AI Readiness, Adoption, and Productivity: Firm-Level Evidence from Low- and Middle-Income Countries*

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Abstract

Can firms in developing economies translate readiness for artificial intelligence (AI) into higher productivity and greater AI adoption? This paper develops the Firm-Level AI Enablement Index (FAEI), a composite measure of Power Reliability, Digital Connectivity, Human Capital, and Institutional Environment. Using World Bank Enterprise Survey data for 44,251 firms across 76 low- and middle-income economies and a 2026 follow-up covering 3,579 firms in seven economies, the analysis examines the relationship between readiness, adoption, and productivity. The findings are as follows. First, the FAEI is strongly associated with labour productivity. A 0.1 increase in FAEI is associated with 11.5 percent higher sales per worker, conditional on country, sector, and survey-year fixed effects. Second, Human Capital shows the strongest positive association among the four pillars, followed by Power Reliability and Digital Connectivity. Third, FAEI is not consistently associated with AI adoption. However, firm-level digital practices, particularly website presence and electronic payments, are positively associ-

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ated with AI adoption and several measures of AI engagement. Fourth, AI adoption is not significantly associated with productivity in the 2026 follow-up and readiness is no more strongly associated with productivity in industries with greater AI exposure. These findings highlight the heterogeneity between the capabilities associated with firm productivity and practices associated with AI adoption. For developing economies, strengthening Human Capital and foundational digital capabilities may be important priorities for improving firm performance and supporting AI adoption.
Keywords: AI readiness, labour productivity, firm-level index, developing countries, AI adoption, enterprise surveys

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1. Introduction

Artificial intelligence (AI) is widely expected to transform production and raise productivity across economies (Brynjolfsson et al., 2021, 2025). The magnitude and timing of these gains, however, remain uncertain. Acemoglu (2025) estimates that AI will increase total factor productivity by less than 1 percent over the next decade. Historical experience also suggests that technological advances do not translate automatically into productivity growth (David, 1990). More generally, firms benefit from new technologies when they possess the skills, infrastructure, and organisational capacity needed to integrate them into production (Brynjolfsson et al., 2021). These complementary capabilities are particularly relevant in developing economies, where firms often face constraints in physical infrastructure, human capital, digital connectivity, and institutional support (Cirera and Maloney, 2017; World Bank, 2019). These constraints motivate the growing use of national AI readiness indices, which assess the enabling conditions for AI development and adoption across economies (Oxford Insights, 2023; Cazzaniga et

al., 2024). Yet national readiness measures leave an important firm-level question unresolved. Do the conditions associated with higher productivity also determine whether firms adopt AI? Answering this question is important because technological readiness does not translate into technological adoption.

Descriptive evidence reveals substantial differences in labour productivity between firms with higher and lower levels of readiness. Firms in the top third of the Firm AI Enablement Index (FAEI), developed in this paper, have 41.7 percent higher sales per worker than firms in the bottom third of the index within the same economy. The difference is positive in 62 of the 76 economies, and the productivity distributions shift towards higher values as readiness increases (Table A.1; Figure 1). The corresponding trend for AI adoption is considerably weaker. In a 2026 follow-up survey, the share of firms reporting AI adoption increases only from 31.8 percent in the bottom third of the FAEI distribution to 34.8 percent in the top third. By contrast, AI adoption is more common among firms with stronger digital business practices, rising from 24.9 percent among firms in the bottom third of the website-and-electronic-payments measure to 43.3 percent among those in the top third (Table A.1). Cross-country comparisons further highlight this heterogeneity. Thailand and Malaysia have similar average FAEI scores in the follow-up sample, 0.70 and 0.71. However, their reported AI adoption rates are 11.7 and 73.4 percent respectively. Kenya and Nigeria have lower average readiness scores, 0.59 and 0.60, but report adoption rates of 42.0 and 42.4 percent (Table A.2). Understanding this heterogeneity requires firm-level evidence which National AI readiness indices fall short of determining, for example whether firm characteristics that are associated with productivity differ from those associated with AI adoption.

Existing literature measure firm-level AI engagement using different sources, including surveys in individual countries (Calvino and Fontanelli, 2026), patent data (Zeng et al., 2025), company websites (Pastor-Merino et al., 2026), and firms-level surveys (Udomsaph, 2025). While these literatures provide useful insights, they offer limited scope for examining firm readiness, productivity, and AI adoption across a large sample of developing economies. This paper addresses this gap by constructing the Firm AI Enablement Index (FAEI) from the World Bank Enterprise Surveys. The index combines four pillars, namely Power Reliability, Digital Connectivity, Human Capital, and the Institutional Environment. Its conceptual structure draws on the IMF AI Preparedness Index and the Oxford Insights Government AI Readiness Index, adapted to the firm level using comparable Enterprise Survey measures. Power Reliability is included as an additional pillar. Unreliable power supply is among the most binding constraints on firms in developing economies (Allcott et al., 2016; Cole et al., 2018). The analysis combines Enterprise Survey data for 44,251 firms across 76 low- and middle-income economies, surveyed between 2022 and 2026, with a 2026 follow-up that collected information on AI adoption and use from 3,579 firms in seven economies. The analysis addresses three questions. First, how strongly is firm AI readiness associated with labour productivity? Which readiness dimensions account for the largest associations? Second, which firm-level conditions are associated with AI adoption and use? Third, does the productivity advantage associated with readiness operate through AI adoption?

The findings reveal that firm AI readiness is positively associated with labour productivity, particularly through Human Capital. However, readiness is not significantly associated with AI adoption. Digital business prac-

tices, particularly website presence and electronic payments, are more closely associated with AI adoption. The analysis further reveals no significant evidence that readiness yields higher productivity advantages in AI-exposed industries or that AI adoption is associated with higher productivity. This paper contributes to the literature in the following. First, it develops a firm-level AI readiness index using comparable survey data from 76 low- and middle-income economies. Second, it provides a framework for examining how different firm capabilities relate to productivity and AI adoption. Third, it investigates whether the productivity advantage associated with readiness is linked to AI adoption or industry exposure to AI, distinguishing the role of foundational firm capabilities from potential AI-related productivity gains. The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 presents the conceptual framework of FAEI, Section 4 describes the data, Section 5 presents the empirical strategy, Section 6 reports the results, and Section 7 concludes.

2. Related Literature

2.1. Firm Productivity and Complementary Capabilities

The literature show that productivity varies widely across firms, even within narrowly defined industries. This variation usually reflects differences in management practices, workforce and capital quality, information technology, research and development, and learning-by-doing (Syverson, 2011; Bloom et al., 2019). Firm performance also depends on the external environment, including competitive pressures and the quality of the business environment, which shape firms' incentives and capacity to improve productivity (Syverson, 2011; Bloom et al., 2019). These differences in firm

capabilities are particularly pronounced in developing economies. Hsieh and Klenow (2009) document substantially larger productivity gaps among manufacturing plants in China and India than in the United States. Such disparities highlight the importance of both firms' internal capabilities and the external conditions that shape their productive capacity. The same factors also determine the returns to technological investment. Historical evidence on electrification and research on general-purpose technologies show that productivity gains from new technologies often require complementary investments in organisational change, business processes and intangible assets (David, 1990; Brynjolfsson et al., 2021). This perspective is particularly relevant to artificial intelligence (AI), whose productivity implications depend not only on access to the technology but also on firms' capacity to integrate it into their operations.

In developing economies, the ability to make these complementary investments is shaped by constraints in infrastructure, finance and institutional capacity. For example, literature show that unreliable electricity reduces manufacturing output (Allcott et al., 2016), while the arrival of fast internet has increased employment in many African economies (Hjort and Poulsen, 2019). Evidence from 54 economies further shows that financial and institutional constraints disproportionately hinder the growth of smaller firms, while financial and legal development ease these constraints (Beck et al., 2005). These external conditions shape firms' capacity to invest in technology, while the productivity gains from such investments also depend on firms' internal capabilities. Bresnahan et al. (2002) show that information technology, workplace reorganisation and skilled labour are complementary inputs into productivity. Acemoglu and Restrepo (2018) demonstrate that the effects of automation depend on its interaction with the tasks workers

perform. The literature therefore points to two interrelated dimensions of firm-level technological capability—the external conditions that enable investment and the internal capabilities that support the productive use of technology.

2.2. AI Readiness, Adoption, and Firm Performance

A growing literature links AI adoption to firm performance. Studies of Spanish and French firms find that AI adopters outperform non-adopters. Adopters also tend to have complementary digital capabilities, including ICT skills, digital infrastructure and experience with other digital technologies (Pastor-Merino et al., 2025; Calvino and Fontanelli, 2026). Part of the performance gap may therefore reflect selection, with firms that have stronger capabilities better placed both to adopt AI and to benefit from it. In developing economies, AI adoption varies widely in both extent and sophistication. Studies using Enterprise Survey and cross-country firm data find that digital readiness is associated with AI adoption in some income groups, and that adoption rates and the use of advanced applications differ across economies (Udomsaph, 2025; Davies et al., 2026). Evidence on other advanced digital technologies adds a further distinction. Firms in lower-income economies use these technologies less intensively, and intensive use is more strongly associated with productivity than initial adoption (Cirera et al., 2026). Whether a firm adopts a technology therefore reveals only part of its capacity to benefit from it.

The literature on general-purpose technologies helps explain this pattern. Productivity gains emerge gradually as firms invest in complementary intangible assets, reorganise production and adapt business processes (David, 1990; Brynjolfsson et al., 2021). The capabilities behind adoption

may therefore differ from those behind productive use. Digital infrastructure and established digital practices can ease uptake (Udomsaph, 2025; Pulito et al., 2026), while workforce skills, managerial capabilities and organisational investments may matter more for integrating new technologies into production (Fontanelli et al., 2025; Cirera et al., 2026). This literature motivates two questions. First, are broad firm-level enabling conditions associated with labour productivity, and which dimensions show the strongest relationships? Second, do the same conditions predict AI adoption, or is adoption more closely associated with specific digital practices?

2.3. Measuring Firm-Level AI Readiness

These questions call for a measure of the enabling conditions that firms face. Two strands of existing work offer partial guidance. The first consists of national AI readiness frameworks. The IMF's AI Preparedness Index and Oxford Insights' Government AI Readiness Index, for example, assess readiness across dimensions such as digital infrastructure, human capital and institutional capacity (Cazzaniga et al., 2024; Oxford Insights, 2023). While these indices are built to compare countries, they cannot distinguish between firms that operate in the same national environment but face different capabilities and constraints.

The second strand measures AI adoption directly at the firm level. Recent studies use web scraping and large language models to detect AI use and its intensity on corporate websites or draw on open-ended survey responses to identify AI use that standard indicators miss (Pastor-Merino et al., 2026, 2025; Udomsaph, 2025). These methods have broadened the evidence on AI diffusion. However, they fail to highlight what conditions enable firms to adopt AI or to turn its use into better performance. In addition, differences

in data sources, geographical coverage and definitions also limit comparisons across studies.

These limitations motivate a firm-level measure of AI readiness that combines the several of national readiness indices with the ability to capture differences across firms within the same economy. Developing such a measure for low- and middle-income economies also requires attention to infrastructure constraints that may limit firms' capacity to deploy technology. In particular, unreliable electricity disrupts business operations and constrains the use of digital technologies, yet national AI readiness frameworks typically capture infrastructure through digital connectivity without treating electricity reliability as a separate dimension. The Firm AI Enablement Index (FAEI) addresses these limitations by measuring enabling conditions at the firm level and incorporating Power Reliability as a distinct dimension of readiness.

