

# AI Diffusion and Productivity Divergence in Developing Economies

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## Abstract

Will the AI revolution accelerate income convergence between developing and developed economies, or will it exacerbate global inequality? Optimists point to leapfrogging; developing economies can bypass technological stages by adopting cutting-edge AI, while skeptics cite absorptive capacity constraints; insufficient human capital prevents the productive deployment of frontier technologies. Existing research focuses on AI's impact in advanced economies through domestic R&D and disembodied diffusion, neglecting the international trade channel which has historically been the primary channel for developing economies to adopt new technologies. We address this gap by providing the first empirical test of the impact of AI diffusion, through the embodied import channel, on productivity growth across the income distribution. In doing so, we (i) create a novel concordance bridging bilateral trade data and AI exposure metrics, (ii) use it to construct a measure of AI-embodied technology diffusion, and (iii) employ this measure to empirically test for leapfrogging and absorptive capacity constraints in a balanced panel of 47 countries from 2012-2022. We find no evidence of leapfrogging: developing economies show no higher marginal returns to AI-embodied diffusion, rather, GDP growth effects are null for both income groups. We find evidence of absorptive capacity constraints: human capital acts as a binding constraint on translating AI-embodied diffusion into productivity gains. Thus, AI-embodied diffusion may operate as a force for divergence rather than convergence in global income.

**Keywords:** Artificial Intelligence, Technology Diffusion, Economic Development, Productivity Growth, International Trade

**JEL Classification:** O33, O14, F14, F62

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# 1 Introduction

The rapid emergence of Artificial Intelligence (AI) as a General Purpose Technology (GPT) has reignited a fundamental debate: will the Fourth Industrial Revolution accelerate income convergence between developing and developed economies, or will it exacerbate it? AI, defined in this paper as systems focused on replicating or exceeding human capabilities for specific singular tasks such as image recognition, made its leap from theoretical research to commercial application starting roughly in 2012. It offers countries worldwide opportunities for productivity gains, economic growth, and innovation across various sectors, but also poses risks such as widening inequality and competitive disadvantages for developing economies that lack the infrastructure and capital necessary to adopt AI technologies at scale.

Historically, industrial revolutions have represented critical junctures, enabling some countries to catch up with advanced economies, while causing others to fall further behind. South Korea was able to rapidly industrialize during the ICT revolution by directly adopting cutting-edge technologies, experiencing what some call a productivity miracle. Advocates of AI's equalizing potential point to the leapfrogging hypothesis—the idea that developing nations can bypass intermediate stages of technological development, like extensive landline infrastructure, and move directly to advanced technologies, like mobile networks (Steinmueller, 2001). On the other hand, skeptics who believe AI will widen global inequality point to the concentration of AI capabilities among wealthy nations, arguing that the digital infrastructure and human capital required to effectively adopt AI create barriers too high for most developing countries to overcome—a phenomenon captured by Nelson Phelps's absorptive capacity hypothesis (Nelson and Phelps, 1966; Keller, 2004). Without sufficient absorptive capacity, developing economies will fail to integrate these technologies as advanced economies do, leading to further divergence in global income.

With limited historical AI adoption data given its relative novelty, this question has been difficult to empirically test. Existing literature has largely focused on AI's impact in advanced economies, where domestic R&D creation and disembodied channels of technological diffusion drive technological progress. However, developing economies are technology users rather than creators; for these nations, the capacity installed is the capacity imported (Keller, 2004; Lipcsey, 2025). Standard metrics of innovation such as patents or domestic R&D stocks therefore fail to capture the reality of AI diffusion in developing economies, who rely primarily on R&D spillovers through international trade in technology-embodied capital and intermediate goods to adopt new technologies. Despite this critical distinction, there remains a significant gap in empirical work quantifying the productivity impacts of AI diffusion through the international trade channel, and comparing these effects across developing

and developed economies. This analysis is essential for assessing whether AI will widen or narrow global income inequality, as well as informing policy implications to help developing economies harness the potential of AI while mitigating its risks.

This paper addresses this gap by providing the first empirical test of the impact of AI diffusion through the international trade channel on economic and productivity growth across the global income distribution. In doing so, we make three novel contributions to the literature on technological diffusion and economic development.

First, we introduce a novel measure of AI-embodied technology diffusion. Building on the methodology of [Caselli and Coleman \(2001\)](#) for measuring computer adoption via imports, we construct a measure of AI-embodied imports per worker to proxy for AI diffusion. Our methodological innovation involves a multi-step concordance that maps bilateral trade flows to industry-level AI exposure scores (AIIE) developed by [Felten et al. \(2021\)](#). This represents our second contribution; the first of its kind to link international trade data with AI exposure estimates. Third, we utilize this measure within a balanced panel of 47 countries spanning 2012–2022 to provide the first empirical test of the effect of embodied AI diffusion on economic and productivity growth. By comparing impacts across developing and developed economies, we directly test the competing leapfrogging and absorptive capacity hypotheses in the context of the AI revolution.

Our results paint a bleak picture of the potential distributional effects of the AI revolution. First, we reject the leapfrogging prediction: we find no statistically significant evidence that developing economies benefit from a higher marginal return to AI-embodied technology diffusion within our sample. Instead, the short-run effect on GDP growth is statistically null for both income groups, consistent with the modern productivity paradox commonly associated with General Purpose Technologies ([Brynjolfsson et al., 2017](#)). Second, we demonstrate that absorptive capacity acts as the binding constraint on translating AI diffusion into productivity gains. Our Total Factor Productivity (TFP) growth regressions reveal a positive and statistically significant interaction effect between AI diffusion and a country’s human capital, implying that the marginal productivity of AI-embodied imports is strictly increasing in the domestic skill base. High-income countries, endowed with high levels of complementary skills, are better positioned to absorb and translate the new embodied technologies into TFP growth, while lower-income countries face a two-fold disadvantage: limited resources to purchase AI-embodied imports at scale, and more importantly, insufficient human capital to effectively translate these imports into productivity gains.

Our findings suggest that the current structure of AI-embodied technology diffusion operates as a force for divergence rather than convergence in global income inequality.

**Related Literature** Our work sits at the intersection of three strands of the literature: the determinants of cross-country differences in income and productivity growth, international technology diffusion through trade, and the economic impacts of AI.

Cross-country income differences are primarily explained by differences in Total Factor Productivity (TFP) rather than factor accumulation, with technology playing a primary role in determining productivity (Hall and Jones, 1999; Easterly and Levine, 2001). TFP, the residual contribution to output that cannot be explained by inputs like labor and capital (Solow, 1957), captures the efficiency with which inputs are combined, and serves as a measure of the technology level in an economy, represented by the term  $A$  in a standard Cobb-Douglas production function  $Y = AK^\alpha L^\beta$ . Other measures of technology include patents and R&D expenditures (Griliches, 1998; Keller, 2004). Understanding changes in TFP sheds light on the potential for developing economies to catch up to rich ones. Following standard practice to avoid spurious influences and simultaneity bias in growth regressions (Keller, 2004), we focus our analysis on TFP growth rather than levels.

