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The Complementarity Dividend: How Digital Capability and Institutional Readiness Condition the Productivity Effects of Artificial Intelligence

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ABSTRACT

Generative artificial intelligence has moved the economic debate from whether machines can perform cognitive tasks to whether economies can convert technical exposure into broadly shared productivity growth. This paper develops the Capability-Complementarity Dividend framework, which treats the effect of artificial intelligence as a joint function of technological exposure, digital capability, human capital and institutional readiness. Using the 2023 International Monetary Fund Artificial Intelligence Preparedness Index merged with World Bank development and labor indicators, the paper analyzes 173 countries. The evidence is deliberately descriptive rather than causal. AI preparedness has a zero-order correlation of 0.802 with GDP per person employed, 0.760 with internet use and -0.217 with unemployment.

After conditioning on GDP per capita and population, the aggregate preparedness coefficient on log productivity becomes negative, while the component estimates diverge: digital infrastructure and human-capital components are positively associated with productivity, whereas innovation-integration and regulation components enter negatively. An interaction model also finds a negative association between preparedness and productivity at higher internet-use levels. These patterns reject a simple linear readiness narrative. They suggest that capability is multidimensional, that readiness components can create institutional frictions and that productivity gains cannot be interpreted as inclusive without observing distributional and labor-market outcomes. The paper contributes a framework for measuring the complementarity problem and a transparent global baseline for future micro-level causal research.

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Introduction

Artificial intelligence is often presented as a general-purpose technology capable of raising productivity, reallocating labor and transforming the distribution of economic opportunity. That proposition is plausible, but it is incomplete. Technologies do not enter empty economies. They are adopted through firms, workers, institutions and infrastructures that shape what the technology can do, who can use it and how its benefits are distributed. The central question is therefore not simply how many occupations are exposed to artificial intelligence. It is whether the surrounding capability system converts exposure into productivity gains without intensifying labor-market inequality.

The modern task-based literature supplies the conceptual foundation for this question. Automation can displace labor from tasks while productivity gains and new-task creation can raise labor demand elsewhere [1-4]. The relative strength of these forces depends on the technology's design, the composition of tasks and the speed with which workers and institutions adapt. Empirical work on robots, information technology and digital organization

shows that productivity effects can be large while remaining uneven across firms, sectors, locations and workers [5-7]. Recent generative-AI experiments add an important result: access to AI assistance can reduce completion time, raise output quality and compress performance differences among workers performing professional writing tasks [8]. Field evidence from customer-support work likewise reports sizable average productivity gains with heterogeneity by worker experience and task type [9].

These findings do not imply that national preparedness indices can be interpreted as causal estimates of AI's effect. They do, however, suggest that a useful macroeconomic baseline should distinguish technical exposure from complementarity. Existing indices often combine infrastructure, skills, innovation, labor-market institutions, regulation and ethics into a single score. Such aggregation is convenient for ranking but potentially misleading for economics. Two countries can have the same composite readiness score while differing sharply in digital access, human capital, innovation capacity and institutional constraint. A high aggregate score may coexist with weak worker capability or with regulatory arrangements that slow experimentation. Conversely, rapid private adoption may coexist with inadequate protections against displacement or discrimination.

This paper introduces the Capability-Complementarity Dividend framework, abbreviated CCD. It has three layers. The first is technological exposure, defined as the extent to which existing tasks can be assisted or substituted by artificial intelligence. The second is capability complementarity, defined as the joint availability of digital infrastructure, relevant skills and productive organizational capacity. The third is distributive governance, defined as training access, worker voice, social protection and regulatory legitimacy. The framework predicts that exposure alone has an ambiguous effect. High exposure with weak capability can produce displacement, low adoption quality or widening inequality. High exposure with strong capability can produce productivity gains, new tasks and broader diffusion. Yet the relationship can be non-monotonic if composite readiness masks tensions among innovation, regulation and worker adjustment.

The empirical contribution is intentionally modest and transparent. The paper merges the 2023 IMF Artificial Intelligence Preparedness Index, which covers 174 countries and four major components, with the World Bank's World Development Indicators. The resulting sample contains 173 country records with varying availability of productivity, internet-use and unemployment measures. The analysis reports descriptive correlations and cross-sectional regression diagnostics for 2023. It also estimates a country fixed-effects panel for a related green-transition paper, but the present article does not treat country-level AI preparedness as a time-varying treatment. The estimates are therefore not interpreted as causal effects.