3. Constructing the Firm AI Enablement Index

3.1. Conceptual Framework

The Firm AI Enablement Index (FAEI) measures firm-level conditions that may support productive activity and the adoption and use of artificial intelligence (AI). Its conceptual structure draws on the IMF AI Preparedness Index and the Oxford Insights Government AI Readiness Index, which treat infrastructure, human capital and institutional capacity as foundations for AI readiness (Cazzaniga et al., 2024; Oxford Insights, 2023). The FAEI adapts these dimensions to the firm level using indicators from the World Bank Enterprise Surveys (WBES). The index comprises four pillars: Power Reliability, Digital Connectivity, Human Capital and the Institutional En-

vironment. Power Reliability is not part of either national framework. It is included here to reflect one of the most binding constraints on firms in developing economies. Unreliable electricity reduces firm output and sales, particularly for firms without backup generation (Allcott et al., 2016; Cole et al., 2018), and shapes which firms can operate in electricity-intensive sectors (Alby et al., 2013).

The four pillars capture complementary aspects of firms' operating conditions. Power Reliability measures firms' exposure to electricity constraints and their capacity to respond to them. Digital Connectivity captures digital presence, electronic transactions and internet disruptions. Human Capital reflects managerial experience, workforce education and training, alongside reported skills constraints. The Institutional Environment pillar captures regulatory and governance frictions that may affect firms' operations and investment decisions. The FAEI combines these pillars into a composite measure while retaining individual pillar scores for separate analysis. The index measures reported enabling conditions, not AI adoption itself or the productivity gains attributable to AI.

3.2. Pillar Construction and Component Indicators

Each pillar is constructed from firm-level indicators in the WBES. The selection follows the conceptual dimensions of the national readiness frameworks, subject to the availability of comparable firm-level measures. Table A.3 maps each component to its counterpart in the IMF AI Preparedness Index and the Oxford Insights Government AI Readiness Index and lists the WBES obstacles considered but not included.

Power Reliability

The *Power Reliability* pillar comprises three indicators: whether electric-

ity is reported as an obstacle to business operations, whether the firm owns or shares a generator, and whether the firm experiences power outages. The obstacle indicator captures firms' reported electricity constraints, while the outage indicator measures exposure to interruptions. Generator ownership is treated as an indicator of backup capacity. In the developing-economy context, it can reflect firms' efforts to maintain operations when grid electricity is unreliable.

Digital Connectivity

The *Digital Connectivity* pillar comprises three components: whether the firm has a website, the intensity of electronic payments, and whether it experiences internet disruptions. Electronic-payment intensity is calculated as the mean of two measures: the share of sales received electronically, and the share of purchases paid electronically. Each measure is expressed as a percentage of the relevant transactions. The electronic-payment component is calculated when at least one of the two measures is available. It is coded as missing only when both measures are unavailable. The Digital Connectivity pillar is then calculated from the website, electronic-payment, and internet-disruption components, provided that all three are observed.

Human Capital

The *Human Capital* pillar comprises four indicators: the top manager's experience, the share of full-time workers with at least secondary education, the provision of formal training, and the extent to which workforce skills are reported as an obstacle to business operations. These measures capture managerial experience, workforce education, investment in employee training, and firms' perceived skills constraints.

Institutional Environment

The *Institutional Environment* pillar comprises eight indicators. Seven

measure reported obstacles associated with access to finance, corruption, business licensing, tax administration, trade regulation, courts, and labour regulation. The eighth measures the share of senior management's time spent dealing with government regulations. The pillar focuses on selected institutional and regulatory constraints relevant to firms' operating conditions. It does not include every obstacle covered by the WBES. The selection prioritises indicators that align with the conceptual dimensions of the national readiness frameworks and capture institutional frictions relevant to firms' capacity to operate and invest in technology. Summary statistics for all component indicators across the four pillars are reported in Table A.4.

3.3. Normalisation and Aggregation

The variables used for the pillars have different units and scales of measurement. Each variable is therefore transformed using fixed, sample-independent bounds to a common range from zero to one. A score of one represents the most favourable enabling condition under the specified transformation. The transformations are based on the component's scale and direction rather than on the observed sample minimum and maximum. For obstacle variables measured from zero to four, where higher values indicate more severe constraints, the normalised score is calculated as $(4 - x)/4$. Percentage measures for which a higher value indicates greater readiness, including electronic-payment shares and the share of workers with at least secondary education, are divided by 100. Percentage measures for which a higher value indicates lower readiness, such as management time spent dealing with regulation, are transformed as $1 - x/100$.

Positive binary indicators, including website ownership, generator ownership, and formal training, retain their zero-one coding. Negative binary

indicators, including power outages and internet disruptions, are reverse-coded as 1 − x. Managerial experience is divided by 40 and capped at one, giving 40 years or more the maximum normalised score. Among firms reporting experience, 4.7 percent are at or above this 40-year cap, and the median is 15 years. Values outside the specified valid ranges are coded as missing. These checks prevent invalid responses from entering the index and preserve the fixed interpretation of the component scores, under which a given normalised value carries the same meaning across firms and economies.

Within each pillar, the normalised components are combined using an arithmetic mean. A pillar score is calculated only when all its constituent components are observed. Let x_{ij} denote the normalised value of component j for firm i, and let J_p denote the set of components assigned to pillar p. The pillar score is:

$$S_{ip} = \frac{1}{|J_p|} \sum_{j \in J_p} x_{ij} \tag{1}$$

provided that all components in pillar p are observed.

The FAEI is calculated as the arithmetic mean of the available pillar scores:

$$\text{FAEI}_i = \frac{1}{|P_i|} \sum_{p \in P_i} S_{ip}, \qquad |P_i| \geq 3 \tag{2}$$

where P_i is the set of observed pillar scores for firm i. A firm receives a composite score when at least three of the four pillars are available. In the estimation sample, 26,356 firms (59.6 percent) are observed on all four pillars and 17,895 (40.4 percent) on three, with Digital Connectivity the most frequently missing pillar. Equal weighting gives each available pillar the same

influence on the composite score, regardless of the number of components within it. The resulting FAEI ranges from zero to one, with higher values indicating more favourable reported enabling conditions. The composite score summarises the four dimensions. The individual pillar scores are retained to examine whether different dimensions exhibit distinct relationships with firm productivity and AI use.

3.4. Validation and Robustness

The FAEI adapts the conceptual structure of national readiness frameworks to firm-level data, but the two types of measures are not identical. National indices assess readiness at the country level, whereas the FAEI captures variation in firms' reported conditions and practices. The design compares firms operating within and across economies rather than to reproduce national rankings. The construction choices are assessed using alternative aggregation and component specifications. These include a geometric mean, principal-component-based weights, and versions of the index that omit one pillar at a time. Additional checks modify the indicators used for the Institutional Environment pillar, including specifications that use alternative measures of financial and corruption constraints and a broader set of reported obstacles. Further checks exclude the perception-based obstacle items, drop generator ownership from the power pillar, restrict the sample to firms observed on all four pillars, and draw random pillar weights. These exercises assess whether the findings depend on equal weighting, a particular pillar, or specific component choices. The corresponding results are reported with the empirical findings. At the country level, the FAEI correlates with established national measures. The correlation with the IMF AI Preparedness Index is 0.766 across 71 economies and with the Oxford Insights index

0.761 across 106 economies, and among developing economies alone these correlations are 0.550 across 45 economies and 0.551 across 75 economies (Table A.5).

4. Data

4.1. World Bank Enterprise Surveys

The analysis uses the World Bank Enterprise Surveys (WBES),[1] nationally representative surveys of formal private-sector firms. The surveys use harmonised questionnaires and cover manufacturing and services establishments with at least five employees. WBES sampling designs stratify firms by size, sector, and subnational region, supporting comparisons across firms and economies. The estimation sample pools surveys conducted between 2022 and 2026 across 76 economies in five regions. The pooled data span 77 survey rounds, with India observed in two waves that are pooled and weighted as a single economy. The sample comprises 44,251 firms: 11,951[2] in Sub-Saharan Africa (SSA), 7,139 in East Asia and Pacific (EAP), 20,138 in South Asia (SA), 2,288 in the Middle East and North Africa (MENA), and 2,735 in Latin America and the Caribbean (LAC). The analysis is weighted with each economy rescaled to sum to one. This weighting scheme gives each economy equal aggregate weight in the pooled estimates, preventing economies with larger samples from dominating the results. Surveys for 31 advanced economies, covering 22,020 firms with a defined FAEI, are used only for validation and comparison and are not part of the estimation sample.

[1] Microdata are publicly available at https://www.enterprisesurveys.org/.

[2] The FAEI is computed for firms with at least three of the four pillars. This covers 44,251 firms, against 26,356 if all four were required.

4.2. Productivity Measures

The main outcome is labour productivity, measured as the natural logarithm of annual sales per full-time employee, expressed in 2009 US dollars. The measure is drawn from the World Bank Firm-Level Factor Ratios database. It provides a comparable measure of firm performance across the economies in the sample. A separate productivity measure is constructed for the 2026 AI follow-up. It uses firms' reported sales and full-time employment in their highest- and lowest-sales months. Monthly sales per worker are calculated for each of the two months and then averaged, with the resulting values converted to US dollars at each economy's six-month average exchange rate over its survey fieldwork window. The natural logarithm of this measure is used in the 2026 productivity regressions. Jordan is excluded from these regressions, with only four firms reporting the required sales information.

4.3. Firm Characteristics

The productivity regressions include firm characteristics that are commonly associated with differences in firm performance. Firm size is measured as the natural logarithm of full-time employment. Firm age is measured as the natural logarithm of years in operation. These controls account for differences in operating scale and firm maturity. An exporter indicator equals one for firms reporting positive direct exports. A foreign-ownership indicator equals one when foreign equity exceeds 10 percent. The regressions also include indicators for whether the firm has a female top manager and whether it has a female owner. These variables account for differences in firms' export orientation, ownership structure, and management characteristics. Their coefficients are not interpreted as causal effects.

4.4. The 2026 AI Follow-up Survey

In 2026, the World Bank conducted a follow-up survey of firms previously interviewed through the Enterprise Surveys in seven economies. The economies and their baseline survey years are India, Kenya, Nigeria, and Thailand (2025); Jordan and Malaysia (2024); and Mexico (2023). Linking the follow-up responses to earlier interviews through the survey firm identifier allows the analysis to relate AI use in 2026 to firm readiness measured before the reported adoption outcomes. The follow-up asks whether firms use AI and, if so, which of six types they use, ranging from chatbots and generative AI to machine learning, workflow automation, and AI-driven machinery. Additional questions cover the tasks and business functions in which AI is used, whether firms pay for AI, whether they use custom or in-house tools, whether they train workers in AI use, when they first adopted AI, and their expectations about AI's productivity effects. Responses of "don't know" are treated as missing rather than recoded as negative answers. The follow-up sample contains 3,579 firms that answered every AI question used in the main analysis. Follow-up weights are rescaled to sum to one within each economy. A comparison with other firms surveyed in the same economies finds no statistically significant differences in readiness or in baseline labour productivity, where the within-economy difference is 0.049 and statistically insignificant (Table A.6, based on the 3,406 follow-up firms with a baseline productivity measure). This comparison provides some evidence against selection on observed readiness, but it does not rule out selection on other firm characteristics.