The literature identifies domestic technical change (R&D creation) and international technology transfer (R&D spillovers) as the major determinants of TFP growth. Most of the world’s creation of new technology is concentrated in a handful of rich countries (Keller, 2004). In terms of AI innovation, the US and China have been identified as the “AI Frontier” (Goldfarb and Treffer, 2018; Lipcsey, 2025; Maslej et al., 2025). For most nations, especially for developing economies who are technology *users* rather than inventors, foreign technology sources account for 90% or more of productivity growth (Keller, 2004), with the contribution of international R&D spillovers far exceeding the effects of domestic R&D (Acharya and Keller, 2007). International R&D spillovers occur when technology investments by one country boost productivity for in another country, as firms learn and benefit from the knowledge embodied in these technologies. Foreign technology diffuses through three main channels: (1) international trade of intermediate and capital goods ("embodied diffusion") coupled with FDI; (2) research collaboration; and (3) inter-firm knowledge transfers—where the latter 2 constitute “disembodied diffusion”(Lipcsey, 2025; Keller, 2004).

There is ample theoretical and empirical evidence that embodied diffusion through international trade is the primary source of technology diffusion, especially for smaller economies (Xu and Wang, 1999; Caselli and Coleman, 2001; Eaton and Kortum, 2001). Canonical models of endogenous growth in open economies predict that trade facilitates access to a wider variety of specialized intermediate inputs, increasing TFP (Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991), while Buera and Oberfield (2020) model how the growth of a country’s stock of knowledge (TFP) is a direct function of its import trade shares and the stocks of knowledge of its trading partners. Empirical work has substantiated this link. Coe

and Helpman (1995) show that a country’s TFP is positively related to the R&D stocks of its trading partners, weighted by import shares, while Ayerst et al. (2023) demonstrate that import-weighted stocks of frontier knowledge significantly increase patenting in importing countries. Amiti and Konings (2007) find that a 10% fall in input tariffs leads to a productivity gain of 12% for firms that import their inputs. Overall, the evidence highlights the significant role of imports in international technology diffusion.

This strong precedent has led researchers to use imports of embodied technology as a proxy for that technology’s adoption or diffusion. Caselli and Coleman (2001) pioneer this methodology to study computer diffusion across countries from 1970–1990, arguing that computers represented an ideal embodied technology; a country could not adopt the technology without physically importing the equipment. Since most countries did not produce computers, the capacity installed was directly measured by the imports of computer equipment per worker. Their findings robustly link computer adoption to manufacturing trade openness and high levels of human capital. Castellani et al. (2022) extended this approach to Industry 4.0 technologies across European countries between 2009–2019, measuring the adoption of Advanced Manufacturing Technologies (AMTs) via import flows of AMT-embodied capital goods. They demonstrate that imports serve as a highly correlated and robust proxy for adoption. This approach is the methodological foundation for our measure of AI diffusion.

Importantly, there are huge differences in how effective countries are in adopting foreign technologies (Keller, 2004). The absorptive capacity hypothesis argues that the mere availability of foreign technology is insufficient; a country requires a threshold level of human capital and R&D competence to adopt these technologies (Nelson and Phelps, 1966). Eaton and Kortum (1996) show that inward technology diffusion is increasing in the level of a country’s human capital, a finding consistent with Xu (2000), and demonstrated by Caselli and Coleman (2001)’s finding of a positive correlation between computer imports and human capital. Conversely, the leapfrogging hypothesis (Steinmueller, 2001; Gerschenkron, 1962) suggests poor countries could gain comparatively more from technological transfer, as they can bypass stages of development to immediately adopt the newest, most productive tools. Empirical evidence from the ICT revolution suggests the ability to leapfrog remains mixed across developing nations (Niebel, 2018).

AI, characterized as the Fourth Industrial Revolution, witnessed its commercial birth circa 2012 (Agrawal et al., 2017). We adopt the definition of “narrow AI” provided by Felten et al. (2021): systems designed to replicate specific human capabilities, such as pattern recognition, perception, or reasoning, rather than general intelligence. Given the scarcity of historical adoption data, researchers have increasingly relied on “AI exposure” estimates, notably the AI Industry Exposure (AIIE) and AI Occupation Exposure (AIOE) indices con-

structed by [Felten et al. \(2021\)](#). These estimates have been used to assess labor market dynamics and productivity effects in advanced economies, finding a modern productivity paradox: despite significant AI investments, aggregate GDP growth effects have yet to materialize ([Brynjolfsson et al., 2017, 2021](#)), likely due to the typical disruptive, short-run adjustment costs typical of GPTs. Empirical evidence for developing economies remains sparse and divided. Optimistic strands of the literature suggest AI integration into global value chains may facilitate leapfrogging ([Kouka and Magalles, 2022; Delera et al., 2022](#)), while other strands suggest a structural disadvantage for developing economies, who have significantly lower AI exposure than their high-income counterparts ([Demombynes et al., 2025](#)). [Lipcsey \(2025\)](#) identifies international trade through global value chains as a channel for AI diffusion in developing economies, noting the difficulty of quantifying this channel due to the imprecision of current global value chain data. We aim to solve this problem.

To summarize, four core insights from the literature provide a clear foundation for our analysis: (i) international R&D spillovers are a major determinant of TFP growth; (ii) international trade of technology-embodied goods is the primary diffusion channel for developing economies; (iii) imports of technology-embodied goods serve as a valid proxy for that technology’s diffusion; and (iv) productivity effects are heterogeneous, contingent upon domestic absorptive capacity. Despite these insights, no research examines AI through the lens of international trade. This likely stems from the absence of specific customs classifications for “AI-embodied” goods. Existing research focuses on AI’s productivity impacts in advanced economies through domestic R&D creation and disembodied diffusion, neglecting embodied diffusion—a dominant channel for technological change in developing economies. To our knowledge, no empirical work quantifies AI diffusion’s productivity impacts through the international trade channel, nor compares these effects across the income distribution. We address this gap with a novel methodological framework that bridges trade statistics and AI exposure metrics, making three specific contributions to the technology diffusion and development literature.

First, we create a novel concordance linking bilateral trade data to AI exposure estimates to identify the “AI knowledge” content of trade flows. By mapping the Central Product Classification (CPC) to [Felten et al. \(2021\)](#)’s AI Industry Exposure (AIIE) estimates, and filtering for capital and intermediate goods, we isolate the volume of embodied technology imports that are highly “exposed” to AI technologies, distinguishing AI-embodied imports from general embodied imports. Second, we leverage this concordance to construct a precise measure of AI-embodied technology diffusion, adopting [Caselli and Coleman \(2001\)](#) and [Castellani \(2022\)](#)’s approach. Based on [Maslej et al. \(2025\)](#)’s identification of the US and China as the “AI Frontier”, we restrict our measure to AI-embodied imports per worker

originating from these leading innovators. Third, we provide the first empirical test of the effect of AI-embodied diffusion on TFP growth and GDP growth using a balanced panel of 47 countries (2012–2022). Our empirical strategy employs country and year fixed effects to control for unobserved heterogeneity. By stratifying our sample into Low-Income (LIC), Lower-Middle-Income (LMIC), and High-Income (HIC) groups, we directly test whether embodied AI diffusion facilitates convergence through leapfrogging, or whether absorptive capacity constraints are rendering it a driver of cross-country divergence.