The results motivate a more demanding interpretation of readiness. The raw correlation between AI preparedness and GDP per person employed is strongly positive at 0.802. The raw correlations with internet use and unemployment are 0.760 and -0.217 respectively. Once GDP per capita and population are included, the aggregate preparedness coefficient on log productivity is negative, while the component estimates are heterogeneous. Digital infrastructure and human capital are positive, while innovation and economic integration and regulation and ethics are negative in the component regression. The interaction between preparedness and standardized internet use is also negative. These results should not be read as evidence that regulation or innovation reduce productivity. They are diagnostic evidence that composite indices are highly collinear with development and that institutional components may capture constraints, policy endogeneity or measurement choices.

The paper makes four contributions. First, it provides a mechanism-based framework that treats AI adoption as a capability-conditioned process rather than a one-dimensional exposure shock. Second, it demonstrates how aggregate readiness can conceal offsetting component relationships. Third, it produces a reproducible global baseline using publicly accessible data and explicit missingness rules. Fourth, it gives a research agenda for the next generation of work: merge occupation-level exposure scores with firm adoption, worker training, wage distributions and institutional measures in repeated panels or natural experiments.

Literature Review and Theoretical Framework From Automation Exposure to Task Reallocation

The task-based approach models production as a collection of tasks performed by labor, capital or a combination of both. Automation displaces labor from tasks in which machines become comparatively effective. Productivity gains lower costs and can expand output, while new tasks can reinstate labor demand [2,3]. The net outcome depends on the rate of automation, the creation of new labor-intensive tasks, capital accumulation and the elasticity

of demand. This framework clarifies why technological change can raise output per worker while lowering labor demand or labor share in particular settings.

The empirical literature has documented several forms of heterogeneity. Robot adoption reduced employment and wages in exposed US commuting zones, with effects concentrated in locations where the technology substituted for routine tasks [5]. Earlier computerization research found that technological change altered the demand for abstract, non-routine and manual tasks in different directions [1]. Job polarization research linked the decline of middle-skill routine work to the interaction between technology, offshoring and occupational structure [10]. At the same time, the race between education and technology suggests that human capital can shape the distribution of gains [11]. The evidence therefore rejects both technological determinism and the assumption that aggregate productivity automatically becomes shared prosperity.

Generative AI changes the exposure map because it can affect non-routine cognitive tasks that earlier waves of automation reached less effectively. Felten, Raj and Seamans construct occupational, industry and geographic exposure measures that distinguish technical applicability from realized adoption [12]. The ILO's global work on generative AI similarly emphasizes that exposure is not equivalent to job loss because augmentation, automation and institutional mediation operate simultaneously [13]. The challenge is to combine exposure measures with capability measures that capture whether workers and firms can use the technology productively. The wider literature reinforces the need for this distinction. Frank and co-authors stress that AI research requires better longitudinal and spatial data on tasks, skills and institutional mechanisms [18]. Surveys of AI's effects on firms and consumers emphasize that productivity, competition and distribution are jointly determined [19]. The "wrong kind of AI" argument warns that automation without new task creation can weaken labor demand [20].

Prediction-based systems may create value only when organizations redesign decision rights and workflows [21]. The growth implications depend on the interaction among capital accumulation, labor supply and the direction of innovation [23]. Historical evidence cautions against treating each technological wave as either uniquely destructive or automatically benign [24]. Work is continuously recomposed across tasks, which makes occupational labels an imperfect measure of exposure [25]. Social skills, digital organization and human interaction can become more valuable even when technical tasks are automated [26,27]. Exposure estimates based on computerizability remain useful benchmarks, but they are not measures of realized adoption [28]. International development reports likewise emphasize that technology changes the nature of work through institutions, skills and social protection [29,30]. The OECD Skills for Jobs database provides a practical bridge between occupational exposure and skill imbalance, while ILOSTAT supplies harmonized labor-market outcomes for future panels [31,32].