The AI outcomes are constructed as follows. *AI adoption* is an indicator equal to one if a firm reports using any AI technology. *Number of AI types* counts the technologies used and ranges from zero to six. It is set to zero for

non-adopters. *Advanced AI use* equals one for firms using machine learning, workflow automation, or AI-driven machinery. Additional binary outcomes identify firms that pay for AI, use custom or in-house AI tools, or provide AI-related training to workers. *Adoption after the baseline interview* equals one for firms that had not adopted AI at baseline but report adopting it in a later month. This outcome is defined only for baseline non-adopters, and firms with an unknown adoption date are excluded. For the AI indicators, missing responses to underlying items remain missing rather than being classified as non-adoption. The follow-up also measures the intensity and scope of AI use among adopters. The *number of AI tasks* counts the tasks in which a firm uses AI, ranging from zero to eight. The *number of business functions* counts the functions in which AI is used, ranging from zero to seven. An *advanced-task indicator* equals one for firms using AI for coding, data analysis, or process control. These measures are defined for adopters who answer all relevant task and function questions. If a response is missing or recorded as "don't know," the corresponding measure is treated as missing rather than zero. Two further outcomes capture expected productivity effects among all firms. The first is an indicator equal to one when a firm expects AI to increase productivity at the current pace of adoption. The second measures the expected percentage change in productivity, with reported increases recorded as positive values, no expected change as zero, and reported decreases as negative values. Reported magnitudes outside the range of zero to 100 percent are coded as missing.

4.5. Website and E-payments and Industry AI Exposure

Several analyses use a website-and-e-payments score, denoted WE, to capture selected digital business practices. The score is the equal-weight

mean of two indicators: whether the firm has a website and the share of purchases paid electronically. Both indicators are expressed on a zero-to-one scale, and the score is calculated when both items are observed. The measure focuses on these two practices rather than the full Digital Connectivity pillar. Section 6.3 examines their relationship with productivity and AI adoption. The analysis also uses industry-level measures of potential exposure to AI. The first is the AI Industry Exposure index developed by Felten et al. (2021). The second is its language-model version (Felten et al., 2023). Both measures use US occupational data to capture the extent to which AI may perform tasks associated with an industry. They measure potential technological exposure, not actual AI adoption by individual firms. Industry exposure scores are mapped to ISIC Revision 4 classes using the US Census Bureau's 2017 NAICS-to-ISIC Revision 4 concordance. Each firm is assigned the score corresponding to the main-product industry reported at its baseline interview. Section 6.5 uses these measures to examine whether the association between readiness and productivity varies with industry AI exposure. Table S1 reports the exposure scores for the ISIC Revision 4 classes represented in the sample and the number of firms in each class.

4.6. Descriptive Statistics

Table 1 presents descriptive statistics. The mean Firm AI Enablement Index (FAEI) is 0.562, with a standard deviation of 0.138. Among the four pillars, the Institutional Environment has the highest mean score (0.715), followed by Digital Connectivity (0.544) and Human Capital (0.532). Power Reliability has the lowest mean score (0.465). These averages indicate substantial variation across the dimensions captured by the index. Readiness also varies across regions. The regional figures show the highest average

readiness in East Asia and Pacific and the lowest in Sub-Saharan Africa (Figure 2). Firms in Sub-Saharan Africa score relatively lower on Power Reliability and Digital Connectivity than on the other readiness dimensions (Figure 3). These patterns highlight the uneven distribution of firm-level enabling conditions across the sample. Firms in developing economies are concentrated at lower readiness than firms in advanced economies (Figure 4). Mean FAEI and pillar scores for each economy and survey wave are reported in Table S2.

The average labour productivity is 9.072, with a standard deviation of 1.775. The typical firm, measured at the geometric mean, has 14.3 full-time employees and has operated for 14.3 years. Services account for 52.1 percent of the sample, retail for 25.8 percent, and manufacturing for 22.1 percent. Direct exporters represent 9.2 percent of firms, while 10.9 percent have foreign ownership exceeding 10 percent. Women hold an ownership stake in 32.8 percent of firms, and 19.6 percent have a female top manager. In the 2026 AI follow-up sample, 33.8 percent of firms report using at least one AI technology, while 15.8 percent use an advanced AI technology. Among firms that had not adopted AI at baseline, 18.4 percent report adoption by the follow-up. The shares of firms that pay for AI, provide AI-related worker training, or use custom or in-house AI tools are 16.2, 15.1, and 13.2 percent, respectively.

5. Empirical Strategy

5.1. Firm Productivity and AI Readiness

The main specification estimates the association between the Firm AI Enablement Index (FAEI) and firm-level labour productivity:

$$\ln(LP_{ict}) = \alpha + \beta\,\mathrm{FAEI}_{ict} + X'_{ict}\gamma + u_c + \lambda_s + v_t + \epsilon_{ict} \tag{3}$$

where LP_{ict} is annual sales per full-time employee, FAEI_{ict} is the index described in Section 3, and X'_{ict} includes firm size, age, export status, foreign ownership, female ownership, and female top-manager status. The specification includes country, sector, and survey-year fixed effects. The OLS regressions are estimated using the high-dimensional fixed-effects estimator of Correia (2016), with standard errors clustered by country (Cameron and Miller, 2015). The analysis also replaces the composite index with its four pillars, entered simultaneously, to examine their respective associations with productivity. Missing pillar values are mean-imputed for this decomposition, with corresponding missingness indicators included to maintain a common estimation sample. For binary AI adoption and use outcomes, the analysis employs linear probability models (LPMs), with country and sector fixed effects and firm-level controls. The same framework is used to examine the associations between individual FAEI components, the website-and-e-payments measure, and AI outcomes. To identify components with consistent predictive value, the analysis applies lasso logistic regression in a leave-one-economy-out procedure. Out-of-sample predictive performance is assessed using the area under the receiver operating characteristic curve (AUC). The industry-exposure analysis estimates OLS models with interactions between readiness measures and industry-level AI exposure. Finally, the 2026 follow-up analysis uses OLS to examine the association between readiness, AI adoption, and the alternative measure of labour productivity.

5.2. AI Adoption and Use

The analysis relates firms' earlier readiness measures to AI outcomes in the 2026 follow-up survey of 3,579 firms across seven economies. Outcomes include AI adoption, advanced AI use, the number of AI types adopted, AI-related training and expenditure, custom or in-house AI, and measures of AI use across tasks and business functions. The analysis also examines firms' expected productivity gains from AI. The regressions include country and sector fixed effects and firm-level controls. With only seven economies in the follow-up at the time of the analysis, inference uses the wild-cluster bootstrap procedure of Roodman et al. (2019), with Webb six-point weights and 999 replications. Missing responses are not treated as non-adoption or non-use.

5.3. AI Exposure and Follow-up Productivity

Two supplementary analyses examine the relationship between readiness, AI exposure, and productivity. First, the productivity specification interacts firm readiness with industry-level AI exposure measures from Felten et al. (2021) and Felten et al. (2023), mapped to ISIC Revision 4 industries. These interactions test whether the association between readiness and productivity varies with industry exposure to AI. Second, the analysis examines productivity in the 2026 follow-up using the logarithm of monthly sales per worker, calculated from the average of firms reported highest- and lowest-sales months. Jordan is excluded, with only four firms reporting sales, leaving 2,969 observations. The paper does not assert causality in all analysis.

6. Empirical Results

6.1. AI Readiness and Labour Productivity

Table 2 shows a strong positive association between the Firm AI Enablement Index (FAEI) and labour productivity. In the preferred specification, which includes country, sector, and survey-year fixed effects alongside firm controls, the FAEI coefficient is 1.087 and is statistically significant at the 1 percent level. The stepwise specifications indicate that accounting for differences across countries explains part of the initial association, while the estimate remains stable after sector and survey-year fixed effects are included. The magnitude is economically meaningful. The estimate shows that a 0.1 increase in the FAEI is associated with 11.5 percent higher sales per worker. The interquartile range of the index, 0.181, corresponds to a productivity gap of 21.7 percent.[3] Figure 1 provides descriptive support for this relationship. The distribution of labour productivity shifts to the right across the bottom, middle, and top FAEI terciles. Table A.1 similarly shows that firms in the top tercile have 41.7 percent higher sales per worker than firms in the bottom tercile, averaged across the 76 economies, with the top-tercile mean exceeding the bottom in 62 of them. Figure 5 presents the corresponding relationship between country-level readiness and productivity across regions.

The firm-level controls reveal additional differences in performance. Foreign ownership is associated with 73.2 percent higher sales per worker, while firm age is positively associated with productivity. Female top-manager status has a negative coefficient, whereas female ownership has a positive coefficient. The results establish a robust association between firm readiness

[3]The 25th and 75th percentiles of the FAEI are 0.527 and 0.708, giving an interquartile range of 0.181.

and productivity. The following analyses examine whether this relationship is concentrated in particular readiness dimensions and whether those same dimensions determine AI adoption.

6.2. The Four Pillars

Table 3 decomposes the FAEI into Power Reliability, Digital Connectivity, Human Capital, and Institutional Environment. Human Capital has the largest coefficient in the preferred specification, at 1.014, and is statistically significant at the 1 percent level. Power Reliability and Digital Connectivity also have positive, statistically significant coefficients of 0.304 and 0.268, respectively. The Institutional Environment coefficient is negative but statistically insignificant. This means that a 0.1 increase in Human Capital is associated with 10.7 percent higher sales per worker, compared with 3.1 percent for Power Reliability and 2.7 percent for Digital Connectivity. This pattern highlights the importance of workforce capabilities relative to the other measured dimensions. Reliable electricity and digital access may support productive activity, but their association with productivity is smaller than that of the workforce capabilities captured by the index. This interpretation is consistent with research emphasising the role of skills and task composition in shaping the economic consequences of technological change (Acemoglu and Restrepo, 2018). The alternative-index estimates reinforce this result. In Table A.7, excluding Human Capital reduces the FAEI coefficient substantially, from 1.087 to 0.575, while excluding the Institutional Environment leaves it close to the baseline estimate. The composite index therefore captures several productive conditions, but its relationship with productivity is particularly robust to the inclusion of Human Capital.

6.3. AI Readiness and AI Adoption

The relationship between the FAEI and AI adoption is considerably weaker than its relationship with productivity. Table 4 examines the individual index components against AI adoption, advanced AI use, and adoption after the baseline interview. Website ownership and electronic payments stand out as the most consistent positive correlates. Having a website is positively associated with all three outcomes, while electronic payments received and made are positively associated with AI adoption and advanced AI use. This pattern is consistent with Udomsaph (2025), who finds that firm-level digital readiness is positively associated with AI adoption in cross-country Enterprise Survey data, although the strength of the relationship varies across income groups. Other components show weaker or less consistent relationships. Power Reliability measures, manager experience, and the share of workers with secondary education are generally not associated with the AI outcomes consistently.