**Outline.** The remainder of this paper proceeds as follows. Section 2 describes the data used in our analysis. Section 3 presents the conceptual framework that guides our empirical analysis. Section 4 describes our empirical strategy and specifications. Section 5 discusses the estimation results. Section 6 concludes.

## 2 Data

We construct a balanced panel to analyze the impact of embodied AI diffusion on economic and productivity growth. Our dataset integrates bilateral product-level trade flows from the United Nations Comtrade database ([United Nations, nd](#)), industry-level AI exposure estimates from [Felten et al. \(2021\)](#), and macroeconomic indicators from the Penn World Table ([Feenstra et al., 2015](#)) and World Bank World Development Indicators ([World Bank, nda](#)). We employ a series of crosswalks to create a novel concordance linking trade classifications to AI exposure metrics, and use this to construct our measure of AI-embodied imports per worker. We briefly describe the data and concordances below and leave the remaining details of the data collection and variable construction to Appendix A.

**Sample description.** Our final estimation sample consists of a balanced panel of 47 countries observed annually from 2012 to 2022, yielding 517 observations. The start date was chosen to align with the widely cited “commercial birth” of modern AI ([Agrawal et al., 2017](#)). We restrict our analysis to 47 countries (16 LIC, 13 LMIC, and 18 HIC) that maintained consistent trade reporting standards throughout the period (See Appendix A). The HIC group is included to establish a comparative baseline for the convergence analysis. To prevent look-ahead bias, we stratify countries into income groups based strictly on their GNI per capita for Fiscal Year 2012 ([World Bank, nda](#)). We define developing economies as those in the LIC and LMIC groups, and developed economies as the HIC group.

**Bilateral trade data.** Data on bilateral imports from the US and China (the AI frontier) to our sample of 47 countries were sourced from the UN Comtrade database ([United Nations, nd](#)), using the CPC Ver2.1 classification, in thousands of current USD. By restricting to imports from the AI frontier, we isolate imports most likely to embody cutting-edge AI knowledge, as these countries account for the vast majority of global AI innovation and R&D investment [Maslej et al. \(2025\)](#); [Lipcsey \(2025\)](#). We focus specifically on imports of capital and intermediate goods, which constitute embodied technology.

**AI Industry Exposure (AIIE) data.** To measure the AI content of the imported capital and intermediate goods, we utilize the AI Industry Exposure (AIIE) estimates developed by [Felten et al. \(2021\)](#). The AIIE is a granular metric constructed by mapping ten distinct AI applications (e.g., image recognition, language modeling, instrumental analysis) to 52 occupational abilities defined in the O\*NET database. By aggregating these ability-level scores up to the industry level, the AIIE measures the degree to which an industry’s inputs and outputs are exposed to AI advances. The underlying scores are standardized as Z-scores with a global mean of 0 and standard deviation of 1. A positive score indicates an industry (and its associated embodied technology) is more AI-intensive than the global average (e.g., Semiconductors, Industrial Robots), while a negative score indicates domination by standard vintage technologies (e.g., Basic Machinery, Standard Textiles).

**Concordances between classifications.** A central methodological contribution of this paper is the construction of a novel concordance mapping trade data to AI exposure estimates. Since bilateral trade flows are reported in the CPC classification, and Felten’s AIIE estimates are indexed to the North American Industry Classification System (NAICS 2017), we required a crosswalk between CPC and NAICS to get AIIE estimates for each CPC category. No official crosswalk exists. We overcome through a multi-step concordance strategy. First, we employ a BEC to CPC concordance to filter the raw CPC data to include only capital and intermediate goods. Second, since there is no official concordance between CPC to NAICS, we first map CPC codes to the International Standard Industrial Classification Revision 4 (ISIC Rev. 4), and then map ISIC Rev. 4 codes to NAICS 2017, using official UN crosswalk tables for both ([World Bank, ndb](#)). All classifications are applied at the maximum level of disaggregation to minimize aggregation bias and noise. This process allowed us to assign a precise AIIE score to each category of imported capital/intermediate good, creating the first concordance that maps CPC trade data directly to AI exposure estimates.

**Macroeconomic variables.** Macroeconomic controls and dependent variables were drawn from standard sources. We measure economic growth using Real GDP per capita (constant 2015 USD) from the WDI (World Bank, [nda](#)). Total Factor Productivity (TFP) is sourced from PWT version 11.0 (Feenstra et al., 2015). Other variables include human capital, investment rate, population growth, trade openness, and rule of law. See Appendix A for a full description of all variables.

**Construction of the AI Diffusion proxy.** We use our CPC to AIIE concordance to construct our primary independent variable  $AI\_Diffusion_{it}$ . We follow Caselli and Coleman (2001)’s approach in constructing a measure of AI-embodied capital and intermediate good imports per worker to proxy for AI diffusion. It’s important to note that Caselli and Coleman validated computer imports as a robust proxy for computer diffusion under the premise that computers are the physical embodiment of computing technology. Extending this logic to AI is not straightforward. Unlike computers, which are a distinct and tangible hardware category, AI is a GPT with significant disembodied components such as algorithms and open-source software that can diffuse across borders without physical trade. We acknowledge that omitting these disembodied flows excludes a major vector of AI diffusion. Nevertheless, we restrict our focus to the embodied channel for two reasons: (i) as discussed in the literature review, embodied technology imports are a primary channel for technology diffusion in developing economies; (ii) for developing economies, the effective deployment of AI software often necessitates complementary physical capital, such as advanced semiconductors, sensors, and automated machinery, which must be imported from the technological frontier. Therefore, we explicitly interpret this measure as AI-embodied diffusion rather than total AI adoption, reflecting that it captures the hardware-intensive component of AI diffusion.

We construct our measure as follows. Let  $M_{ikt}^{US+CN}$  denote the value of imports of capital and intermediate good  $k$  by country  $i$  from the United States and China (the AI Frontier) in year  $t$ . Let  $AIIE_k$  denote the normalized, time-invariant AI Industry Exposure score for good  $k$ . The AI diffusion proxy is calculated as:

$$AI\_Diffusion_{it} = \frac{\sum_k (M_{ikt}^{US+CN} \times AIIE_k)}{L_{it}} \quad (1)$$

where  $L_{it}$  is the total labor force of country  $i$  at year  $t$ . Intuitively, this formula weighs each imported good by its AI intensity (captured by  $AIIE_k$ ), sums across all goods, and normalizes by the workforce to capture AI-embodied imports per worker. The numerator thus represents the total “AI knowledge” embodied in a country’s capital and intermediate

goods imports from the technological frontier.

