Why Countries Differ in Artificial Intelligence Readiness: An Augmented Solow Analysis of Growth and Institutions

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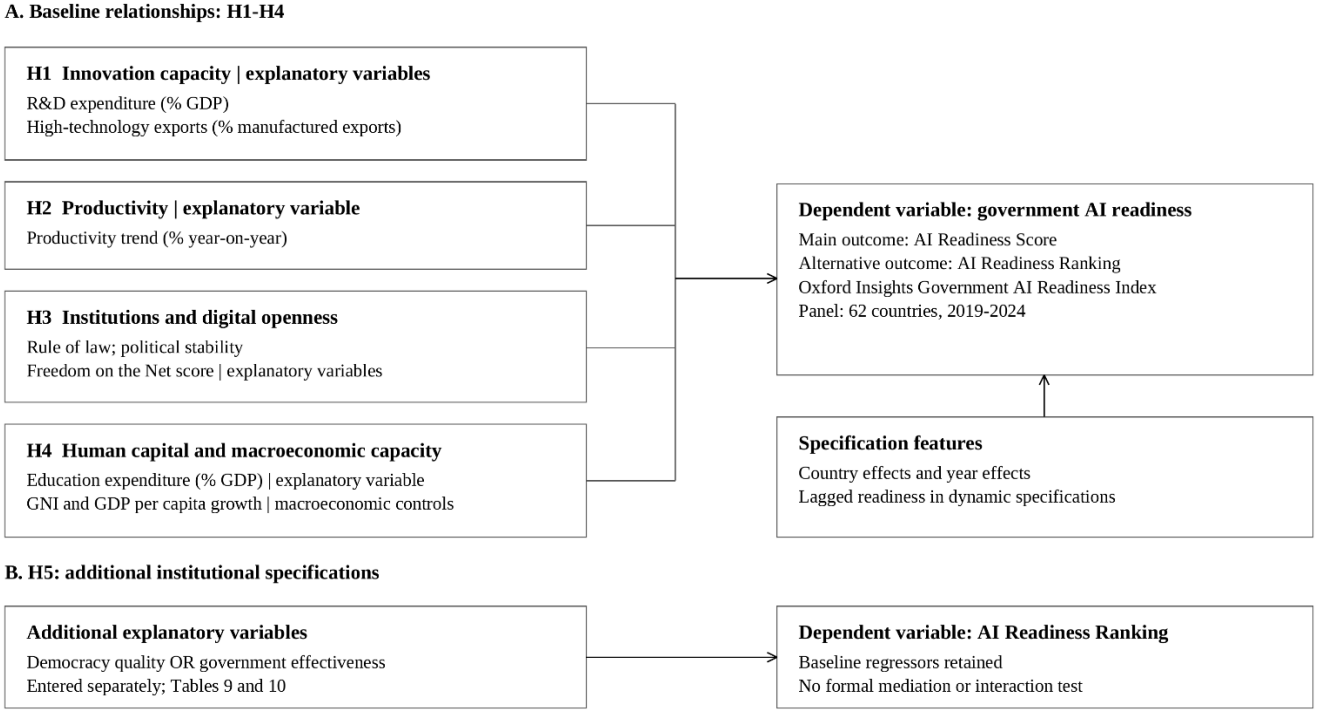
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The international macroeconomic question motivating this paper is whether differences in domestic absorptive capacity help explain unequal preparedness for globally advancing technological frontier. Although artificial intelligence technologies can diffuse across borders, the institutional, innovative and human capital capabilities needed to deploy them remain unevenly distributed. These differences raise a question relevant to technological catch up: what domestic conditions are associated with countries' preparedness to benefit from advances in AI? This study investigates those conditions through a country analysis of government AI readiness, connecting preparedness to innovation investment, participation in technology-intensive trade and institutional quality.