Table 5 compares the website-and-e-payments measure (WE) with the full FAEI. WE is the average of website ownership and the share of purchases paid electronically. In the separate specifications, WE is positively associated with all seven AI outcomes. Its coefficient for AI adoption is 0.264, equivalent to a 26.4-percentage-point difference across the full index scale in the linear probability model. By contrast, the full FAEI coefficient for AI adoption is statistically insignificant, as are its coefficients for most other AI outcomes. When WE and the FAEI without the digital pillar enter jointly, the association between WE and AI outcomes remains positive and statistically significant. The FAEI without the digital pillar is positively and significantly associated with only one of the seven outcomes, the provision of AI training, and shows no significant association with the other six, in-

cluding AI adoption and advanced AI use. These results indicate that the relationship between measured readiness and AI use is concentrated in a narrower set of digital practices rather than distributed uniformly across all four pillars.

The selection and prediction exercises reinforce the importance of specific digital practices. In the leave-one-economy-out lasso results in Table A.8, website ownership and the share of purchases paid electronically are the only components selected in all seven folds for both AI adoption and advanced AI use, each with a positive coefficient. Table A.9 evaluates predictive performance in economies excluded from estimation. For AI adoption, adding these two items to basic firm characteristics raises mean area under the receiver operating characteristic curve (AUC) from 0.594 to 0.624, with an improvement in all seven held-out economies. Adding the full FAEI instead produces a mean AUC of 0.589 and adding the four pillars 0.612. The same broad pattern appears for advanced AI use. The digital measure improves mean AUC from 0.613 to 0.628, with an improvement in six of the seven held-out economies, while the full FAEI does not improve performance relative to the baseline model.

This finding is consistent with the broader literature distinguishing technology adoption from the complementary capabilities required to benefit from new technologies (David, 1990; Brynjolfsson et al., 2021). Research on AI adoption likewise highlights the role of firms' existing digital capabilities (Calvino and Fontanelli, 2026; Pastor-Merino et al., 2025). The present results add a firm-level comparison. The composite index is strongly associated with general productivity, while website ownership and electronic purchasing practices are more associated with AI adoption. The distribution of WE also varies systematically across firms and regions. Table S3 shows that the

measure is lowest in Sub-Saharan Africa and highest in Latin America and the Caribbean (Figure 6), and that it rises with firm size. Table A.10 further shows that WE is positively associated with labour productivity, on a common sample of 28,302 firms on which the FAEI alone has a coefficient of 0.825. When WE and the FAEI without the digital pillar enter the productivity regression together, both remain statistically significant, at 0.628 for WE and 0.722 for the FAEI without the digital pillar. The non-digital capabilities therefore retain an independent association with productivity, consistent with Table A.7, in which the index stays significant when the digital pillar is set aside. Website ownership and electronic purchasing are associated with higher productivity alongside the rest of the index. Some component-level associations are counterintuitive, suggesting that internet disruptions and regulatory burden may partly reflect firms' underlying digital engagement and operating environments rather than direct constraints on AI adoption.

6.4. Depth of AI Use and Expected Productivity Gains

Table 6 examines the number of AI-related tasks, the number of business functions using AI, and the use of advanced AI tasks among adopters who answered all relevant questions (1,183 firms). WE is not statistically significantly associated with any of these measures. The four pillars also show no consistent relationship with task counts or advanced AI tasks. The Institutional Environment has a positive, weakly significant association with the number of business functions using AI. The results for expected productivity gains, estimated on 3,323 firms, differ. Human Capital is positively associated with the probability that a firm expects AI to raise productivity, with a coefficient of 0.145, statistically significant at the 5 percent level. The

Institutional Environment is negatively associated with expecting a productivity gain, with a coefficient of −0.298, also statistically significant at the 5 percent level. Its coefficient for the expected percentage gain is −10.780 and is weakly significant. The positive coefficient on Human Capital for the expected percentage gain is not statistically significant at conventional levels. These estimates concern firms' expectations, not realised productivity effects. The findings thus suggest that workforce capabilities are associated with greater optimism about AI's potential benefits.

6.5. Industry Exposure to AI

Table 7 tests whether the productivity association of readiness is stronger in industries whose tasks are more exposed to AI. The test uses the AI Industry Exposure index of Felten et al. (2021) and the language-model exposure measure of Felten et al. (2023). Both measures draw on US occupational data and are matched to firms' industries. The interaction terms between the FAEI and the two exposure measures are not statistically significant. The same is true for the interactions between WE and each exposure measure. The estimated associations between readiness and productivity therefore do not differ from the measured industry exposure in these specifications. The main coefficients, which apply at an exposure of zero, the mean of the standardised US scale, remain positive and statistically significant, at 0.858 and 0.880 for the FAEI specifications (42,265 firms) and 0.629 and 0.644 for the WE specifications (33,615 firms). In the website-and-e-payments specifications, industry AI exposure itself has a positive coefficient of 0.104. These results suggest that the association between readiness and productivity is not demonstrably concentrated in industries with higher measured AI exposure.

6.6. AI Adoption and Productivity in 2026

Table 8 examines the association between readiness, AI adoption, and productivity in the 2026 follow-up. The analysis covers 2,969 firms across six economies. The productivity measure is based on monthly sales per worker in US dollars, averaged across the reported highest- and lowest-sales months. It differs from the annual productivity measure used in the main analysis. The FAEI coefficient is 0.247 without AI adoption and 0.252 when AI adoption is included. Neither is statistically significant, and the conventional 95 percent confidence interval for the 0.247 estimate runs from −0.990 to 1.483, which includes the main-analysis estimate of 1.087. AI adoption itself has a negative, statistically insignificant coefficient of −0.047. The corresponding WE coefficients are also statistically insignificant, as is the AI adoption coefficient in those specifications. The follow-up therefore provides no clear evidence of an association between the readiness measures, AI adoption, and this alternative productivity outcome.

6.7. Robustness

The positive association between the FAEI and labour productivity holds across most alternative index constructions, with two exceptions noted below. Table A.7 reports a coefficient of 0.802 for the geometric-mean index and 1.026 for the PCA-weighted index, both statistically significant. Excluding individual pillars also leaves the coefficient positive and statistically significant, although omitting Human Capital reduces its magnitude. Alternative specifications of the institutional pillar yield similarly positive estimates. The index is also robust to excluding the perception-based obstacle items, with the coefficient rising to 1.241 and remaining significant at the 1 percent level. Two component checks are weaker. Rebuilding the power pillar with-

out generator ownership reduces the coefficient to 0.521, significant only at the 10 percent level, which indicates that generator ownership carries weight in the association. Generator ownership rises with firm size, and part of this association may reflect firm resources beyond the size control.[4] Restricting the sample to the 26,356 firms observed on all four pillars gives a positive coefficient of 0.744 that is not statistically significant at conventional levels. The random-weight exercise provides additional evidence that the result is not driven by the equal weighting of the four pillars. Across 1,000 randomly generated sets of weights, the median coefficient is 0.788, and 91.7 percent of estimates are statistically significant at the 5 percent level. Figures 7 and 8 show that the productivity pattern persists under the alternative aggregation methods, while Figure 9 shows that the FAEI distribution broadly overlaps between firms observed on all four pillars and firms scored using three.

The additional AI analyses reveal more outcome-specific patterns. Table A.11 shows that Digital Connectivity is positively associated with AI adoption and the number of AI types used, while Human Capital is associated with AI training and weakly associated with the number of AI types. Table S4 finds no consistent relationship between Power Reliability and AI adoption or advanced AI use across alternative power measures. In the Kenya and Nigeria subsample, with standard errors clustered by sampling stratum, Table S5 shows that the FAEI is not significantly associated with AI adoption or advanced AI use, while Digital Connectivity is positively associated with adoption after baseline. Overall, the robustness results support the positive association between the composite readiness index and labour productivity.

[4] In the estimation sample, 34.5 percent of small firms (5 to 19 employees), 52.0 percent of medium firms (20 to 99), and 60.0 percent of large firms (100 or more) own or share a generator, weighted by the per-economy survey weight.

The AI analyses yield a more specific conclusion. Digital practices are the most consistent correlates of adoption, while the broader index and its other pillars show limited and outcome-dependent associations with AI use.

7. Conclusion

This paper develops a firm-level measure of AI readiness and examines its association with labour productivity and AI use across Low- and Middle-Income economies. Using World Bank Enterprise Survey data for 44,251 firms in 76 economies and a 2026 AI follow-up covering 3,579 firms in seven economies, the analysis shows that the conditions associated with general firm productivity differ from those most closely associated with AI adoption. The first main finding is that firms with higher AI readiness are more productive. The paper find that a 0.1 increase in the Firm AI Enablement Index (FAEI) is associated with 11.5 percent higher sales per worker, and this relationship holds across most alternative index constructions. Next, Human Capital has the strongest association among the four pillars, highlighting the importance of workforce capabilities alongside reliable electricity and digital connectivity. The result reinforces the view that productive performance depends on complementary firm-level conditions, rather than access to individual technologies.

The second finding relates to AI adoption. The composite FAEI is not consistently associated with whether firms use AI, while website ownership and electronic payments are positively associated with a range of AI outcomes. These digital practices also improve out-of-economy prediction relative to basic firm characteristics. Thus, an index that captures broad enabling conditions for productive activity may not identify the specific prac-

tices most closely associated with technology uptake. Among the measured readiness dimensions, Human Capital is more closely associated with productivity, whereas established digital practices are more associated with AI adoption, although Human Capital remains associated with the provision of AI training. Third, the analysis does not establish that AI adoption explains the productivity advantage of more ready firms. The relationship between readiness and productivity does not differ significantly with the industry-level AI exposure measures, and the 2026 follow-up reveals statistically insignificant associations between readiness, AI adoption, and the alternative productivity measure. The available data, therefore, do not establish AI adoption as the channel linking readiness to productivity.

These findings have implications for policies intended to expand AI use in developing economies. Human capital remains important for strengthening firms' productive capabilities, while website presence and electronic payment practices may help identify firms that are closer to adopting AI. The estimates do not show that promoting these practices would raise adoption. Such measures should complement, rather than replace, investments in reliable electricity, digital infrastructure, and the institutional conditions under which firms operate. The regional differences in readiness and digital practices, particularly the weaker infrastructure and connectivity scores in Sub-Saharan Africa, also caution against assuming that firms across developing economies face the same constraints or require identical interventions.

Several limitations qualify these conclusions. The estimates are associational and may reflect unobserved firm characteristics that influence both readiness and productivity. Although the World Bank Enterprise Surveys have panel data across survey waves, the number of firms consistently observed across successive rounds may be inadequate support a comparable

within-firm analysis at the scale of this study. The AI results rely on a follow-up covering seven economies at the time of the analysis, which constrains statistical precision and the generalisability of those findings. In addition, the 2026 productivity measure is based on reported monthly sales in US dollars and is less directly comparable with the annual productivity measure used in the main analysis. Several index components are self-reported, though excluding the perception-based items strengthens the productivity association, and 40.4 percent of firms are scored on three of the four pillars.

Future research could examine whether firms that adopt AI subsequently experience productivity gains, which complementary investments support the effective integration of AI into business processes, and how these relationships vary across sectors and economic contexts. Longer firm panels with consistent measures of AI adoption, intensity of use, and productivity would help distinguish the conditions associated with initial adoption from those that enable firms to realise economic benefits. The central contribution of this paper is to show that firm-level AI readiness has different empirical relationships with productivity and AI adoption. Human capital is most strongly associated with productivity, while basic digital practices are more consistently associated with AI use. Distinguishing these relationships can help researchers and policymakers evaluate AI readiness more precisely and design interventions that address the different constraints firms face.

