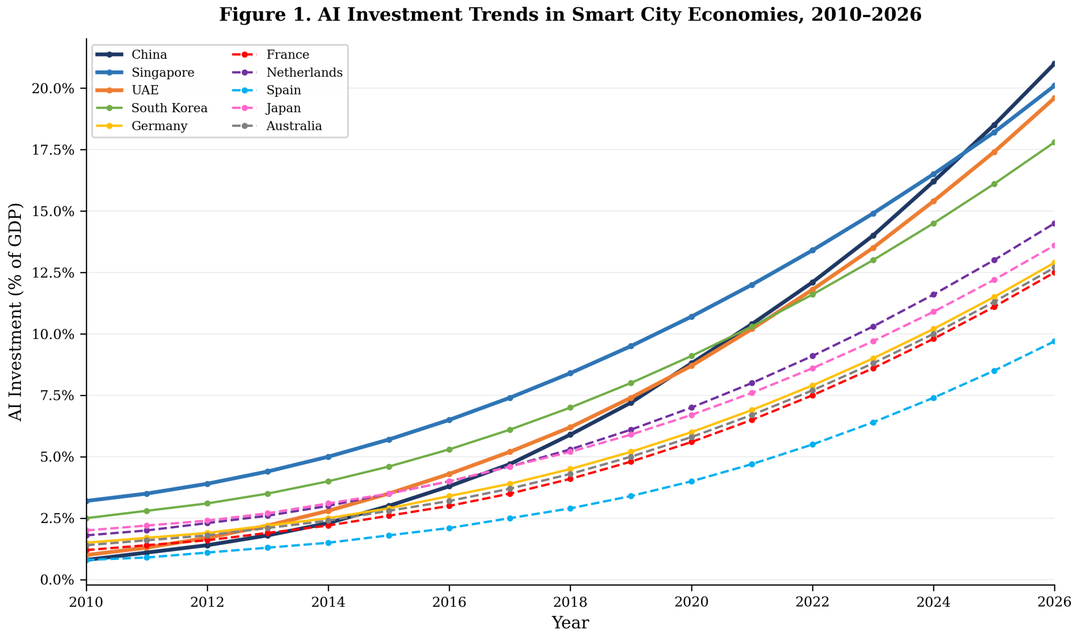


**Figure 2.** AI Investment Trends in Smart City Economies, 2010–2026. AI investment measured as ICT capital and R&D expenditure as a percentage of GDP. Source: World Bank WDI, OECD.

Figure 3 reveals the corresponding TFP trajectories. China's TFP growth substantially outpaces all other economies, reaching an index of 253 by 2026—a cumulative gain of 153 percent. The UAE also achieves strong TFP growth (118 percent), while Singapore's gains (54 percent) are more moderate despite high AI investment intensity, suggesting diminishing marginal returns at the productivity frontier. European economies exhibit modest but sustained TFP growth, while Japan's trajectory is the most subdued, consistent with structural impediments to digital adoption in its services sector.