Table 1: Summary Statistics by Income Group (2012–2022)

Variable	Full Sample (All)	Low Income (LIC)	Lower-Middle (LMIC)	High Income (HIC)
<i>Dependent Variables</i>				
$\Delta \ln \text{RGDP pc}$ (Annual %)	1.86 (3.35)	2.23 (3.25)	2.25 (3.93)	1.25 (2.88)
$\Delta \ln \text{TFP}$ (Annual %)	-0.23 (2.76)	-0.59 (3.53)	-0.46 (3.53)	0.10 (1.35)
<i>Primary Independent Variables</i>				
<b>AI Embodied Imports / Worker</b> (USD)	<b>747,847</b> (1,054,950)	<b>58,202</b> (60,946)	<b>209,576</b> (167,995)	<b>1,749,615</b> (1,116,940)
Total Capital Imports / Worker (USD)	1,541,358 (2,208,144)	152,281 (188,723)	506,663 (410,357)	3,523,373 (2,483,762)
<i>Control Variables</i>				
Human Capital Index (1-4)	2.56 (0.83)	1.84 (0.55)	2.22 (0.43)	3.45 (0.23)
Investment Rate (% of GDP)	23.90 (6.03)	25.70 (7.26)	24.09 (7.02)	22.42 (3.34)
Trade Openness (% of GDP)	75.35 (34.48)	64.17 (30.35)	71.33 (33.39)	87.00 (34.88)
Rule of Law (-2.5 to 2.5)	0.20 (1.11)	-0.67 (0.35)	-0.55 (0.40)	1.51 (0.48)
Population Growth (Annual %)	1.48 (1.11)	2.38 (0.76)	1.72 (0.98)	0.50 (0.54)
<b>Observations</b>	<b>517</b>	<b>176</b>	<b>143</b>	<b>198</b>

*Notes:* Means are reported with standard deviations in parentheses. The sample consists of a balanced panel of 47 countries over the period 2012–2022. Income groups are stratified based on 2010 GNI per capita (World Bank FY2012 classifications). “AI Embodied Imports” refers to the value of capital and intermediate goods imported from the US and China, weighted by their AI Industry Exposure (AIIE). “Total Capital Imports” refers to the unweighted value of the same basket.

Table 1 presents summary statistics by income group. A striking disparity is immediately evident in our primary measure of interest: HICs import, on average, over 30 times more AI-embodied technology per worker (\$1,749,615) than LICs (\$58,202). When comparing these figures to total embodied imports per worker, we note a difference in composition. While HICs import roughly 23 times more total embodied technology per worker than LICs (\$3.52M vs. \$0.15M), the ratio for AI-embodied technology is higher (approximately 30 times), suggesting that high-income countries disproportionately import AI-intensive technologies. The table also reveals differences in complementary inputs: the average Human Capital Index is 3.45 for HICs, compared to 1.84 for LICs.

To further describe these patterns, we present two figures visualizing the trends over time and the cross-sectional relationship with human capital.

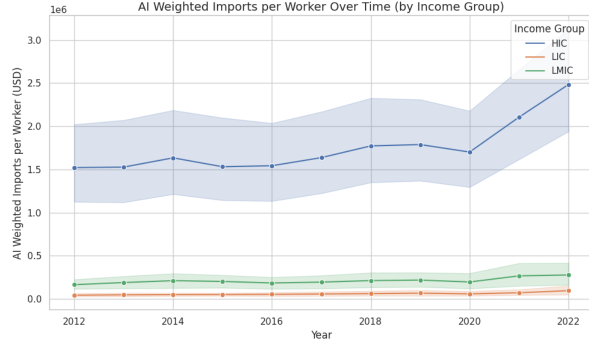


Figure 1: Evolution of AI-Embodied Technology Imports

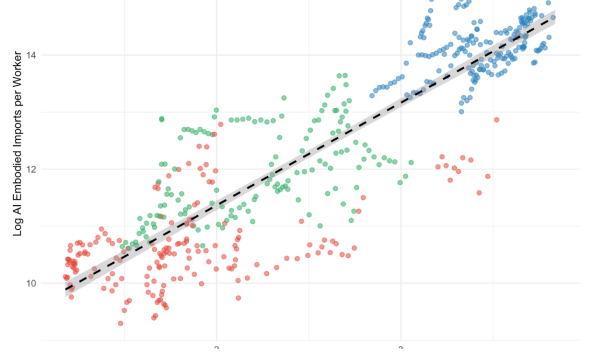


Figure 2: AI Diffusion vs. Human Capital

Figure 1 plots the average value of AI-embodied imports per worker for each income group over the sample period. The data show an upward trend in AI-embodied imports across all three groups since around 2015. However, the slope of the trajectory differs markedly by income level: HICs exhibit a steep increase in AI-embodied imports, particularly after 2015, while the trends for LICs and LMICs remain comparatively flatter throughout the period. Figure 2 displays the cross-sectional relationship between the Human Capital Index and the log of AI-embodied imports per worker, showing a positive correlation. We observe distinct clustering by income group: HICs (blue) are largely located in the upper-right quadrant, corresponding to higher human capital and higher AI-embodied imports, while LICs (red) are concentrated in the lower-left quadrant.

### 3 Conceptual Framework

We describe a conceptual framework drawing on two theoretical perspectives in the technology diffusion and development literature to guide our empirical analysis: the leapfrogging hypothesis and the absorptive capacity hypothesis. These frameworks motivate our analysis of the effect of AI-embodied technology diffusion on economic growth and productivity growth across the income distribution.

#### 3.1 Leapfrogging: Vintage Capital and Economic Growth

The leapfrogging hypothesis, rooted in [Gerschenkron \(1962\)](#)’s theory of economic backwardness, posits that developing countries can bypass intermediate stages of technological development by directly adopting the most advanced technologies. [Steinmueller \(2001\)](#) applies this insight to ICT, arguing that latecomers can “leapfrog” over earlier technological gen-

erations. In the context of embodied technology, this insight is formalized through vintage capital theory. Consider an aggregate production function where output depends on both the quantity and quality (vintage) of technology-embodied inputs:

$$Y_{it} = A_{it}K_{it}(v_{it})^\alpha L_{it}^{1-\alpha} \quad (2)$$

where  $v_{it}$  represents the average vintage (quality) of technology-embodied capital and intermediate goods. In this framework, newer embodied technology incorporates superior capabilities, such that  $\frac{\partial Y}{\partial v} > 0$ —a unit of frontier embodied technology is more productive than a unit of older vintage. For developing countries importing AI-embodied capital and intermediate goods, this creates the potential for leapfrogging. By directly importing state-of-the-art AI-intensive machinery, semiconductors, components, and equipment from the technological frontier (US and China), late adopters can access inputs of higher average vintage ( $v$ ) than developed countries, whose stocks include substantial legacy equipment and components. If the marginal product of high-vintage technology is sufficiently large, this should drive faster transitional growth in GDP per capita, enabling convergence toward the income frontier.

The key theoretical prediction is that the marginal product of frontier technology should be higher for developing economies than for developed economies. Late adopters face a larger technology gap and benefit more from accessing cutting-edge embodied technology, while early adopters experience diminishing returns as they approach the technology frontier.