Declaration of competing interest

The author declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The World Bank Enterprise Survey microdata and the 2026 AI follow-up data are available to registered users from the World Bank, at enterprisesurveys.org and the World Bank Microdata Library.

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Tables

Table 1: Descriptive Statistics

	Mean	SD	Min	Max
Panel A: The FAEI and Its Pillars				
Firm AI Enablement Index (FAEI) [0,1]	0.562	0.138	0.063	1.000
Power Reliability	0.465	0.235	0.000	1.000
Digital Connectivity	0.544	0.248	0.000	1.000
Human Capital	0.532	0.186	0.006	1.000
Institutional Environment	0.715	0.192	0.069	1.000
Panel B: Productivity Measures				
Labour productivity, sales/worker (ln, WB)	9.072	1.775	-4.537	16.443
Value-added per worker (ln, WB)	8.295	1.736	-4.239	13.780
Panel C: Firm Characteristics				
Total employees (ln)	2.663	1.037	0.000	9.393
Firm age, years (ln)	2.660	0.705	0.000	5.268
Exporter (=1)	0.092	0.289	0.000	1.000
Foreign owned (>10%) (=1)	0.109	0.311	0.000	1.000
Manufacturing sector (=1)	0.221	0.415	0.000	1.000
Retail sector (=1)	0.258	0.437	0.000	1.000
Services sector (=1)	0.521	0.500	0.000	1.000
Female top manager (=1)	0.196	0.397	0.000	1.000
Female owner (=1)	0.328	0.469	0.000	1.000
Panel D: AI Use				
AI adoption (=1)	0.338	0.473	0.000	1.000
Advanced AI use (=1)	0.158	0.365	0.000	1.000
Adoption after the baseline interview (=1)	0.184	0.388	0.000	1.000
Number of AI types used	0.809	1.393	0.000	6.000
AI training for workers (=1)	0.151	0.358	0.000	1.000
Pays for AI (=1)	0.162	0.369	0.000	1.000
Custom or in-house AI (=1)	0.132	0.339	0.000	1.000
N (Panels A–C)				44,251
N (Panel D)				3,579

Notes: Panels A–C: productivity estimation sample; Panel D: 2026 AI follow-up sample. Weighted by survey weights.

Table 2: FAEI and Labour Productivity

	Ln. Labour Productivity			
	(1)	**(2)**	**(3)**	**(4)**
FAEI	1.840***	1.154***	1.087***	1.087***
	(0.394)	(0.287)	(0.291)	(0.291)
Employees (ln)	0.108***	0.045	0.085**	0.085**
	(0.039)	(0.034)	(0.034)	(0.034)
Firm age (ln)	0.360***	0.211***	0.205***	0.205***
	(0.061)	(0.034)	(0.034)	(0.034)
Exporter (=1)	0.045	0.012	0.065	0.065
	(0.103)	(0.060)	(0.063)	(0.063)
Foreign-owned (>10%)	0.461***	0.568***	0.549***	0.549***
	(0.119)	(0.089)	(0.089)	(0.089)
Female manager (=1)	-0.472**	-0.318***	-0.328***	-0.328***
	(0.228)	(0.066)	(0.067)	(0.067)
Female owner (=1)	0.319*	0.120***	0.118***	0.118***
	(0.167)	(0.041)	(0.041)	(0.041)
Constant	6.725***	7.703***	7.649***	7.649***
	(0.311)	(0.138)	(0.143)	(0.143)
Country FE	No	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes
Survey year FE	No	No	No	Yes
N	44,251	44,251	44,251	44,251
Adj. R2	0.080	0.437	0.447	0.447

Notes: Col (1) firm controls, no fixed effects; col (2) adds country FE; col (3) adds sector FE; col (4) adds survey year FE. SE clustered at country level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3: FAEI Pillars and Labour Productivity

	Ln. Labour Productivity			
	(1)	**(2)**	**(3)**	**(4)**
Power Reliability	0.514**	0.340***	0.304***	0.304***
	(0.231)	(0.108)	(0.106)	(0.106)
Digital Connectivity	0.658***	0.265**	0.268**	0.268**
	(0.158)	(0.110)	(0.110)	(0.110)
Human Capital	1.101***	1.055***	1.014***	1.014***
	(0.223)	(0.164)	(0.164)	(0.164)
Institutional Environment	-0.348	-0.231	-0.218	-0.218
	(0.287)	(0.156)	(0.159)	(0.159)
Employees (ln)	0.059	0.023	0.062*	0.062*
	(0.045)	(0.034)	(0.034)	(0.034)
Firm age (ln)	0.313***	0.186***	0.181***	0.181***
	(0.050)	(0.034)	(0.035)	(0.035)
Exporter (=1)	-0.015	-0.022	0.029	0.029
	(0.091)	(0.060)	(0.064)	(0.064)
Foreign-owned (>10%)	0.358***	0.547***	0.529***	0.529***
	(0.116)	(0.086)	(0.086)	(0.086)
Female manager (=1)	-0.437**	-0.309***	-0.320***	-0.320***
	(0.189)	(0.064)	(0.065)	(0.065)
Female owner (=1)	0.243*	0.107**	0.105**	0.105**
	(0.125)	(0.041)	(0.040)	(0.040)
Constant	7.321***	7.828***	7.761***	7.761***
	(0.318)	(0.189)	(0.194)	(0.194)
Country FE	No	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes
Survey year FE	No	No	No	Yes
N	44,251	44,251	44,251	44,251
Adj. R2	0.167	0.446	0.455	0.455

Notes: All four pillars enter jointly; FE added stepwise. A firm with one missing pillar has it mean-imputed with a missing-indicator dummy (estimated, not shown). SE clustered at country level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4: Association between AI Adoption and FAEI Components

	AI Adoption	Advanced AI Use	Adoption after Baseline
	(1)	**(2)**	**(3)**
Panel A: Power Reliability			
Electricity not an obstacle	0.046	-0.005	0.099*
	(0.042)	(0.040)	(0.057)
Has power generator	-0.012	0.021	-0.024
	(0.048)	(0.013)	(0.037)
No power outage	-0.050	-0.037	-0.053
	(0.056)	(0.042)	(0.073)
Panel B: Digital Connectivity			
Has own website	0.132***	0.065**	0.112**
	(0.030)	(0.024)	(0.035)
Electronic payments received (share of sales)	0.217**	0.205**	0.213**
	(0.057)	(0.099)	(0.077)
Electronic payments made (share of purchases)	0.143**	0.109**	0.102
	(0.043)	(0.046)	(0.049)
No internet disruption	-0.108***	-0.090**	-0.036
	(0.038)	(0.023)	(0.038)
Panel C: Human Capital			
Manager experience	0.033	-0.032	-0.076
	(0.079)	(0.046)	(0.070)

(continued on next page)

	AI Adoption	Advanced AI Use	Adoption after Baseline
	(1)	**(2)**	**(3)**
Workers with secondary education (share)	0.114	0.023	0.091
	(0.107)	(0.055)	(0.105)
Firm offers formal training	0.046*	0.038	0.042*
	(0.027)	(0.022)	(0.020)
Workforce skills not an obstacle	0.016	0.008	0.031
	(0.064)	(0.032)	(0.066)
Panel D: Institutional Environment			
Finance not an obstacle	-0.138	-0.064	-0.034
	(0.059)	(0.043)	(0.048)
Corruption not an obstacle	0.037	0.010	0.015
	(0.063)	(0.031)	(0.065)
Licensing not an obstacle	-0.072	0.003	0.020
	(0.076)	(0.036)	(0.093)
Tax administration not an obstacle	-0.146	-0.065	-0.065
	(0.092)	(0.043)	(0.091)
Trade regulations not an obstacle	-0.146*	-0.081	-0.114
	(0.069)	(0.082)	(0.087)
Courts not an obstacle	-0.047	-0.037	0.058

(continued on next page)

	AI Adoption	Advanced AI Use	Adoption after Baseline
	(1)	**(2)**	**(3)**
	(0.083)	(0.071)	(0.096)
Labour regulations not an obstacle	0.012	0.000	0.025
	(0.052)	(0.031)	(0.053)
Less management time on regulation	-0.457**	-0.024	-0.232
	(0.144)	(0.061)	(0.190)
Country FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
N	3,579	3,579	2,801

Notes: Each coefficient is from a separate regression of the AI outcome on one FAEI component, with firm controls and country and sector fixed effects (19 per column, 57 in all); components are scaled 0 to 1. Column (3) excludes firms that adopted AI before the baseline. OLS, with linear probability models for binary outcomes, weighted by the follow-up weight. SE clustered by country; stars from the wild-cluster bootstrap (Webb weights, 999 reps). * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: Website and E-payments, the FAEI, and AI Use

	AI Adoption	Advanced AI Use	Adoption after Baseline	Number of AI Types	AI Training for Workers	Pays for AI	Custom or In-house AI
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Panel A: Separately							
Website and e-payments	0.264***	0.160**	0.206**	0.780**	0.146**	0.226**	0.147**
	(0.041)	(0.054)	(0.051)	(0.231)	(0.054)	(0.080)	(0.076)
FAEI	0.053	0.022	0.176	0.442	0.169	0.149	0.214*
	(0.125)	(0.099)	(0.222)	(0.303)	(0.110)	(0.093)	(0.096)
Panel B: Together							
Website and e-payments	0.263***	0.163**	0.201**	0.772**	0.133**	0.218**	0.147*
	(0.038)	(0.055)	(0.049)	(0.228)	(0.050)	(0.076)	(0.080)
FAEI without the digital pillar	-0.026	-0.070	0.121	0.144	0.282**	0.162	-0.001
	(0.153)	(0.080)	(0.142)	(0.311)	(0.101)	(0.112)	(0.108)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,579	3,579	2,801	3,579	3,579	3,579	3,579

Notes: WE (website and e-payments) is the mean of a website indicator and the share of purchases paid electronically. Panel A: separate regressions; Panel B: WE and the FAEI without the digital pillar (Power, Human Capital, Institutions) entered together. Column (3) excludes firms that adopted AI before the baseline. OLS, with linear probability models for binary outcomes, weighted by the follow-up weight. SE clustered by country; stars from the wild-cluster bootstrap (Webb weights, 999 reps). * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: FAEI, Depth of AI Use, and Expected Gains

	Number of AI Tasks	Business Functions Using AI	Advanced AI Tasks	Expects AI Productivity Gain	Expected Gain (%)
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Panel A: Website and e-payments					
Website and e-payments	-0.281	-0.027	0.115	0.045	3.378
	(0.646)	(0.570)	(0.153)	(0.053)	(3.023)
Panel B: Four pillars					
Power Reliability	0.527	-0.299	-0.047	-0.072	-1.211
	(1.382)	(1.100)	(0.246)	(0.061)	(1.334)
Digital Connectivity	-0.838	-0.316	-0.023	0.046	0.892
	(0.803)	(0.638)	(0.149)	(0.080)	(2.346)
Human Capital	-0.653	-0.867	-0.006	0.145**	6.368
	(0.711)	(0.632)	(0.185)	(0.057)	(3.329)
Institutional Environment	1.054	1.857*	0.148	-0.298**	-10.780*
	(0.678)	(1.088)	(0.162)	(0.106)	(5.039)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
N	1,183	1,183	1,183	3,323	3,323