Productivity, Organization and The Complementarity Problem

The productivity literature emphasizes that general-purpose technologies often require complementary investments in organization, skills, infrastructure and business processes. Information technology's productivity effects were associated with organizational capital and managerial practices rather than hardware alone [14]. The modern productivity paradox similarly reflects the delay between invention, diffusion and complementary innovation [7].

These insights apply to generative AI. Access to a model is not equivalent to effective adoption. Users must know when to delegate, how to verify outputs and how to redesign workflows.

The field evidence is consistent with this complementarity view. In a preregistered experiment, ChatGPT reduced time spent on writing tasks by 40%, raised quality by 18% and compressed the gap between lower- and higher-performing participants [8]. In customer support, AI assistance raised issues resolved per hour by 15% on average, with larger gains among less experienced workers [9]. These results show that assistance can be productivity-enhancing and equalizing within a task environment. They do not establish that national AI readiness improves productivity, because adoption conditions and institutional settings differ across economies.

The Capability-Complementarity Dividend Framework

The CCD framework defines the net economic effect of AI exposure as a function of four elements: exposure, digital capability, human capability and governance. Let E denote the occupation or sector's technical exposure to AI. Let D denote digital infrastructure and usage. Let H denote human capital, training and skill transferability. Let G denote institutions, regulation, worker voice and social protection. The framework's reduced-form relationship is:

$$Y = f(E, D, H, G, E \times D, E \times H, E \times G) + \text{controls} + \text{error}.$$

The framework does not require every interaction to be positive. A high regulatory score may identify legitimate governance, but it may also capture administrative burdens or a country's response to prior problems. A high innovation score may identify productive experimentation, but it may also reflect capital-intensive activity that raises productivity while displacing labor. The key prediction is therefore conditional and potentially nonlinear.

The first hypothesis is that AI preparedness is positively related to productivity before conditioning on the development level because prepared economies combine technology, skills and organization. The second hypothesis is that digital infrastructure and human capital should remain positively associated with productivity when the index is decomposed. The third hypothesis is that innovation and regulation components can diverge from the aggregate relationship because they capture distinct mechanisms. The fourth hypothesis is that the preparedness-productivity relationship can flatten or reverse at high levels of internet use if the index reflects saturation, measurement overlap or institutional constraints. These hypotheses are designed as empirical diagnostics rather than causal claims.

Materials and Methods

Data Sources and Sample Construction

The principal capability measure is the IMF Artificial Intelligence Preparedness Index. The index covers 174 countries and combines four components: digital infrastructure; innovation and economic integration; human capital and labor-market policies; and regulation and ethics [15]. The IMF metadata state that source data are compiled from eight institutions, including the International Labour Organization, the International Telecommunication Union, the United Nations, UNCTAD, the Universal Postal Union, the World Bank and the World Economic Forum [16]. The index is a

2023 cross-section. It is used as an observed capability measure, not as a treatment variable.

Economic and labor outcomes are drawn from the World Bank World Development Indicators. The analysis uses GDP per person employed as the productivity outcome, GDP per capita as a development control, total population as a scale control, internet users as a digital-use measure and modeled unemployment as a labor-market outcome [17-32]. The World Bank data were downloaded through the public API on 20 August 2026. The WDI API's current series for CO2 emissions per capita has changed over time, so the green-transition companion analysis uses the current carbon series excluding LULUCF and documents the archived-series issue in the replication notes.

The country-year data were merged by ISO3 country code. For the 2023 cross-section, the index contains 173 matching country records. Availability varies by outcome. The productivity sample contains 166 non-missing observations, the AI index sample contains 165 non-missing observations, internet use contains 163 non-missing observations and unemployment contains 170 non-missing observations. The maximum estimation sample is therefore smaller than the country count.

Estimation Strategy

The first specification is a descriptive correlation matrix. The second is an ordinary least squares model of log productivity on the composite AIPI score, log GDP per capita and log population. The third replaces the composite index with the four AIPI components. The fourth model's unemployment and internet use as outcomes. The fifth adds an interaction between AIPI and standardized internet use. All standard errors are heteroskedasticity-robust HC3 standard errors.

The models are not causal. The index is measured once, the outcomes are measured in the same broad period and the index is partly constructed from variables related to development. Conditioning on GDP per capita may also introduce over-control or collider concerns. The purpose of the models is to show how the sign and magnitude of relationships change under simple conditioning, not to estimate an exogenous treatment effect.