### 3.2 Absorptive Capacity: Human Capital and Productivity Growth

The absorptive capacity hypothesis, developed by [Nelson and Phelps \(1966\)](#), offers a complementary perspective on technology diffusion. This framework argues that the mere availability of advanced technology is insufficient for productivity growth; countries must possess adequate human capital to absorb and deploy foreign technologies effectively. Let  $T(t)$  denote the world technology frontier—the maximum achievable TFP using best-practice techniques, defined in our context by the US and China AI frontier. Let  $A_{it}$  represent the actual TFP level in country  $i$ . According to [Nelson and Phelps \(1966\)](#), TFP growth depends on the “gap” to the frontier and the “absorptive capacity” (proxied by human capital,  $H$ ) to close that gap:

$$\frac{\dot{A}_{it}}{A_{it}} = \Phi(H_{it}) \left[ \frac{T_t - A_{it}}{A_{it}} \right] \quad (3)$$

where  $\Phi'(H) > 0$ . Countries with higher education levels can more rapidly absorb foreign technologies and close the gap to the frontier. The standard Nelson-Phelps formulation assumes that education ( $H$ ) alone drives technological catch-up through domestic innovation

and imitation. However, [Alvarez et al. \(2013\)](#) argue that international trade is the mechanism through which producers in developing countries access superior technologies. Synthesizing these perspectives, we modify the absorptive capacity function to depend on both human capital and technology imports:

$$\Phi(\cdot) = f(H_{it}, AI\_Diffusion_{it}) \quad (4)$$

In this extended framework, AI-embodied imports serve as the *vehicle* through which frontier technology  $T(t)$  physically enters the domestic economy, while human capital  $H_{it}$  acts as the *decoder* that determines how effectively this embedded knowledge translates into productivity gains. The mechanism operates through two complementary channels. First, AI-embodied imports expose domestic firms to state-of-the-art capabilities embedded in frontier capital and intermediate goods ([Alvarez et al., 2013](#)). Second, the rate at which these imports translate into TFP growth depends critically on human capital ([Nelson and Phelps, 1966](#)). Without sufficient  $H$ , firms cannot effectively reverse-engineer, adapt, or deploy the complex technologies embedded in AI-intensive imports.

This framework yields two key predictions. First, the effectiveness of technology imports should be increasing in human capital: countries with higher  $H$  should derive greater TFP growth from the same volume of imports. Second, for countries with very low  $H$ , foreign technology may remain underutilized or misallocated, potentially generating no productivity gains—or even negative effects if adoption imposes learning costs that exceed immediate benefits. Importantly, this hypothesis suggests that absorptive capacity, not capital vintage, is the binding constraint on technology diffusion. Even if developing countries import state-of-the-art AI-embodied capital and intermediate goods, they may fail to translate these imports into productivity or output growth without the complementary human capital needed to operate, maintain, and adapt complex technologies.

These two theoretical frameworks generate contrasting predictions about the distributional effects of AI-embodied technology diffusion. The leapfrogging hypothesis predicts that developing countries should experience higher marginal returns to frontier technology, driving convergence in the global income distribution. The absorptive capacity hypothesis predicts that productivity gains depend critically on human capital, implying divergence as high-skill countries benefit while low-skill countries fail to productively deploy imported technologies. Our empirical strategy tests both mechanisms by examining effects on economic growth and productivity growth across the income distribution.

## 4 Empirical Specification

We translate the theoretical frameworks outlined in Section 3 into econometric specifications. The first tests the leapfrogging hypothesis by examining whether AI-embodied imports accelerate economic growth, with particular attention to differential effects across the income distribution. The second tests the absorptive capacity hypothesis by investigating whether the productivity effects of AI-embodied imports depend on human capital.

### 4.1 Economic Growth Specification

Our first specification examines the impact of AI-embodied imports on real GDP per capita growth. Following [Niebel \(2018\)](#), we estimate an augmented Solow growth model that isolates the contribution of AI-embodied technology from general capital accumulation:

$$\Delta \ln y_{it} = \beta_0 + \beta_1 \ln y_{i,t-1} + \beta_2 \ln AI\_Diffusion_{it} + \beta_3 \ln Embodied_{it} + \beta_4 \ln I_{it} + \mathbf{X}'_{it}\Gamma + \alpha_i + \delta_t + \epsilon_{it} \quad (5)$$

where  $\Delta \ln y_{it}$  is the annual growth rate of real GDP per capita for country  $i$  in year  $t$ , and  $\ln y_{i,t-1}$  is the lagged log GDP per capita, capturing conditional convergence. Our primary variable of interest is  $\ln AI\_Diffusion_{it}$ , the log of AI-embodied imports per worker constructed in Section 2. A positive and significant coefficient ( $\beta_2 > 0$ ) would indicate that AI-embodied imports shift the production frontier outward, driving transitional growth.

To isolate the AI-specific effect, we include two critical controls. First,  $\ln Embodied_{it}$  denotes the log of non-AI embodied imports per worker (general capital and intermediate goods imports), controlling for the effect of standard technology diffusion. Second,  $\ln I_{it}$  is the log investment rate, controlling for domestic capital accumulation. By including both,  $\beta_2$  captures the excess growth premium associated specifically with the AI content of imports, testing whether AI-embodied technology offers a “vintage capital” premium over standard embodied technology. The vector  $\mathbf{X}_{it}$  includes standard growth controls: human capital index, population growth, trade openness (log), and rule of law ([Mankiw et al., 1992](#)). We include country fixed effects ( $\alpha_i$ ) to control for time-invariant country characteristics and year fixed effects ( $\delta_t$ ) to absorb common macroeconomic shocks. Standard errors are clustered at the country level.

To directly test the leapfrogging hypothesis, we estimate Equation (4) separately for developed (HIC) and developing (LIC/LMIC) economies. The leapfrogging hypothesis predicts that  $\beta_2$  should be significantly larger for developing countries than for developed countries ( $\beta_2^{Dev} > \beta_2^{HIC}$ ), reflecting higher marginal returns to frontier technology for late adopters.

Given AI’s status as a GPT, we anticipate short-run adjustment dynamics. As documented by [Brynjolfsson et al. \(2017\)](#), GPTs typically exhibit a “J-curve” pattern which shows a modern productivity paradox. This suggests we may observe limited effects on aggregate economic growth during our 2012–2022 sample period, even if countries are beginning to absorb frontier knowledge at the productivity level.

## 4.2 Productivity Growth Specification

Our second specification tests the absorptive capacity hypothesis by examining how human capital moderates the effect of AI-embodied imports on TFP growth:

$$\Delta \ln TFP_{it} = \alpha + \lambda \ln TFP_{i,t-1} + \gamma_1 H_{it} + \gamma_2 \ln AI\_Diffusion_{it} + \gamma_3 (H_{it} \times \ln AI\_Diffusion_{it}) + \mathbf{Z}'_{it} \beta + \alpha_i + \delta_t + \epsilon_{it} \quad (6)$$

where  $\Delta \ln TFP_{it}$  is the annual TFP growth rate, and  $\ln TFP_{i,t-1}$  is lagged log TFP, capturing the catch-up dynamic in the Nelson-Phelps framework. The crucial term is the interaction  $H_{it} \times \ln AI\_Diffusion_{it}$ , where  $H_{it}$  is the human capital index. The absorptive capacity hypothesis predicts  $\gamma_3 > 0$ : countries with higher human capital should derive greater TFP growth from the same volume of AI-embodied imports. The main effect  $\gamma_2$  captures the average effect of AI-embodied imports at mean human capital levels, which may be zero or negative if the typical country in our sample lacks sufficient absorptive capacity to productively deploy frontier technologies. The vector  $\mathbf{Z}_{it}$  includes general embodied imports (log) and trade openness (log) to ensure we capture AI-specific rather than general trade-induced productivity effects. We again include country and year fixed effects, with standard errors clustered at the country level.