Notes: Columns (1)–(3): adopters answering every task and function item; (4)–(5): firms reporting the direction and size of the expected change. OLS, with linear probability models for binary outcomes, weighted by the follow-up weight. SE clustered by country; stars from the wild-cluster bootstrap (Webb weights, 999 reps). * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 7: FAEI, Industry AI Exposure, and Labour Productivity

	Ln. Labour Productivity			
	(1)	**(2)**	**(3)**	**(4)**
FAEI	0.858***	0.880***		
	(0.234)	(0.235)		
Website and e-payments			0.629***	0.644***
			(0.088)	(0.088)
AI exposure of the industry	0.061		0.104**	
	(0.109)		(0.047)	
Language-model AI exposure		-0.010		0.068
		(0.113)		(0.049)
FAEI × AI exposure	0.115			
	(0.178)			
FAEI × language-model exposure		0.175		
		(0.184)		
Website and e-payments × AI exposure			-0.018	
			(0.066)	
Website and e-payments × language-model exposure				-0.033
				(0.065)
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N	42,265	42,265	33,615	33,615
Adj. R2	0.346	0.344	0.356	0.355

Notes: AI exposure: AI Industry Exposure (Felten, Raj and Seamans 2021), built from US occupational data and matched to each firm's ISIC class at baseline; (2), (4): language-model version. Productivity is from the baseline surveys. SE clustered at country level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 8: FAEI, AI Adoption, and Productivity in 2026

	Ln. Labour Productivity (2026)			
	(1)	**(2)**	**(3)**	**(4)**
FAEI	0.247	0.252		
	(0.481)	(0.476)		
Website and e-payments			0.080	0.093
			(0.221)	(0.226)
AI adoption (=1)		-0.047		-0.061
		(0.147)		(0.152)
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N	2,969	2,969	2,969	2,969
Adj. R2	0.336	0.336	0.341	0.341

Notes: 2026 follow-up, six economies; monthly sales per worker in US dollars. Jordan is excluded (only four firms reported sales). SE clustered by country; stars from the wild-cluster bootstrap (Webb weights, 999 reps). * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Appendix Tables

Table A.1: Labour Productivity and AI Use by Readiness Level

	Bottom third	**Middle third**	**Top third**
Panel A: Labour productivity			
Sales per worker above the bottom third (%)	Reference	18.0	41.7
Economies with top above bottom third			62 of 76
N	14,786	14,756	14,709
Panel B: AI use by FAEI third			
AI adoption (%)	31.8	33.1	34.8
Advanced AI use (%)	15.9	15.6	16.4
N	1,194	1,192	1,193
Panel C: AI use by WE third			
AI adoption (%)	24.9	32.3	43.3
Advanced AI use (%)	12.1	14.1	22.1
N	1,236	1,300	988

Notes: Panel A: productivity estimation sample; thirds of the FAEI within each economy; percentage difference in sales per worker from the bottom third, averaged across economies. Panels B–C: AI sample; thirds over the pooled sample; WE: website and e-payments score. Weights sum to one within each economy for every third. The website-and-e-payments thirds are uneven, reflecting ties and firms with a missing score.

Table A.2: FAEI and AI Adoption by Economy

	N	**FAEI**	**WE**	**AI adoption (%)**
Thailand	346	0.70	0.61	11.7
Mexico	372	0.58	0.68	20.0
India	1,333	0.62	0.47	22.9
Jordan	334	0.59	0.51	24.3
Kenya	356	0.59	0.72	42.0
Nigeria	701	0.60	0.55	42.4
Malaysia	137	0.71	0.69	73.4

Notes: FAEI and WE (website and e-payments score) are measured at the earlier Enterprise Survey interview and weighted by the per-economy Enterprise Survey weight (as in Tables 2 and 3); AI adoption is from the 2026 follow-up and weighted by the follow-up weight.

Table A.3: FAEI Components and the IMF and Oxford Insights AI Readiness Indices

FAEI component	WBES	IMF AI Preparedness Index	Oxford Insights 2023
Panel A: Power Reliability			
Electricity not an obstacle	c30a	–	–
Has power generator	c10	–	–
No power outage	c6	–	–
Panel B: Digital Connectivity			
Has own website	c22b	Digital infrastructure: private sector e-commerce environment (p. 3)	Infrastructure: adoption of emerging technologies (p. 40)
Electronic payments received (share of sales)	k33	Digital infrastructure: use of mobile phones for online transactions (digital payments; pp. 3-4)	–
Electronic payments made (share of purchases)	k38	Digital infrastructure: use of mobile phones for online transactions (digital payments; pp. 3-4)	–
No internet disruption	c39	Digital infrastructure: accessible and secured internet access (pp. 2-3)	Infrastructure: broadband quality (p. 40)
Panel C: Human Capital			
Manager experience	b7	–	–
Workers with secondary education (share)	l9b	Human capital: human capital index (schooling; p. 3)	Human capital: skills in the population (p. 40)
Firm offers formal training	l10	Labour market: active labour market policies (retraining; p. 3)	–
Workforce skills not an obstacle	l30b	Human capital: skillset of graduates (perception survey; p. 3)	Human capital: skills in the population (p. 40)
Panel D: Institutional Environment			
Finance not an obstacle	k30	Innovation: domestic credit to the private sector (p. 3)	Innovation capacity: VC availability (p. 39)
Corruption not an obstacle	j30f	Regulation and ethics: voice and accountability (p. 4)	Governance and ethics: accountability (p. 38)
Licensing not an obstacle	j30c	Regulation and ethics: legal framework adaptability to digital business (p. 4)	Governance and ethics: regulatory quality (p. 38)
Tax administration not an obstacle	j30b	Regulation and ethics: government effectiveness (p. 4)	Governance and ethics: regulatory quality (p. 38)
Trade regulations not an obstacle	d30b	Economic integration: tariffs and non-tariff barriers (p. 3)	–
Courts not an obstacle	h30	Regulation and ethics: legal frameworks and enforcement (p. 4)	–
Labour regulations not an obstacle	l30a	Labour market: flexibility and policies (p. 3)	–
Less management time on regulation	j2	Regulation and ethics: government effectiveness (p. 4)	Innovation capacity: time spent dealing with government regulations (same WBES item; p. 39)
Panel E: Obstacles considered and not used			
Crime theft and disorder	i30	No counterpart in either index	
Tax rates	j30a	A fiscal level rather than regulatory quality	
Access to land	g30a	A physical asset with no digital or AI link	
Transport	d30a	Physical infrastructure with no AI link	
Informal-sector competition	e30	Market structure rather than an enabling condition	
Political instability	j30e	Largely national; absorbed by country fixed effects	

Notes: Pages refer to the IMF AIPI documentation note (Cazzaniga and others 2024) and Oxford Insights (2023), Annex I. –: no counterpart; neither index covers electricity.

Table A.4: FAEI: Component Variables

Variable	Dir.	Mean	SD	Min	Max
Panel A: Power Reliability					
Electricity obstacle (0–4)	−	1.626	1.367	0.000	4.000
Has power generator	+	0.399	0.490	0.000	1.000
Experienced power outage	−	0.597	0.490	0.000	1.000
Panel B: Digital Connectivity					
Has own website	+	0.522	0.500	0.000	1.000
Electronic payments received (% of sales)	+	44.030	33.956	0.000	100.000
Electronic payments made (% of purchases)	+	44.466	36.363	0.000	100.000
Experienced internet disruption	−	0.396	0.489	0.000	1.000
Panel C: Human Capital					
Manager experience (years)	+	17.732	10.938	1.000	70.000
Workers with at least secondary education (%)	+	65.402	36.298	0.000	100.000
Firm offers formal training	+	0.315	0.464	0.000	1.000
Workforce skills obstacle (0–4)	−	1.132	1.169	0.000	4.000
Panel D: Institutional Environment					
Finance access obstacle (0–4)	−	1.690	1.389	0.000	4.000
Corruption obstacle (0–4)	−	1.488	1.406	0.000	4.000
Business licensing obstacle (0–4)	−	1.112	1.174	0.000	4.000
Tax administration obstacle (0–4)	−	1.348	1.241	0.000	4.000
Trade regulations obstacle (0–4)	−	1.212	1.245	0.000	4.000
Courts obstacle (0–4)	−	0.914	1.145	0.000	4.000
Labour regulations obstacle (0–4)	−	0.948	1.059	0.000	4.000
Management time on regulations (%)	−	9.777	18.637	0.000	100.000
N					44234

Notes: Dir. is the index direction: + raises the sub-index score, − is reverse-coded before rescaling to $[0, 1]$ against fixed bounds. Statistics cover all firms with the variable observed, weighted by the per-economy survey weight. Each sub-index needs all its components; the composite FAEI needs at least three of the four pillars.

Table A.5: Agreement with National AI Readiness Indices

	All economies			Developing economies		
	Economies	**Pearson**	**Spearman**	**Economies**	**Pearson**	**Spearman**
FAEI vs Oxford Insights total score	106	0.761	0.737	75	0.551	0.500
FAEI vs IMF AI Preparedness Index	71	0.766	0.754	45	0.550	0.516
Digital Connectivity vs Oxford Data & Infrastructure	103	0.832	0.825	72	0.588	0.601
Human Capital vs Oxford Technology Sector	106	0.463	0.449	75	0.289	0.262
Institutional Environment vs Oxford Government	106	0.426	0.427	75	0.349	0.276

Notes: Country means, latest WBES wave. Sources: Oxford Insights (2023), pp. 47–53; the IMF AI Preparedness Index (Cazzaniga et al., 2024), as reported in World Bank Policy Research Working Paper 11073, Table A.2.

Table A.6: A Comparison Between the Follow-up Sample and the Full Sample

	In follow-up	**Not in follow-up**	**Difference within economy**
FAEI	0.644	0.660	-0.003
			(0.007)
Power Reliability	0.567	0.616	-0.009
			(0.009)
Digital Connectivity	0.706	0.699	0.005
			(0.014)
Human Capital	0.569	0.550	-0.004
			(0.007)
Institutional Environment	0.736	0.776	-0.006
			(0.003)
Log labour productivity	10.049	10.380	0.049
			(0.048)
N	3,406	12,845	16,251

Notes: Baseline firms in the surveys that fed the follow-up, compared on the FAEI, its four pillars, and baseline labour productivity. Difference within economy; SE clustered by economy; with seven economies, stars use wild-cluster bootstrap p-values (Webb six-point weights, 999 reps). * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.7: Robustness to Alternative Index Constructions

	Ln. Labour Productivity			
Panel A: Aggregation				
	(1)	**(2)**	**(3)**	
FAEI	1.087***			
	(0.291)			
Geometric mean		0.802***		
		(0.222)		
PCA weights			1.026***	
			(0.290)	
N	44,251	44,251	44,251	
Panel B: Leaving out one pillar				
	(4)	**(5)**	**(6)**	**(7)**
FAEI without Power Reliability	0.905***			
	(0.266)			
FAEI without Digital Connectivity		0.856***		
		(0.246)		
FAEI without Human Capital			0.575**	
			(0.237)	
FAEI without Institutional Environment				1.111***
				(0.220)
N	44,251	44,251	44,251	44,251
Panel C: Other institutions measures				
	(8)	**(9)**		
Institutions: objective measures	1.156***			
	(0.294)			
Institutions: all 13 obstacles		1.125***		
		(0.309)		
N	41,572	43,884		
Panel D: Component sensitivity				
	(10)	**(11)**	**(12)**	
Excluding perception items	1.241***			
	(0.237)			
Without generator ownership		0.521*		
		(0.301)		
Four-pillar sample only			0.744	
			(0.450)	
N	41,582	44,251	26,356	
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

Notes: Each column re-estimates Table 2, col (4), with one index version. Panel C, institutions pillar: (8) credit constraints and bribery for the finance and corruption obstacles; (9) all 13 obstacles. Panel D: (10) drops the perception-based obstacle items; (11) drops generator ownership; (12) restricts to the four-pillar sample. SE clustered by country. With 1,000 random pillar weights the median coefficient is 0.788, significant in 91.7% of draws. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.8: Selection of the FAEI Components That Predict AI Use

	AI Adoption	Advanced AI Use
	(1)	**(2)**
Electronic payments made (share of purchases)†	7	7
Has own website†	7	7
Has power generator	5	7
Electronic payments received (share of sales)	4	7
No power outage	7	1
Workers with secondary education (share)	4	3
Electricity not an obstacle	3	4
No internet disruption	4	1
Manager experience	0	5

Notes: Number of seven lasso logits, each leaving out one economy, that select the component. † Website and e-payments: selected in at least six for both outcomes, with a positive coefficient when the selected components enter one logit.