The empirical framework is motivated by an augmented Solow model (Solow, 1956; Mankiw, Romer and Weil, 1992) and incorporates insights from endogenous growth theory (Romer, 1990) and institutional economics (Acemoglu, Johnson and Robinson, 2005), complemented by the International Product Life Cycle (Vernon, 1979) and Dunning's OLI perspective (Dunning, 1980). It organises the explanatory variables into four channels: innovation capacity, represented by R&D expenditure and high technology exports (H1); productivity represented by productivity trends (H2); institutional quality and digital openness, represented by rule of la, political stability and internet freedom (H3); and human capital and macroeconomic capacity, represented by education expenditure and GNI and GDP per capita growth (H4). Together, these channels connect domestic economic capabilities and participation in technology intensive trade to cross country differences in AI preparedness as in the below figure.

Figure 1. Conceptual and empirical framework of government AI readiness

Theoretical foundations: augmented Solow; endogenous growth; institutional economics; IPLC; OLI



Baseline empirical specification and explanatory variables grouped by hypotheses H1-H4 as below.

$$\ln AIR_{it} = \beta_0 + \underbrace{\beta_1 \ln PROD_{it}}_{\text{H2: Productivity}} + \underbrace{\beta_2 \ln RND_{it} + \beta_3 \ln HTX_{it}}_{\text{H1: Innovation}} + \underbrace{\beta_4 FON_{it} + \beta_5 PS_{it} + \beta_6 RL_{it}}_{\text{H3: Institutions and digital openness}} + \underbrace{\beta_7 GNIgr_{it} + \beta_8 GDPgr_{it} + \beta_9 \ln EDU_{it}}_{\text{H4: Human capital and macroeconomic capacity}} + \alpha_i + \lambda_t + \varepsilon_{it}.$$

In this specification AIRit denotes government AI readiness for country(i) and year (t), with country and year effects accounting for time invariant national characteristics and common annual shocks. The dynamic specification adds lagged readiness to capture persistence while separate extensions examine democracy quality and government effectiveness under the institutional transmission hypothesis (H5).

The analysis draws on a panel of 62 countries over 2019-2024, combining Government Readiness index from Oxford Insights (Government AI Readiness Index, 2019–2024 editions; Oxford Insights, 2019–2024) with macroeconomic and institutional indicators from the World Bank (World Development Indicators and Worldwide Governance Indicators; World Bank, 2025) and internet freedom measures from Freedom

House (Freedom on the Net, 2019–2024 editions; Freedom House, 2019–2024). Readiness scores serves as the principal outcome and country rankings as an alternative measure capturing preparedness rather than realised AI adoption or productivity gains.

We estimate baseline panel GMM and dynamic system GMM specifications (Blundell and Bond, 1998), using internal instruments to address potential simultaneity and restricting instrument lag depth and collapsing the instrument matrix to limit instrument proliferation (Roodman, 2009). Income group estimations examine heterogeneity in the reported relationships, while principal component analysis provides an alternative representation of the explanatory variables through composite factors.

Preliminary estimates indicates persistence in government AI readiness and positive conditional associations with R&D expenditure, productivity growth and high technology exports. Rule of law, political stability, internet freedom and education expenditure also enter positively in the dynamic score specification, linking preparedness to institutional conditions and human capital investment alongside innovation capacity and participation in technology intensive trade.

The contribution is to connect international differences in government AI preparedness to the domestic capabilities emphasised by growth theory, extending cross-country panel evidence that has examined AI readiness mainly in relation to employment outcomes (Marinaș et al., 2024), with the short panel, index construction and internal instrument assumptions limiting causal interpretation: the institutional extensions estimate additional conditional relationships rather than formal mediation, and the analysis does not establish effects on subsequent adoption, productivity or convergence. For international macroeconomics, the findings direct attention to the uneven domestic foundations from which countries approach a shared technological frontier: innovation investment, education, institutional quality and digital openness are associated with preparedness to participate in advances whose economic benefits remain to be realised.

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