## 5 Results

This section presents our main empirical findings. We first examine the impact of AI-embodied imports on economic growth, testing the leapfrogging hypothesis through split-sample regressions across developed and developing economies. We then investigate the role of absorptive capacity by analyzing how human capital moderates the productivity effects of AI-embodied technology diffusion.

**Economic Growth: Testing the Leapfrogging Hypothesis** Table 2 presents estimates of our augmented Solow growth specification (Equation 4), examining the impact of

AI-embodied imports on real GDP per capita growth. Column (1) reports results for the full panel, while Columns (2) and (3) stratify the sample into developed (HIC) and developing (LIC/LMIC) economies to test for heterogeneity in returns to AI-embodied technology diffusion.

In the full sample (Column 1), we find no statistically significant relationship between AI-embodied imports and economic growth. The coefficient on  $\ln AI\_Diffusion_{it}$  is small and statistically indistinguishable from zero ( $\beta_2 = -0.017, p > 0.10$ ). Importantly, this null result persists even while controlling for general embodied imports ( $\ln Embodied_{it}$ ) and domestic capital accumulation ( $\ln I_{it}$ ), both of which exhibit positive point estimates. This lack of an immediate growth dividend is consistent with the short-run productivity paradox we anticipated in Section 4 (Brynjolfsson et al., 2021). Our results suggest that during the 2012–2022 period, the global economy remained in the “installation phase” of AI technology, where the costs of diffusion had been incurred but aggregate GDP effects had not yet emerged.

Columns (2) and (3) provide a direct test of the leapfrogging hypothesis. The leapfrogging prediction posits that late-adopting economies should experience higher marginal returns to frontier technology than early adopters ( $\beta_2^{Dev} > \beta_2^{HIC}$ ). We find no evidence supporting this hypothesis. The coefficient for developing economies is negative and statistically indistinguishable from zero ( $\beta_2 = -0.015, p > 0.10$ ), providing no evidence of a “catch-up” premium. While the coefficient for developed economies is positive ( $\beta_2 = 0.013$ ), it also lacks statistical significance. We therefore reject the leapfrogging hypothesis: AI-embodied imports do not appear to offer developing countries a unique opportunity to bypass technological stages and accelerate convergence during our sample period.

However, a structural divergence emerges in the control variables that foreshadows our TFP results. For developed economies, the human capital index is a positive and statistically significant driver of growth ( $\beta = 0.101, p < 0.05$ ). In contrast, human capital is insignificant for developing economies. This pattern suggests that while developed nations possess the complementary skills to leverage new technologies, developing nations may lack the absorptive capacity to translate imported technology into economic growth—precisely the mechanism we test in our TFP specification.

**Productivity Growth: The Role of Absorptive Capacity** Table 3 examines the mechanism underlying our null GDP growth results by testing the absorptive capacity hypothesis. We estimate the determinants of TFP growth, explicitly interacting our AI-embodied imports measure with the human capital index. The results provide strong empirical support for the absorptive capacity hypothesis in the context of AI technology diffusion.

The interaction term ( $H_{it} \times \ln AI\_Diffusion_{it}$ ) is positive and statistically significant

Table 2: Impact of AI Diffusion on Real GDP per Capita Growth (2012–2022)

<b>Dependent Variable:</b> $\Delta \ln \text{RGDP}_{pc}$	(1) <b>Full Sample</b>	(2) <b>Developed (HIC)</b>	(3) <b>Developing (LIC/LMIC)</b>
$\ln \text{AI Embodied Imports}_{it}$	-0.017 (0.029)	0.013 (0.047)	-0.015 (0.028)
$\ln \text{General Embodied Imports}_{it}$	0.038 (0.028)	0.026 (0.052)	0.035 (0.027)
$\ln \text{Initial Income}_{i,t-1}$	-0.163*** (0.027)	-0.189* (0.092)	-0.168*** (0.036)
$\ln \text{Investment Rate}_{it}$	0.014 (0.010)	0.009 (0.028)	0.012 (0.012)
$\text{Human Capital Index}_{it}$	-0.019 (0.027)	0.101** (0.048)	-0.048 (0.036)
$\ln \text{Trade Openness}_{it}$	0.042* (0.022)	0.001 (0.024)	0.053* (0.029)
$\text{Rule of Law}_{it}$	0.001 (0.011)	-0.027 (0.017)	-0.006 (0.020)
$\text{Population Growth}_{it}$	-0.010*** (0.003)	-0.004 (0.004)	-0.012 (0.009)
Observations	434	180	254
R-squared (Within)	0.227	0.807	0.649
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

*Notes:* Clustered standard errors (by country) in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All specifications include country and year fixed effects. “General Embodied Imports” controls for non-AI capital flows to isolate the AI-specific effect.

( $\gamma_3 = 0.023$ ,  $p < 0.05$ ). This implies that the marginal productivity effect of AI-embodied imports is strictly increasing in a country’s human capital stock. In other words, the ability to translate frontier technology imports into productivity gains is conditional on the domestic skill base. Countries with higher human capital derive greater TFP growth from the same volume of AI-embodied imports, while countries with low human capital experience minimal or no productivity gains.

Critically, the main effect of AI-embodied imports is negative and marginally significant ( $\gamma_2 = -0.139$ ,  $p < 0.10$ ). Interpreted alongside the interaction term, this suggests that for countries at mean human capital levels in our sample ( $H \approx 2.56$ ), the net effect of AI-

embodied imports on TFP growth is initially negative. This is consistent with the GPT adoption literature: importing frontier technologies imposes immediate costs—organizational restructuring, worker retraining, and experimentation—without generating offsetting productivity gains unless firms possess sufficient human capital to absorb and deploy the embedded knowledge. This “adoption penalty” is most severe for low-income countries (where  $H \approx 1.8$ ), while high-income countries (where  $H \approx 3.5$ ) are able to mitigate these costs through their superior human capital stocks.

By contrast, the control for general embodied imports is positive and marginally significant ( $\beta = 0.094$ ,  $p < 0.10$ ), consistent with the standard view that capital deepening boosts productivity. The distinct behavior of AI-embodied imports—imposing a penalty that is mitigated only by high human capital—highlights the unique challenge that frontier AI technologies pose for developing economies. Unlike standard capital goods, AI-embodied technologies require substantial complementary skills to translate into productivity improvements.