Table A.9: Predicting AI Use in Economies Left Out of Estimation

	AI Adoption					Advanced AI Use				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
India	0.625	0.635	0.611	0.636	0.655	0.669	0.666	0.659	0.684	0.676
Jordan	0.464	0.508	0.459	0.541	0.533	0.607	0.619	0.607	0.635	0.600
Kenya	0.538	0.577	0.538	0.535	0.567	0.522	0.526	0.523	0.511	0.529
Malaysia	0.636	0.672	0.623	0.622	0.664	0.554	0.591	0.553	0.560	0.599
Mexico	0.617	0.628	0.615	0.647	0.632	0.620	0.625	0.619	0.639	0.622
Nigeria	0.598	0.623	0.597	0.593	0.614	0.612	0.640	0.608	0.621	0.649
Thailand	0.679	0.725	0.680	0.710	0.723	0.705	0.728	0.697	0.650	0.733
Mean	0.594	0.624	0.589	0.612	0.627	0.613	0.628	0.609	0.614	0.630
Economies above (1) or (6)		7/7	1/7	4/7	7/7		6/7	1/7	5/7	6/7

Notes: AUC in the held-out economy; logit fitted on the other six. (1), (6): firm traits; (2), (7): + website and e-payments; (3), (8): + FAEI; (4), (9): + pillars; (5), (10): components re-selected.

Table A.10: Website and E-payments and Productivity

	Ln. Labour Productivity		
	(1)	**(2)**	**(3)**
Website and e-payments	0.646***		0.628***
	(0.100)		(0.100)
FAEI		0.825**	
		(0.335)	
FAEI without the digital pillar			0.722**
			(0.291)
Country FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
N	28,302	28,302	28,302

Notes: Common sample across columns. (1) WE alone; (2) the FAEI; (3) WE and the FAEI without the digital pillar entered together. SE clustered by country. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

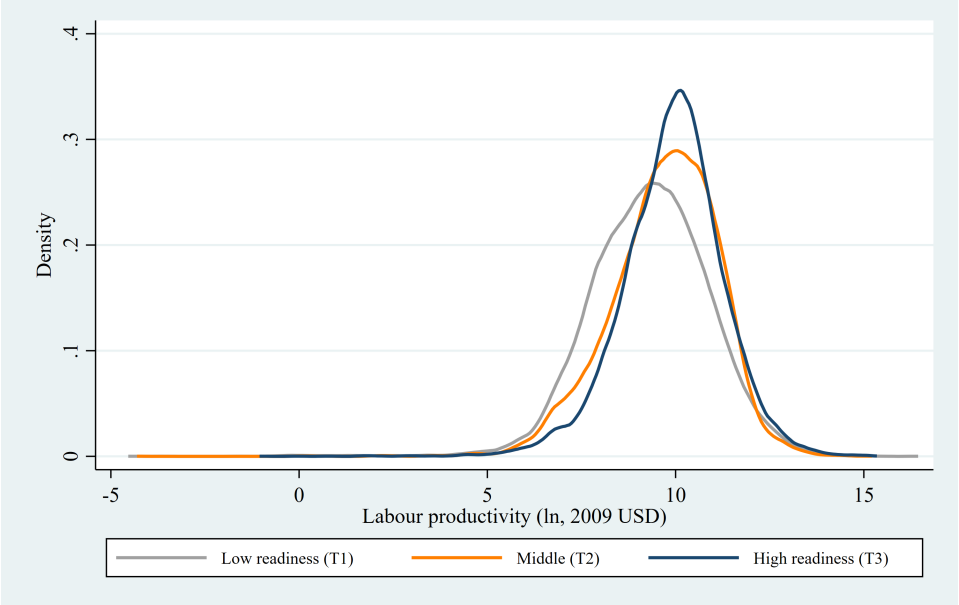
Table A.11: The FAEI Pillars and AI Use

	AI Adoption	Number of AI Types	Pays for AI	Custom or In-house AI	AI Training for Workers
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Power Reliability	-0.042	0.019	0.089	0.019	0.066
	(0.090)	(0.261)	(0.063)	(0.087)	(0.084)
Digital Connectivity	0.196*	0.571*	0.079	0.141	0.075
	(0.069)	(0.213)	(0.076)	(0.093)	(0.041)
Human Capital	0.261	0.661*	0.141	0.125	0.264**
	(0.184)	(0.371)	(0.112)	(0.068)	(0.097)
Institutional Environment	-0.283	-0.591	-0.105	-0.047	-0.147
	(0.201)	(0.411)	(0.152)	(0.057)	(0.095)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
N	3,579	3,579	3,579	3,579	3,579

Notes: The four pillars enter together; missing pillars mean-filled and flagged. OLS, with linear probability models for binary outcomes, weighted by the follow-up weight. SE clustered by country; stars from the wild-cluster bootstrap (Webb weights, 999 reps). * $p<0.10$, ** $p<0.05$, *** $p<0.01$

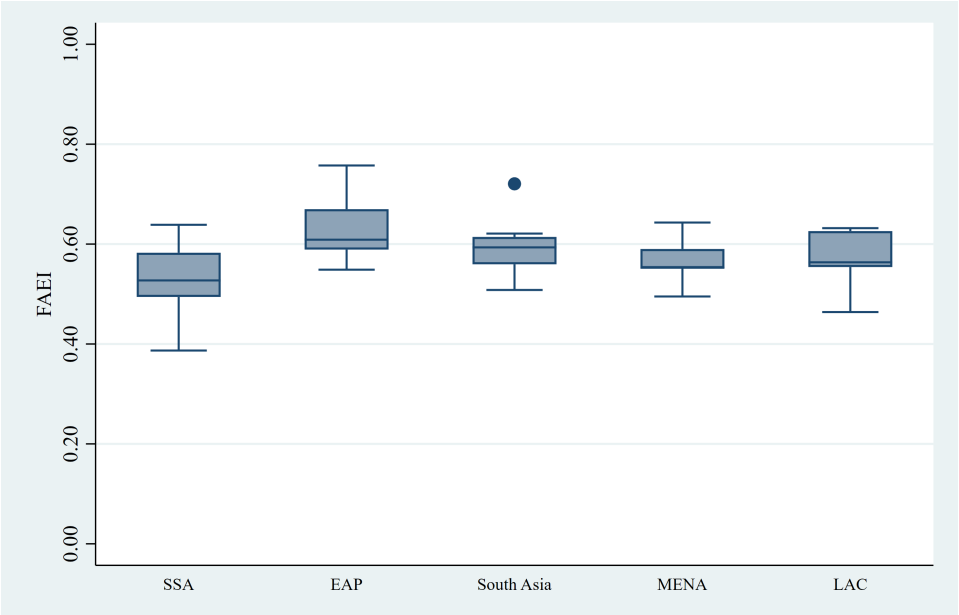
Figures

Figure 1: Labour-Productivity Distribution by FAEI Tercile



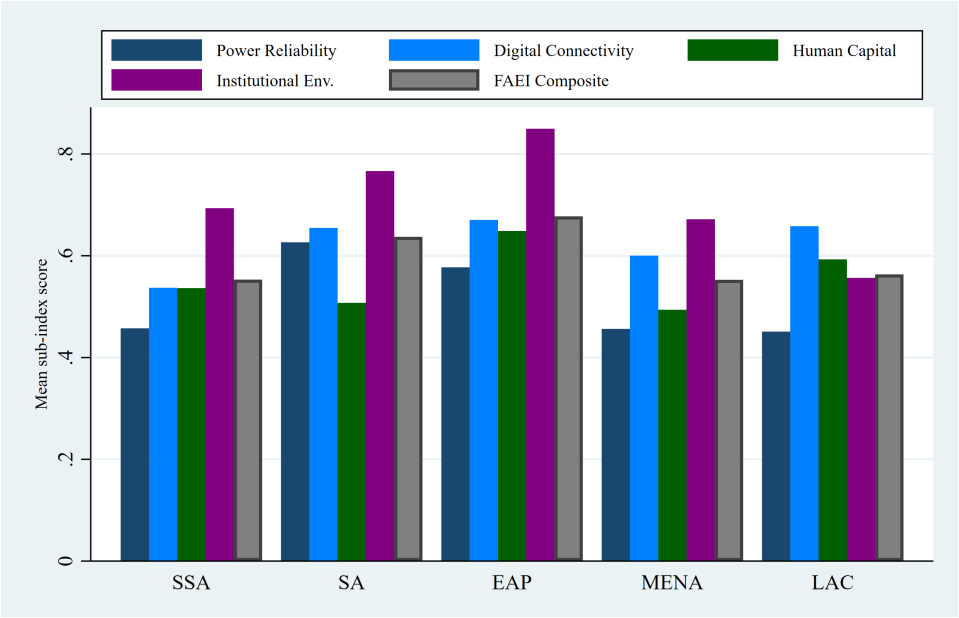
Notes: Kernel densities of log labour productivity for the bottom, middle and top FAEI terciles; the high-readiness density is shifted right (whole-distribution shift, not just the mean).

Figure 2: The FAEI by Region



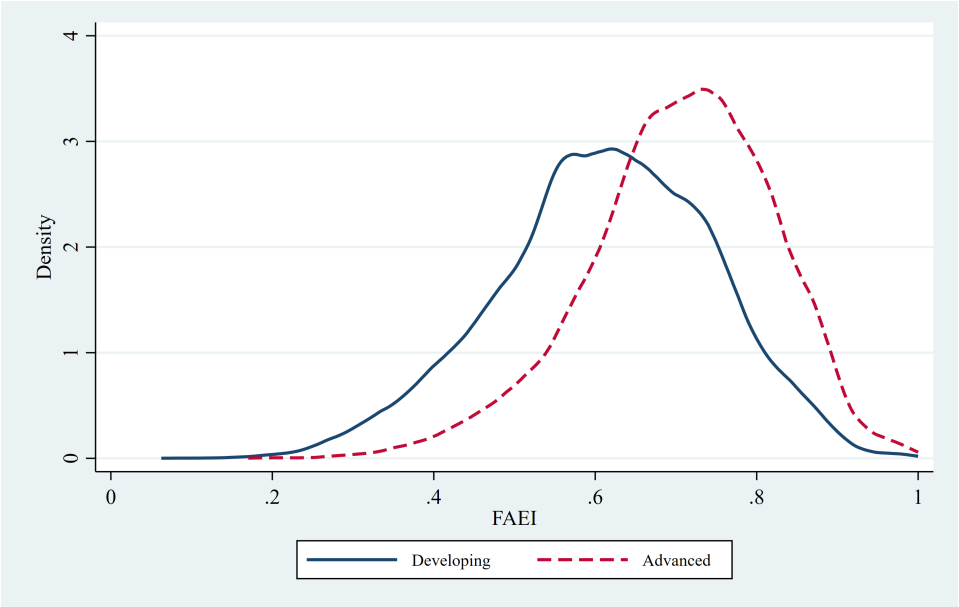
Notes: Country means, most recent survey wave. Box plots by SSA, EAP, SA, MENA, LAC.