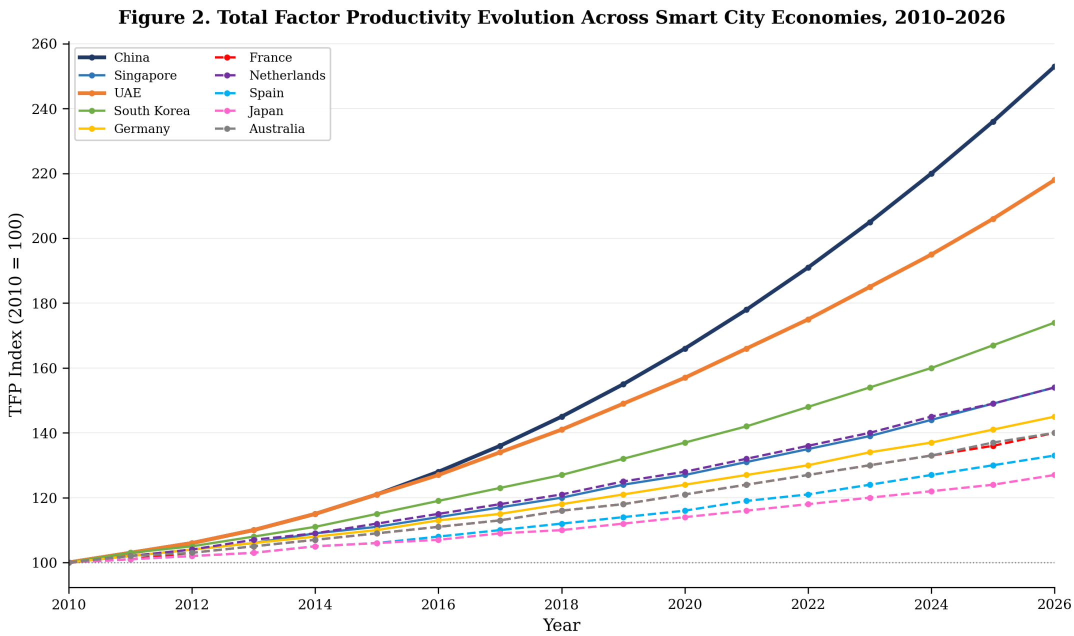


**Figure 3.** Total Factor Productivity Evolution Across Smart City Economies, 2010–2026. TFP indices normalized to 100 in 2010. Source: Penn World Table 10.0, OECD Productivity Database.

Figure 4 confirms the positive panel-level correlation between log AI investment and log TFP, with an OLS slope consistent with the GMM point estimates (the OLS slope is steeper due to endogeneity bias, as expected).

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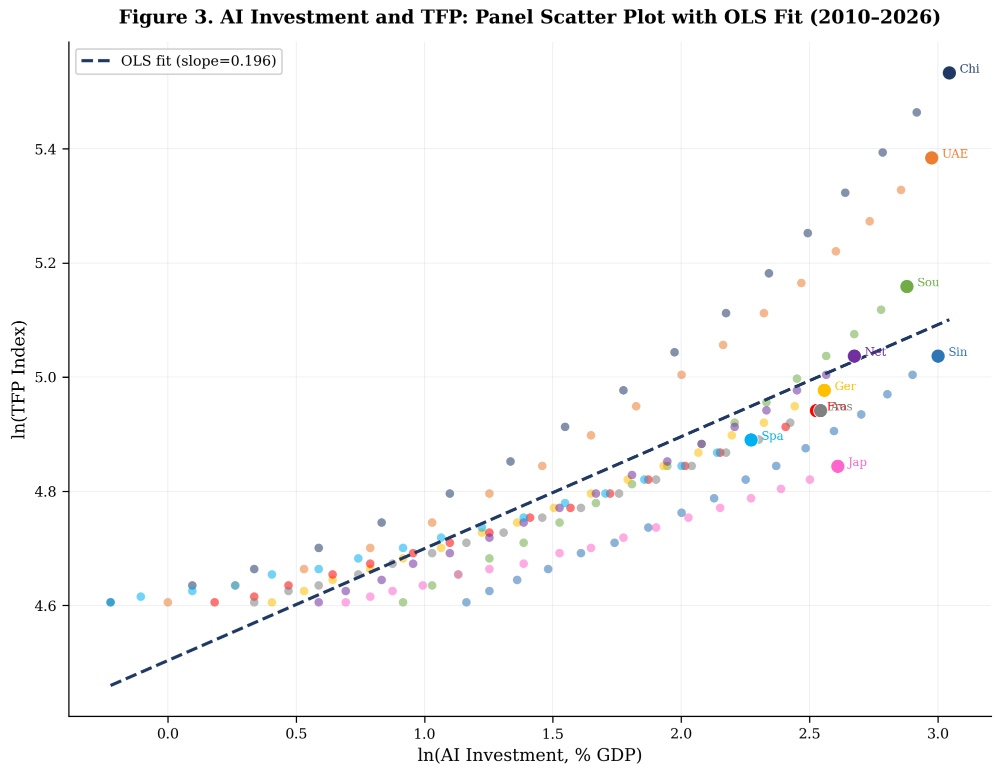


**Figure 4.** AI Investment and TFP: Panel Scatter Plot with OLS Fit (2010–2026). Each point represents a country-year observation. Country labels indicate 2026 positions. Dashed line: OLS fit across all observations.