Table 3: TFP Growth and Absorptive Capacity (2012–2022)

<b>Dependent Variable:</b> $\Delta \ln \text{TFP}_{it}$	(1) <b>Full Sample</b>
<b>Interaction (<math>H_{it} \times \ln \text{AI Imports}_{it}</math>)</b>	<b>0.023**</b> <b>(0.008)</b>
$\ln \text{AI Embodied Imports}_{it}$ (Main Effect)	-0.139* (0.066)
Human Capital Index $_{it}$	-0.377** (0.107)
$\ln \text{General Embodied Imports}_{it}$	0.094* (0.055)
$\ln \text{Initial TFP}_{i,t-1}$	-0.308*** (0.066)
$\ln \text{Trade Openness}_{it}$	0.007 (0.028)
Observations	374
R-squared (Within)	0.193
Country FE	Yes
Year FE	Yes

*Notes:* Clustered standard errors (by country) in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . The dependent variable is the annual growth rate of Total Factor Productivity (TFP). The interaction term tests whether the effect of AI imports on TFP depends on the level of human capital.

**Discussion** Our findings paint a concerning picture of AI-embodied technology diffusion’s distributional effects. We reject the leapfrogging hypothesis: developing economies do not benefit from higher marginal returns to frontier technology. Instead, we find strong evidence for the absorptive capacity hypothesis: human capital acts as the binding constraint on translating AI-embodied imports into productivity gains. Taken together, these results suggest that so far, AI-embodied technology diffusion operates as a force for divergence rather than convergence in the global income distribution. High-income countries, endowed with complementary skills, are positioned to absorb frontier technologies and translate them into TFP growth. Low-income countries face a dual disadvantage: limited resources to purchase AI-embodied imports at scale, and insufficient human capital to productively deploy the technologies they do import. Rather than enabling catch-up growth, AI-embodied diffusion in its current form reinforces existing inequalities in the global economy.

## 6 Conclusion

This paper set out to answer a fundamental question: will AI diffusion be a force for convergence or divergence in global income? We provide the first empirical test of this question by examining the impact of AI diffusion through the international trade channel on economic and productivity growth across the global income distribution—the primary channel through which developing countries access frontier technologies. We make three key contributions: First, we construct a novel concordance linking bilateral trade data to AI exposure estimates, creating the first measure that isolates AI-embodied capital and intermediate goods imports from general technology flows. Second, we leverage this concordance to construct a measure of AI-embodied imports per worker as a proxy for AI diffusion, following [Caselli and Coleman \(2001\)](#)’s validated methodology. Third, using a balanced panel of 47 countries from 2012 to 2022, we provide empirical evidence on the effect of embodied AI diffusion on economic and productivity growth across the income distribution, testing for the leapfrogging and absorptive capacity hypotheses.

Our findings reveal a concerning answer to the question motivating this paper. We reject the leapfrogging hypothesis: AI-embodied imports do not offer developing countries the opportunity to bypass technological stages and accelerate convergence, as South Korea did during the ICT revolution. Instead, we find no significant GDP growth effects for either developed or developing economies during our sample period, consistent with the short-run productivity paradox associated with General Purpose Technologies (GPTs). However, our TFP growth results uncover the mechanism underlying this divergence. We find strong empirical support for the absorptive capacity hypothesis articulated by [Nelson and Phelps](#)

(1966): the productivity gains from AI-embodied imports depend critically on human capital. The positive and statistically significant interaction between AI imports and human capital indicate that only countries with higher skill bases can translate frontier technology into TFP growth. Importantly, the negative main effect of AI imports suggests that for countries with average or below-average human capital, importing frontier AI technologies imposes adoption costs without offsetting productivity gains. Rather than the equalizing force envisioned by leapfrogging advocates, AI-embodied technology diffusion operates, at least in the short run, as a force for divergence: high-income countries with complementary skills capture productivity gains while low-income countries bear costs without benefits, reinforcing the very inequalities that proponents hoped AI might help overcome.

**Policy Implications** Our findings carry three important implications for policymakers. First, simply importing AI-intensive goods is insufficient without complementary investments in human capital. Policies facilitating AI adoption must be coupled with investments in education and technical training to build absorptive capacity. Second, our results highlight the limits of technology transfer as a standalone development strategy, pointing to the need for targeted industrial policies that bundle technology imports with organizational restructuring and worker training. Third, without policy intervention, AI diffusion may reinforce rather than reduce global inequality, underscoring the urgency of international cooperation to ensure equitable access to both AI technologies and the complementary inputs needed to deploy them productively.

**Limitations and Future Research** Several limitations of our analysis point toward important directions for future research. First, our measure captures AI-embodied imports using industry-level AI exposure estimates from Felten et al. (2021) rather than direct measures of AI adoption. This approach is necessitated by the lack of customs classifications for “AI-embodied” goods and limited historical AI adoption data. While the AIIE estimates provide a validated proxy for AI intensity across industries, they capture potential exposure to AI technologies rather than actual deployment. As more granular data on AI adoption become available, future research should validate our findings using direct measures of AI capital stocks and utilization rates. Second, we focus exclusively on embodied diffusion, omitting disembodied channels such as cloud services, open-source algorithms, and knowledge transfers that play an increasingly important role in AI diffusion. Our estimates therefore represent a lower bound on total AI diffusion and may understate the productivity effects for countries that leverage disembodied channels effectively. Future work should develop comprehensive measures capturing both channels. Third, our analysis faces standard

endogeneity concerns that challenge causal interpretation. Countries that import more AI-embodied technologies may differ systematically from non-importers in unobservable ways that also affect productivity growth. While our country fixed effects control for time-invariant heterogeneity and our controls address observable confounders, reverse causality and omitted variable bias remain potential concerns. Future research could employ shift-share instrumental variable strategies to establish causal effects more definitively. Finally, our 2012–2022 sample captures only the early installation phase of AI and misses the large language model revolution beginning in late 2022. Extended time horizons can examine whether productivity effects emerge with longer lags. Data limitations also restrict our sample to 47 countries, limiting statistical power for detecting heterogeneous effects within income groups.

Despite these limitations, our analysis provides the first systematic evidence that AI-embodied technology diffusion through international trade operates, at least in the short run, as a force for divergence rather than convergence in the global income distribution. The mechanism is clear: human capital acts as the binding constraint on translating frontier AI technologies into productivity gains. High-income countries, endowed with complementary skills, are positioned to absorb and deploy AI-embodied imports productively. Low-income countries face a dual disadvantage: limited resources to import at scale and insufficient absorptive capacity to benefit from the technologies they do import. Without policy intervention to build human capital and facilitate effective technology deployment, AI diffusion risks reinforcing rather than reducing global income inequality in the decades ahead.

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# Appendix

## A Data

### A.1 Sample Composition

Our final estimation sample consists of a balanced panel of 47 countries observed annually from 2012 to 2022, stratified into income groups based on their 2010 GNI per capita following World Bank Fiscal Year 2012 classifications.<sup>1</sup> We restrict our analysis to 47 countries (16 LIC, 13 LMIC, and 18 HIC) that maintained consistent trade reporting standards throughout the period. Data gaps in the excluded sample appear uncorrelated with the timing of AI technology shocks. To prevent look-ahead bias, we stratify countries into income groups based strictly on their GNI per capita for Fiscal Year 2012 ([World Bank](#), [nda](#)). This ensures that our classification is exogenous to subsequent growth trajectories observed during the sample period, mitigating the endogeneity that would arise if countries were selected or classified based on ex-post economic outcomes.