Reproducibility and Missingness

All data acquisition and analysis code is included in the supporting files. The core scripts are `scripts/download_wdi.py`, `scripts/download_imf_ai_pi_excel.py`, `scripts/analyze_papers.py` and `scripts/extract_results.py`. The code saves raw downloads, a merged analysis file, model summaries, coefficient tables and figures. No simulated observations are used. Missing values are retained as missing and excluded only from the relevant regression through complete-case estimation.

Results and Observations

Descriptive Evidence

The 2023 AIPI mean is 0.476 with a standard deviation of 0.152. The median is 0.465 and the interquartile range is 0.355 to 0.582. Mean GDP per person employed is 58,544 constant 2021 PPP dollars, while the median is 45,002. Mean internet use is 71.3% and the median is 81.8%. Mean unemployment is 6.86% and the median is 5.21%.

Table 1: Descriptive Variables and Source Coverage

Variable	Operational definition	Source	2023 usable observations
AI preparedness	IMF composite AIPI score	IMF, mirrored in World Bank Data360	165
Labor productivity	GDP per person employed, constant 2021 PPP dollars	World Bank WDI	166
Development	GDP per capita, constant 2015 US dollars, log transformed	World Bank WDI	159 in main model
Digital use	Individuals using the internet, percent of population	World Bank WDI	163
Unemployment	Unemployment, total, percent of labor force	World Bank WDI	170
Scale	Total population, log transformed	World Bank WDI	159 in main model

Note: Values are taken from the Acquired Public Data and Reflect Available Observations for the Relevant Specification.

The zero-order AIPI-productivity correlation is 0.802. This large positive association is consistent with the proposition that prepared economies are also more productive. The AIPI-internet correlation is 0.760, which confirms that the composite index is closely related to digital access and usage. The AIPI-unemployment correlation is -0.217. This negative association is economically plausible but should not be interpreted as evidence that AI preparedness reduces unemployment, because high-preparedness countries differ systematically in education, industrial structure, demographics and labor-market institutions.

Conditional Productivity Models

In the baseline productivity model, the AIPI coefficient is -0.956 with a robust standard error of 0.417 and a p-value of 0.022. The model contains 159 observations and has an R-squared of 0.912. The reversal from a positive zero-order correlation to a negative conditional coefficient illustrates the danger of interpreting a composite readiness score as a structural productivity effect. Once GDP per capita and population are included, the remaining variation in AIPI may capture dimensions that do not map monotonically into labor productivity, or it may reflect multicollinearity and measurement overlap.

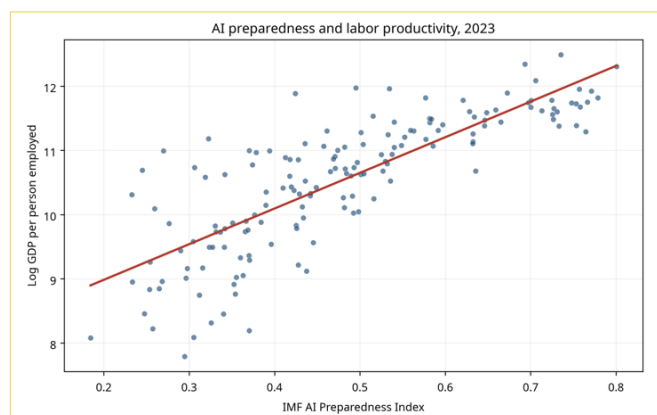


Figure 1: AI Preparedness and Labor Productivity, 2023

The component regression is more informative than the aggregate score. The digital-infrastructure component has a coefficient of 4.814 with a robust standard error of 1.548. The human-capital and labor-market component has a coefficient of 4.718 with a standard error of 1.599. Both are positive in the conditional diagnostic. The innovation and economic-integration component have a coefficient of -3.630 and the regulation-and-ethics component has a coefficient of -6.559. The component model has an R-squared of 0.937.