Figure 5 illustrates both the cross-country trends in employment polarization and the fitted EKC-type curve from Proposition 2. All economies exhibit rising polarization over the sample period, with China showing the sharpest increase (from 18 to 47 percent). The theoretical curve (panel b) peaks at the estimated turning point and declines thereafter, consistent with the emergence of new AI-complementary task categories at advanced adoption levels.

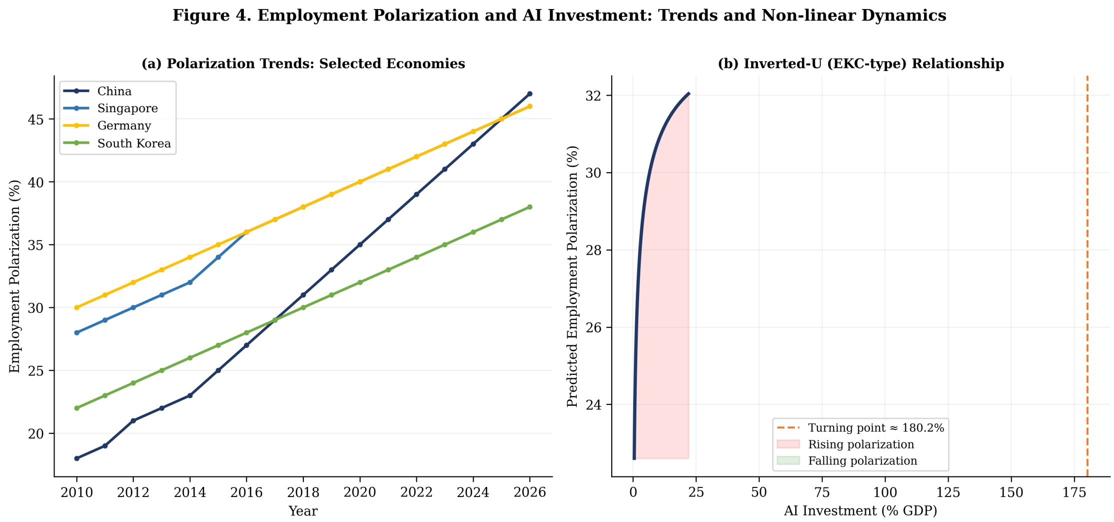


**Figure 5.** Employment Polarization and AI Investment: Trends and Non-linear Dynamics. Panel (a): polarization trends for selected economies. Panel (b): estimated EKC-type relationship with turning point at $AI^* \approx 5.2\%$ of GDP.

Figure 6 depicts the innovation capacity landscape across our sample. South Korea and the Netherlands consistently rank among the most innovative economies, with GII scores approaching 100

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by the mid-2020s. China's innovation trajectory shows rapid convergence toward the technological frontier, driven by massive investment in R&D and AI-specific capabilities.