**Low-Income Countries (LIC, n=16):** Burkina Faso, Cambodia, Ethiopia, Gambia, Kyrgyz Republic, Lao PDR, Madagascar, Malawi, Mozambique, Nepal, Niger, Rwanda, Tanzania, Togo, Uganda, Zimbabwe.

**Lower-Middle-Income Countries (LMIC, n=13):** Bolivia, Cote d'Ivoire, Egypt, El Salvador, Fiji, Guatemala, India, Indonesia, Mauritania, Nigeria, Senegal, Vietnam, Zambia.

**High-Income Countries (HIC, n=18):** Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Korea (Rep.), Netherlands, New Zealand, Norway, Poland, Spain, Sweden, Switzerland, United Kingdom.

### A.2 Variable Definitions and Data Sources

Table 4 provides detailed descriptions of all variables used in our empirical analysis, including data sources, units of measurement, and sample coverage.

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<sup>1</sup>World Bank country classifications as of July 1, 2011: Low Income (LIC): GNI per capita \$1,005 or less; Lower-Middle Income (LMIC): GNI per capita between \$1,006 and \$3,975; High Income (HIC): GNI per capita of \$12,276 or more.

Table 4: Variable Definitions and Data Sources

Variable	Source	Description	Unit/Scale	N
<i>Dependent Variables</i>				
GDP per Capita (Real)	WDI	GDP per capita at constant prices. Primary measure of economic output and growth.	Constant 2015 US\$	517
GDP per Capita (PPP)	WDI	GDP per capita adjusted for purchasing power parity. Robustness measure for standard of living.	Constant 2021 Intl \$	517
Total Factor Productivity	PWT 11.0	TFP at constant national prices. Measures productive efficiency and technology level.	Index (2017=1)	429
<i>Primary Independent Variables</i>				
AI Embodied Imports per Worker	UN Comtrade, Felten et al. (2021)	Value of capital and intermediate goods imported from US and China, weighted by AI Industry Exposure scores, normalized by labor force.	Current US\$ per worker	517
General Embodied Imports per Worker	UN Comtrade	Total value of capital and intermediate goods imports (unweighted by AI exposure), normalized by labor force.	Current US\$ per worker	517
<i>Control Variables</i>				
Investment Rate	WDI	Gross fixed capital formation as share of GDP. Measures domestic capital accumulation.	% of GDP	478
Human Capital Index	PWT 11.0	Index of human capital per person, based on years of schooling and returns to education. Measures workforce skill.	Index	517
Population Growth	WDI	Annual population growth rate. Controls for capital dilution in growth regressions.	Annual %	517
Trade Openness	WDI	Sum of exports and imports as share of GDP. Measures economy’s integration with global markets.	% of GDP	489
Rule of Law	WGI	Perceptions of quality of contract enforcement, property rights, police, courts.	−2.5 to +2.5	517
Labor Force	PWT 11.0	Number of persons engaged in economic activity. Used as denominator for per-worker calculations.	Millions	517

*Notes:* WDI = World Bank World Development Indicators. PWT = Penn World Table. WGI = Worldwide Governance Indicators. N refers to total observations across all 47 countries and 11 years (2012–2022).

### A.3 Control Variable Justification

Our empirical specifications follow standard practices in the cross-country growth literature, drawing on two major traditions: the Augmented Solow Model (Mankiw et al., 1992) and Barro-style reduced-form growth regressions (?).

From the Augmented Solow framework, we include: (1) *Initial Income* to test for conditional convergence; (2) *Physical Capital Investment* to capture capital deepening; (3) *Human Capital* as a critical factor input; and (4) *Population Growth* to control for capital dilution effects.

From the Barro tradition, we include: (1) *Trade Openness*, identified by [Sachs and Warner \(1995\)](#) and subsequent literature as a robust growth determinant; and (2) *Rule of Law* as a proxy for institutional quality, following ?’s findings on governance and growth.

The robustness literature ([Levine and Renelt, 1992](#); [Sala-i Martin, 1997](#)) confirms that investment, human capital, trade openness, and institutions are among the most robust correlates of economic growth across alternative specifications.

## B Concordance Methodology

### B.1 Multi-Step Mapping Procedure

A central methodological contribution of this paper is the construction of a novel concordance linking bilateral trade data (Central Product Classification, CPC) to industry-level AI exposure estimates (North American Industry Classification System, NAICS 2017). No official crosswalk between these systems exists.

**Step 1: Filtering for Embodied Technology.** We employ the Broad Economic Categories (BEC) classification to filter raw CPC data, retaining only capital and intermediate goods while excluding final consumption goods.

**Step 2: CPC to ISIC Rev. 4.** We map CPC codes to the International Standard Industrial Classification Revision 4 (ISIC Rev. 4) using official World Bank concordance tables ([World Bank, ndb](#)).

**Step 3: ISIC Rev. 4 to NAICS 2017.** We then map ISIC Rev. 4 codes to NAICS 2017 codes using official concordance tables. To align industry definitions, we selected the dominant (modal) ISIC division associated with each NAICS two-digit sector in the Statistics Canada concordance. Where multiple ISIC divisions mapped to a single NAICS sector, we retained the most frequently occurring mapping. This approach minimizes double-counting while maintaining consistency with cross-national datasets such as OECD STAN and WIOD.

**Step 4: Assigning AI Exposure Scores.** We assign [Felten et al. \(2021\)](#)’s AI Industry Exposure (AIIE) scores to each CPC product category via the NAICS codes. Where a single

CPC category mapped to multiple NAICS industries, we assigned the unweighted mean of the associated AIIE scores, following standard practices for harmonizing trade and industry classifications ([Acemoglu et al., 2020](#)).

## B.2 Treatment of Missing AI Exposure Values

Upon constructing our master concordance, 35.2% of CPC-to-NAICS linkages (5,060 rows) were missing AIIE scores. This missingness is non-random and stems from the construction methodology of [Felten et al. \(2021\)](#), which aggregates occupation-level AI exposure scores from the U.S. O\*NET database. O\*NET primarily surveys civilian, market-based occupations; consequently, industries with sparse O\*NET coverage lack calculated AIIE scores.

**Hierarchical Imputation Strategy.** We implement a hierarchical imputation approach grounded in the assumption that a 4-digit sub-industry’s occupational composition is best proxied by its 3-digit parent industry. This practice is standard in applied economics when merging datasets of differing aggregation levels ([Autor et al., 2013](#)).

Our imputation proceeds in two stages:

1. *3-Digit Parent Imputation:* For a 4-digit NAICS industry with missing AIIE, we impute the mean AIIE score of its 3-digit NAICS parent.
2. *2-Digit Sector Imputation:* If the 3-digit parent average is also missing, we escalate to the 2-digit NAICS sector average.

This process successfully imputed 4,809 rows. The remaining 251 unresolved rows correspond entirely to NAICS Sector 92 (Public Administration). These industries are systematically out-of-scope for the O\*NET-based measure. Given our focus on AI diffusion via international trade, the removal of these non-market, largely non-traded functions is appropriate. Our final concordance excludes these 251 observations, yielding 14,142 product-industry linkages.