These component results are not evidence that innovation or regulation harm productivity. The four components are highly correlated, the index is a cross-section and the coefficients are identified from residual variation after conditioning on GDP per capita and population. The substantive result is instead that the composite score conceals different mechanisms. Digital access and human capital appear to be productivity complements, while innovation and regulatory dimensions may reflect adjustment costs, capital intensity, prior policy failures or measurement conventions. A stronger paper would estimate these mechanisms using repeated firm and worker data.

Interaction with Digital Use

The interaction model includes AIPI, standardized internet use, their interaction, log GDP per capita and log population. The AIPI main effect is -0.759 with a standard error of 0.415 and a p-value of 0.067. The interaction coefficient is -0.534 with a standard error of 0.237 and a p-value of 0.024. The interaction is negative rather than positive.

The negative interaction does not falsify the CCD framework. It is consistent with a non-monotonic version of the framework in which internet access is a necessary but insufficient complement. At high levels of connectivity, additional readiness may be associated with saturation, adjustment costs or institutional frictions. It may also reflect the fact that high-income countries have more complete digital measurement and more mature labor-market institutions, making simple cross-sectional comparisons difficult. The result therefore motivates threshold models and panel designs rather than a claim of a universal positive complementarity dividend.

Labor-Market Diagnostic

The unemployment model yields an AIPI coefficient of -22.460 with a standard error of 6.773 and a p-value below 0.001. The R-squared is 0.138 and the sample contains 160 observations. The large coefficient is not a plausible causal estimate. The index ranges over a narrow interval, the model omits many labor-market determinants and the data are contemporaneous. The value of the estimate is diagnostic: the cross-sectional relationship between national preparedness and unemployment is not captured by the productivity model alone. A full test of the CCD framework must examine wages, employment transitions, occupational composition, worker training and within-country distributional outcomes.

Discussion

The evidence supports a qualified conclusion. AI preparedness

is strongly associated with productivity and digital use in raw cross-country data, but this association is largely entangled with development level. Conditioning on GDP per capita changes the sign of the composite preparedness coefficient. Decomposing the index reveals positive relationships for digital infrastructure and human capital alongside negative relationships for innovation and regulation components. The interaction between preparedness and internet use is also negative.

The contribution is therefore not the claim that AIPI causes productivity. The contribution is the demonstration that a one-dimensional readiness score is not an adequate economic theory. The economic meaning of readiness depends on which component changes, which outcome is considered and whether the analysis is about average productivity, unemployment or distribution. A country may be digitally connected but weak in skills. It may be innovative but concentrated in capital-intensive sectors. It may regulate AI intensively because it has already experienced social harms. A composite score cannot distinguish these pathways without a mechanism-based decomposition.

The results also clarify the policy implication of the CCD framework. Digital infrastructure and human capital are likely to be necessary complements, but they are not sufficient for inclusive growth. Policy should therefore evaluate AI programs through a balanced scorecard that tracks productivity, employment, wage dispersion, training access, worker voice, model reliability and firm diffusion. The relevant policy unit is not only the country. It is the firm, occupation, region and worker transition.

Three limitations are important. First, the AIPI is a single-year measure. Second, the World Bank outcomes are national aggregates with heterogeneous definitions and missingness. Third, the cross-sectional regressions cannot separate selection, reverse causality and common development factors. The paper does not claim a causal effect and should not be used to forecast employment or GDP.

The next empirical step is a repeated country-sector-occupation panel. Occupation exposure scores can be mapped to ILO or national labor-force survey employment shares. Firm-level AI adoption can be measured with enterprise surveys, job postings or administrative data. Training, collective bargaining and worker consultation should be measured directly. The resulting design could use pre-period task exposure, staggered enterprise adoption or policy discontinuities to estimate capability-conditioned effects.

Conclusion

This paper proposes the Capability-Complementarity Dividend framework for analyzing AI's economic effects. The framework treats exposure, digital capability, human capital and governance as interacting layers. In a 2023 global baseline, raw AI preparedness is strongly correlated with labor productivity, but the conditional relationships are heterogeneous and partly reverse sign. The finding is a warning against headline rankings and a call for mechanism-based measurement.

A credible AI-growth strategy should not ask only whether a country is ready. It should ask ready for what, through which capability and with what distributional consequence. The answer requires more granular data than a composite index. The present paper provides a transparent baseline, a reproducible data pipeline and a framework for that next generation of research.

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