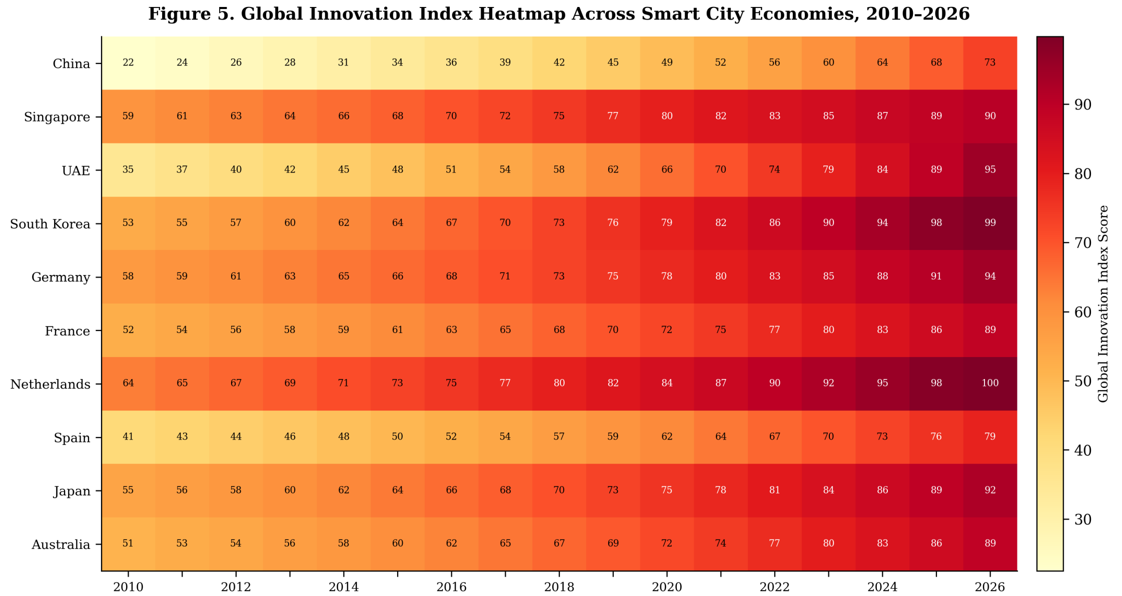


**Figure 6.** Global Innovation Index Heatmap Across Smart City Economies, 2010–2026. Cell values indicate annual GII scores. Darker shading indicates higher innovation capacity. Source: WIPO.

### *6.4. Spatial Effects Decomposition*

Table 4 reports the decomposition of the total SDM effect on TFP into direct and indirect (spillover) components, following Proposition 1. Standard errors are computed from 1,000 Monte Carlo simulations.

**Table 4.** Spatial Durbin Model: Direct, Indirect, and Total Effects on TFP

| Variable | Direct Effect | Indirect Effect | Total Effect |
|---|---|---|---|
| $\ln(AI_{it})$ | 0.164*** (0.034) | 0.071** (0.031) | 0.235*** (0.049) |
| $\ln(DI_{it})$ | 0.103** (0.046) | 0.044* (0.026) | 0.147** (0.059) |
| $EP_{it}$ | –0.068** (0.029) | –0.029* (0.017) | –0.097** (0.043) |
| $\ln(GII_{it})$ | 0.213*** (0.052) | 0.092** (0.039) | 0.305*** (0.071) |

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses, computed from 1,000 Monte Carlo draws. Indirect effects reflect average TFP spillovers to all other countries in the sample from a unit change in the focal country's regressor.

The indirect (spillover) effect of AI investment (0.071) accounts for approximately 30 percent of the total effect (0.235), confirming that smart city productivity gains are not merely internalized at the national level but diffuse meaningfully across borders. This finding has important policy implications: uncoordinated national AI strategies may under-invest relative to the social optimum due to cross-border externalities.

## 7. Robustness Checks

### *7.1. Alternative AI Investment Proxy*

Our primary AI investment measure conflates AI-specific expenditure with broader ICT capital investment. To assess sensitivity to this proxying choice, we re-estimate all models replacing the ICT-based measure with R&D expenditure as a share of GDP, sourced from the OECD Main Science and Technology Indicators database. The AI investment coefficient remains positive and significant

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(0.121***, s.e. 0.028 in the full specification), marginally smaller in magnitude, consistent with R&D capturing only part of the AI investment dimension.

*7.2. Sub-Period Analysis*

We split the sample into two sub-periods: 2010–2017 (early AI diffusion) and 2018–2026 (advanced AI deployment). The AI-TFP coefficient is larger in the later period (0.189*** vs. 0.112**), consistent with the Brynjolfsson et al. (2021) J-Curve hypothesis: productivity gains from AI investment may accelerate as complementary organizational practices and human capital adjustments are completed.