Figure 3: Pillar Gaps Across Regions



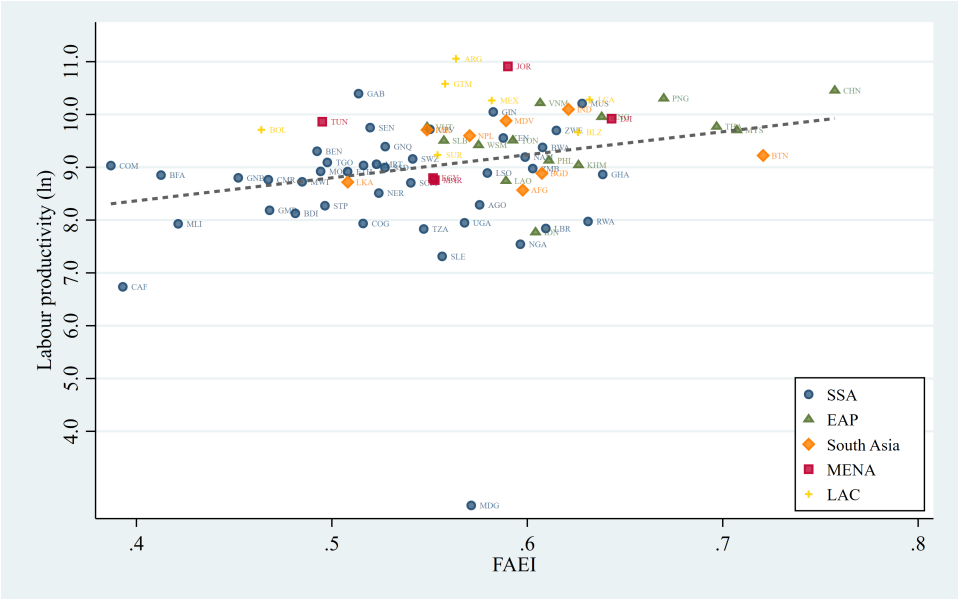
Notes: Grouped bar chart of sub-index means by region.

Figure 4: The FAEI: Developing vs Advanced Economies



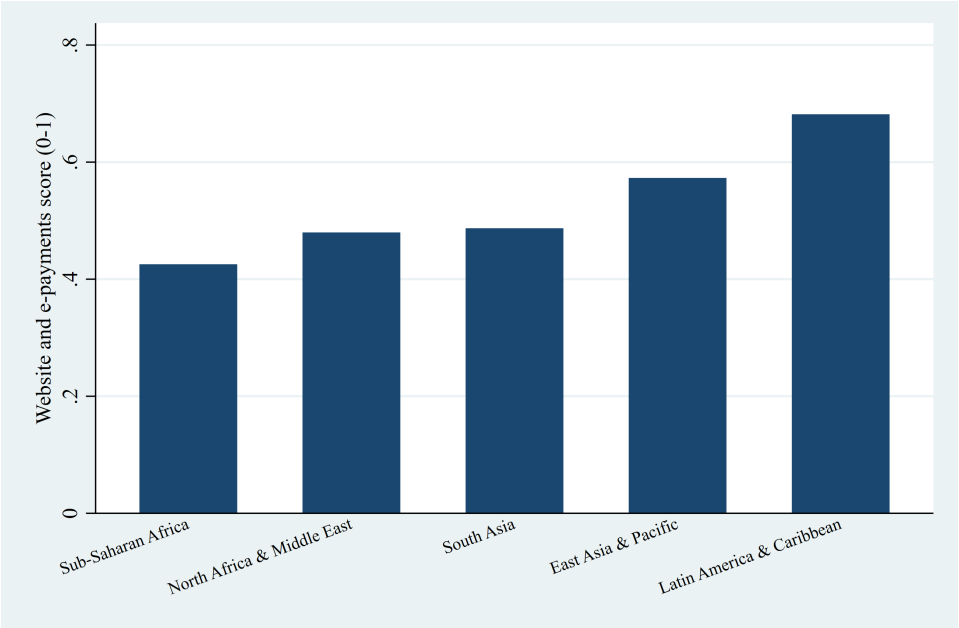
Notes: Kernel densities of the FAEI score for developing and advanced samples, showing the readiness gap.

Figure 5: The FAEI and Productivity Across Regions



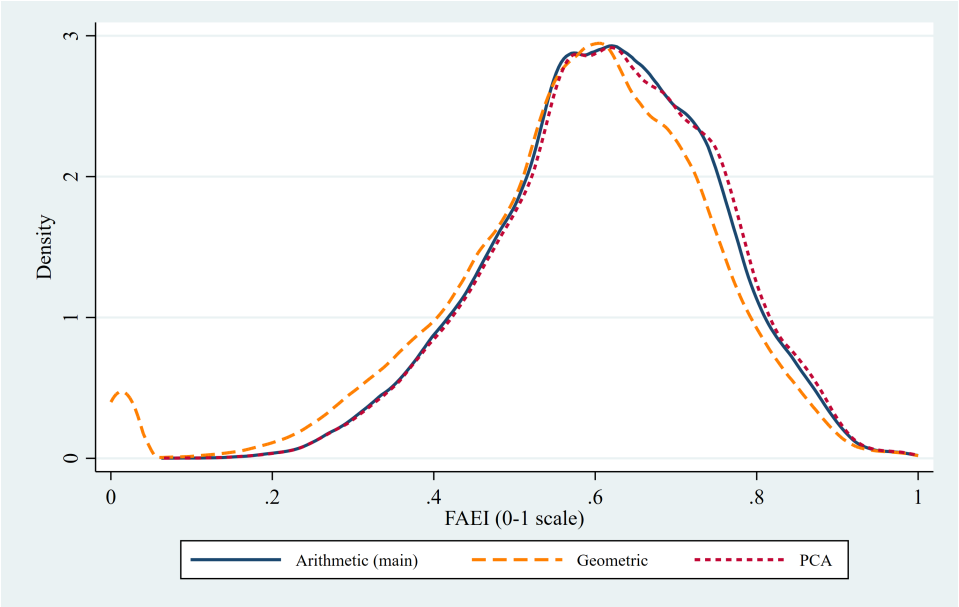
Notes: Country means, most recent survey wave. FAEI score vs log LP by region, points labelled with ISO3 codes.

Figure 6: Website and E-payments by Region



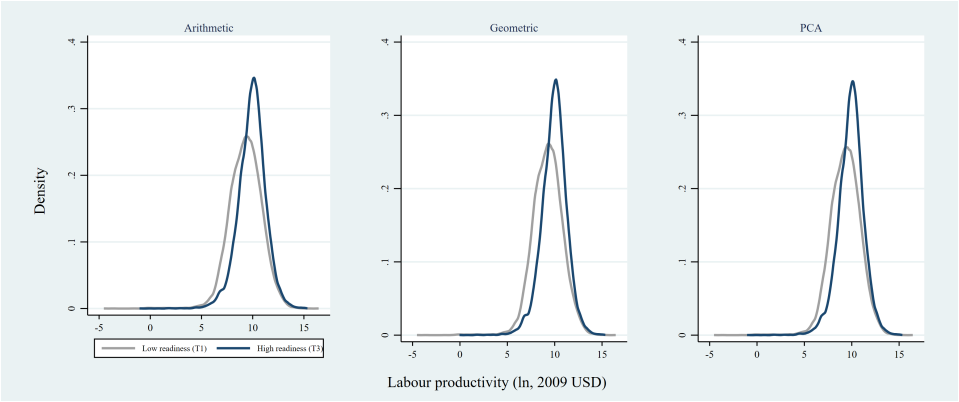
Notes: Mean website and e-payments score by region, developing economies, each economy weighted equally.

Figure 7: The FAEI Distribution under Three Aggregation Methods



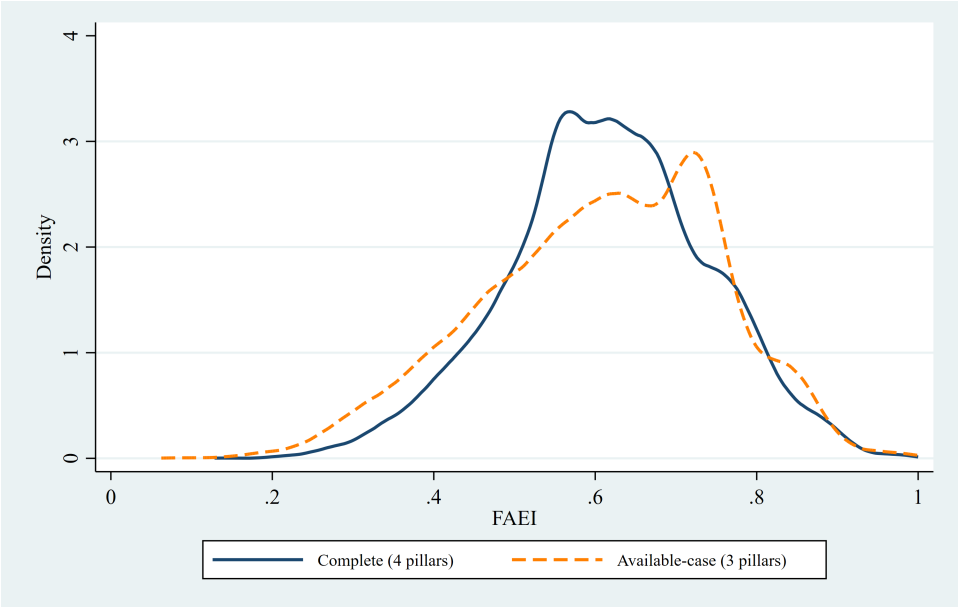
Notes: Kernel densities of the arithmetic (main), geometric, and PCA composites on the 0-1 scale, same firms. The arithmetic and PCA composites nearly coincide; the geometric composite sits lower, placing firms with one weak pillar near zero.

Figure 8: Labour Productivity by FAEI Tercile under Three Aggregation Methods



Notes: Log-labour-productivity densities for the bottom (T1) and top (T3) FAEI terciles, terciles defined three ways (arithmetic, geometric, PCA) on the same firms. The top tercile is shifted right in every panel.

Figure 9: The FAEI Distribution for Four-Pillar and Three-Pillar Firms



Notes: Kernel densities of the FAEI for firms observed on all four pillars (complete) versus firms scored on exactly three pillars. The distributions broadly overlap.