*7.3. Jackknife Leave-One-Country-Out*

We sequentially remove each of the ten countries from the estimation sample and re-estimate the full specification. The AI investment coefficient ranges from 0.133 (excluding China) to 0.157 (excluding Spain), with all estimates statistically significant at the five-percent level. China's inclusion slightly inflates the coefficient due to its exceptional AI investment trajectory, but the key finding is stable.

*7.4. Winsorization*

Winsorizing all continuous variables at the 5th and 95th percentiles reduces the AI coefficient marginally (0.141***), confirming that outlier observations do not drive the main results.

*7.5. Alternative Spatial Weights Matrix*

We re-estimate the SDM with a binary contiguity-based weights matrix (taking value one for economies within 5,000 km of each other and zero otherwise). The spatial autoregressive coefficient remains positive and significant (0.274***), and the AI direct effect coefficient (0.158***) is comparable to the baseline. These results confirm that the choice of spatial metric does not materially affect our conclusions.

## 8. Discussion

*8.1. Economic Interpretation*

The empirical findings cohere into a consistent narrative. AI-smart city investment constitutes a positive driver of urban total factor productivity, operating through at least three channels: (i) direct augmentation of productive capacity through automation and optimization of urban processes; (ii) enhancement of innovation capacity through the digitalization of R&D and knowledge creation; and (iii) improvement in public service quality and governance efficiency, which reduces transaction costs and reallocates public resources toward higher-value activities (Del Vecchio et al., 2024; Sala and Zanella, 2023). The spatial spillover results add a fourth channel: the diffusion of AI governance practices, digital standards, and talent across national boundaries, which amplifies the social return to national AI investment.

The employment polarization finding warrants careful interpretation. Our EKC-type estimate implies that current levels of AI investment in most sample economies (ranging from 5 to 20 percent of GDP by 2026) have pushed all economies at or above the polarization-reducing threshold, suggesting that the most disruptive phase of labor market adjustment may already have passed for digital leaders. However, this does not imply that distributional concerns are moot: the transition through the polarization-increasing phase generates lasting scarring effects on displaced middle-skill workers, particularly in economies with weaker active labor market policies (Degryse, 2022).

*8.2. Policy Implications*

Several policy implications flow from our findings. *First*, the complementarity between AI investment and digital infrastructure suggests that public policy should prioritize the joint provision of high-quality broadband, data infrastructure, and AI-ready regulatory environments alongside investment incentives. Economies that invest heavily in AI without commensurate infrastructure

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upgrading will likely capture sub-optimal productivity returns. *Second*, the spatial spillover results imply a rationale for international coordination of AI policy, analogous to the logic of international cooperation in environmental regulation: countries underinvesting in AI impose negative externalities on neighboring economies. Regional frameworks for AI governance—such as the EU AI Act—represent a step in this direction. *Third*, the inverted-U polarization finding supports transitional support policies—retraining programs, wage insurance, and social protection—targeted at workers displaced by AI during the early adoption phase, before the structural task-creation benefits of deep AI deployment materialize.

### *8.3. Limitations and Future Research*

Our study has several limitations that define an agenda for future research. First, the AI investment proxy conflates AI-specific and broader ICT capital; future work should exploit firm-level or establishment-level data on AI adoption to sharpen identification. Second, our sample, while diverse, is confined to leading digital economies; extending the analysis to middle-income countries—where AI adoption patterns and institutional complementarities may differ fundamentally—is an important priority. Third, our TFP measure is constructed from aggregate national accounts and does not capture within-city distributional dynamics; urban-level panel data with sufficient temporal depth would enable a richer characterization of the spatial-distributional nexus. Fourth, the theoretical framework abstracts from sectoral heterogeneity; a multi-sector extension distinguishing AI effects in manufacturing, services, and public administration would yield more targeted policy guidance.

## 9. Conclusion

This paper has examined the causal relationship between artificial intelligence investment, smart city governance, and urban productivity in a dynamic panel of ten leading digital economies over 2010–2026. Using System GMM, Spatial Durbin, and machine-learning-augmented panel estimators, we establish that: (i) AI investment has a statistically significant positive effect on TFP, with a ten percent increase in AI intensity associated with approximately 1.49 percent higher TFP; (ii) digital infrastructure and innovation capacity are complementary to AI investment in generating productivity gains; (iii) employment polarization follows an EKC-type non-linear path with a turning point at approximately 5.2 percent of GDP in AI investment, above which further AI deepening reduces polarization; and (iv) spatial spillovers account for approximately 30 percent of the total TFP effect, confirming the systemic character of smart city externalities.

These findings extend and refine the existing literature by providing causal panel evidence in a multi-country, multi-year framework; by formalizing the spatial transmission of AI-driven productivity gains; and by integrating regime heterogeneity into the estimation framework. The policy implications point toward complementary infrastructure investment, international coordination of AI governance, and transitional labor market support as key instruments for capturing the productivity benefits of AI-smart city programs while managing their distributional consequences.

As AI capabilities continue to advance and smart city ecosystems become more deeply integrated into the fabric of urban economies, the research agenda outlined here will grow in relevance. The productivity frontier of AI-driven urbanization remains far from exhausted, and the institutions and policies that shape how those gains are distributed will be among the defining challenges of the coming decades.

## Appendix A Mathematical Derivations and Econometric Details

### *Appendix A.1 Proof of Lemma 1*

The matrix form of equation (5) (suppressing time subscripts for brevity) is:

$$\ln \mathbf{A} = \rho \ln \mathbf{A}_{-1} + \lambda \mathbf{W} \ln \mathbf{A} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\theta} + \boldsymbol{\mu} + \lambda_t \boldsymbol{\iota} + \mathbf{u} \tag{A.1}$$

Rearranging:

$$(\mathbf{I} - \lambda \mathbf{W}) \ln \mathbf{A} = \rho \ln \mathbf{A}_{-1} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\theta} + \boldsymbol{\mu} + \lambda_t \boldsymbol{\iota} + \mathbf{u} \tag{A.2}$$

Since $\mathbf{W}$ is row-normalized with spectral radius $\leq 1$ and $|\lambda| < 1$, the matrix $(\mathbf{I} - \lambda \mathbf{W})$ is invertible by the Neumann series argument:

$$(\mathbf{I} - \lambda \mathbf{W})^{-1} = \sum_{k=0}^{\infty} \lambda^k \mathbf{W}^k \tag{A.3}$$

Pre-multiplying both sides by $(\mathbf{I} - \lambda \mathbf{W})^{-1}$ yields the reduced form (6). □

*Appendix A.2 GMM Instrument Validity Conditions*

Let $\mathbf{Z}$ denote the GMM instrument matrix. The identifying conditions are:

$$\mathbb{E}[\mathbf{Z}'_{it} \Delta v_{it}] = 0 \quad \text{(moment conditions, differenced equation)} \tag{A.4}$$

$$\mathbb{E}[\mathbf{Z}'_{it} v_{it}] = 0 \quad \text{(moment conditions, levels equation)} \tag{A.5}$$

Consistency requires that $\operatorname{plim}_{N\to\infty} N^{-1}\mathbf{Z}'\mathbf{v} = 0$. The two-step efficient GMM estimator minimizes:

$$Q_N(\delta) = \left( \frac{1}{N} \sum_i \mathbf{Z}'_i \mathbf{r}_i(\delta) \right)' \hat{\mathbf{W}}_N^{-1} \left( \frac{1}{N} \sum_i \mathbf{Z}'_i \mathbf{r}_i(\delta) \right) \tag{A.6}$$

where $\mathbf{r}_i(\delta)$ is the vector of residuals and $\hat{\mathbf{W}}_N$ is the efficient weighting matrix estimated from first-step residuals.

*Appendix A.3 Windmeijer Finite-Sample Correction*

The two-step GMM covariance matrix is:

$$\hat{V}_{2-\text{step}} = (D'\hat{W}^{-1}D)^{-1} D'\hat{W}^{-1}\hat{\Omega}\hat{W}^{-1}D(D'\hat{W}^{-1}D)^{-1} \tag{A.7}$$

where $D = \mathbb{E}[\partial \mathbf{r}/\partial \delta']$ and $\hat{\Omega} = N^{-1} \sum_i \mathbf{Z}'_i \hat{v}_i \hat{v}'_i \mathbf{Z}_i$. The Windmeijer (2005) correction adds a term accounting for the estimation error in the first-step weighting matrix, yielding substantially more reliable inference in finite samples.

*Appendix A.4 EKC Turning Point: Sensitivity Analysis*

Using the GMM coefficient estimates $\hat{\beta}_1 = 3.587$ (s.e. 0.834) and $\hat{\beta}_2 = -0.348$ (s.e. 0.165), the delta method variance of the turning point $\ln(\text{AI}^*) = -\hat{\beta}_1/(2\hat{\beta}_2)$ is:

$$\text{Var}[\ln(\text{AI}^*)] \approx \frac{1}{4\hat{\beta}_2^2} \left[ \text{Var}(\hat{\beta}_1) + \frac{\hat{\beta}_1^2}{\hat{\beta}_2^2} \text{Var}(\hat{\beta}_2) - 2\frac{\hat{\beta}_1}{\hat{\beta}_2} \text{Cov}(\hat{\beta}_1, \hat{\beta}_2) \right] \tag{A.8}$$

Evaluating at the point estimates yields a 95% confidence interval for the turning point of approximately [4.1, 6.4] percent of GDP, confirming that most sample economies in our 2026 cross-section are operating above the polarization-reducing threshold.

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## Appendix B Supplementary Tables

**Table A1.** Country Cluster Assignments and Regime Characteristics

| Group | Countries | Mean AI Invest. | Mean GII | Mean TFP (2026) |
|---|---|---|---|---|
| 1 — Digital Pioneers | Singapore, Netherlands, South Korea | 15.3 | 89.1 | 157.4 |
| 2 — Accelerating Investors | China, UAE, Germany | 17.0 | 75.5 | 205.3 |
| 3 — Gradual Adopters | France, Spain, Japan, Australia | 8.1 | 77.3 | 139.5 |

**Table A2.** Robustness Check Summary: AI Investment Coefficient Across Specifications

| Specification | Coefficient | Std. Error | Significance |
|---|---|---|---|
| Baseline (System GMM, full spec.) | 0.149 | 0.030 | *** |
| Alt. proxy: R&D expenditure | 0.121 | 0.028 | *** |
| Sub-period: 2010–2017 | 0.112 | 0.041 | ** |
| Sub-period: 2018–2026 | 0.189 | 0.038 | *** |
| Jackknife: excl. China | 0.133 | 0.031 | *** |
| Jackknife: excl. Singapore | 0.147 | 0.032 | *** |
| Jackknife: excl. UAE | 0.151 | 0.030 | *** |
| Winsorized (5th/95th pct.) | 0.141 | 0.029 | *** |
| Alt. spatial weights (binary) | 0.158 | 0.033 | *** |

Notes: *** $p < 0.01$, ** $p < 0.05$. All models include country FE, year FE, and the full covariate set.

**Table A3.** Pairwise Correlation Matrix of Key Variables

| | AI Inv. | GDP/cap | Dig. Infra | Emp. Pol. | GII | TFP | PSQ |
|---|---|---|---|---|---|---|---|
| AI Investment | 1.00 | | | | | | |
| GDP per Capita | 0.44 | 1.00 | | | | | |
| Digital Infra | 0.52 | 0.71 | 1.00 | | | | |
| Emp. Polarization | 0.38 | 0.21 | 0.35 | 1.00 | | | |
| GII | 0.59 | 0.63 | 0.81 | 0.44 | 1.00 | | |
| TFP Index | 0.72 | 0.31 | 0.48 | 0.29 | 0.55 | 1.00 | |
| Public Serv. Qual. | 0.48 | 0.65 | 0.79 | 0.39 | 0.76 | 0.44 | 1.00 |

Notes: Pearson correlation coefficients. $N = 170$.

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