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Artificial Intelligence and Labour Markets in Southeast Asia: An Empirical Examination

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The increase in artificial intelligence (AI) has affected industries and job roles, leading to concerns about its impact on labour markets. This study investigates AI's effect on employment and wages within the ASEAN region by using a patent-based measure of AI exposure. The results show that while AI typically displaces jobs, the impact differs by country. Most ASEAN countries experienced a reinstatement effect, except Indonesia and Thailand where displacement occurred, and Singapore which showed a complementarity effect. Education is identified as an important policy tool to mitigate AI's negative impacts on the labour market, promoting job complementarity.

I. Introduction

Over the past decade, the technological landscape has undergone significant transformation, primarily driven by advancements in various automation technologies. Initially, discussions on automation focused on robotics and software. However, the rapid rise of ChatGPT has brought artificial intelligence (AI) into prominence, sparking a competitive pursuit for AI dominance, particularly within Silicon Valley. AI's ability to automate complex tasks and perform advanced cognitive functions indicates a potential restructuring of industry frameworks, job roles, and workforce dynamics, raising global concerns about its impact on employment and wages.

The growing interest in the labour market implications of AI has expanded research in this domain. Economists have developed various models to analyse AI's effects; however, these models often combine AI with other forms of automation, such as robotic process automation, overlooking the unique predictive enhancements of AI. A fundamental characteristic of automation technology is its capacity to extend the range of tasks that can be executed by capital, thereby increasing capital's task share at the expense of labour. This shift induces a displacement effect, where capital replaces tasks previously performed by labour, reducing labour demand and exerting downward pressure on employment and wages. Additionally, this displacement effect, by increasing output, lowers labour's share of national

income and decouples wage growth from productivity improvements.

In their seminal work, Acemoglu and Restrepo (2019) identify counterbalancing forces to the displacement effect of automation. These include the productivity effect, where cost savings from automation elevate consumer demand and labour demand for non-automated tasks; the capital accumulation effect, where automation enhances capital production and subsequently labour demand; deepening automation, which improves machine productivity and further increases labour demand; and the creation of new, high-productivity, labour-intensive tasks, raising labour's share and mitigating the impact of automation.

The theoretical impact of AI on employment and wages remains ambiguous, dependent on factors such as AI development, deployment, and market conditions. Additionally, the distribution of displacement and productivity effects, along with the creation of new jobs across various industries, regions, and socio-demographic groups, is also uncertain.

Due to this theoretical ambiguity, researchers have increasingly turned towards empirical studies to assess the real-world effects of AI-enabled automation. This shift necessitates precise measurement methods for AI. Earlier research employed a task-based approach to evaluate AI, focusing on the automatability of different jobs and their tasks. Autor, Levy, and Murnane (2003) proposed that computers could replace routine tasks, using data from the US Department of Labour to evaluate automatability. Frey

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and Osborne (2017) expanded this model to account for recent technological advancements, predicting that nearly half of US jobs are at high risk of automation based on the ONET database and expert opinions. Arntz, Gregory, and Zierahn (2016) refined this approach by assessing the automatability of individual jobs rather than broad occupations, thereby revealing a lower risk of job automation and emphasizing task variability within occupations.

Despite its meticulous approach, the task-based method for measuring AI's impact on labour markets faces criticism for its ad hoc nature and reliance on subjective judgment, which often requires extensive technical knowledge difficult to obtain for emerging technologies. Webb (2019) addressed these limitations by introducing an objective, patent-based methodology that leverages natural language processing to link detailed patent information with occupational data, thus objectively assessing technology's impact on the workplace. By analyzing verb-noun pairs from patents and job descriptions, Webb's method quantifies occupational exposure to automation, indicating that higher education roles are more susceptible to AI, while lower-skilled jobs face greater risks from robotics and software. This approach also correlates increased AI exposure with declines in employment and wages. Extending this methodology to European labour markets, Albanesi et al. (2023) identified a positive relationship between AI automation and employment shares, highlighting a contrasting impact of AI on employment in Europe compared to the United States.

This study evaluates the impact of AI on employment in ASEAN countries from 2015 to 2020, utilizing Webb's (2019) patent-based AI measures. The findings indicate varied effects of AI on employment and wages, with a general trend towards a displacement effect in the ASEAN region. Country-specific analyses reveal reinstatement effects in most nations, displacement effects in Indonesia and Thailand, as well as a complementarity effect in Singapore. Correlations with technology adoption and structural attributes generally relate to reinstatement effects, positively impacting employment but adversely affecting wages. Education, particularly in Mathematics, emerges as a key policy response to counteract AI's labour market implications.

The study is motivated by several factors. Primarily, it aims to elucidate the impact of AI on labour markets in Southeast Asia—an area that has not been extensively explored—utilizing an innovative patent-based methodology. This research seeks to address a gap by illuminating the economic dynamics influenced by AI in the region and highlighting the variability of these effects across different country contexts. Education is emphasized as a crucial mechanism for mitigating the adverse impacts of AI on the labour market, laying the groundwork for informed policy-making amidst rapid digitalization.

The paper is structured as follows: Section II elaborates on the research methodology and data utilized for analysis. Section III presents the empirical results, while Section IV concludes the paper by summarizing the main findings and their implications.

II. Methodology and Data

A. Empirical model

To examine the relationship between occupational exposure to AI and changes in employment shares and relative wages, we adopt the methodology of Albanesi et al. (2023). This involves estimating these relationships using the coefficients β_c within the specified regression model:

$$y_{o,c} = \alpha_c + \alpha_o + \beta_c X_{o,c} + \beta_d D_c + \varepsilon_{o,c} \quad (1)$$

The dependent variable, $y_{o,c}$, represents either the change in the employment share of occupation o in country c during the sample period, or the change in the wage distribution position of occupation o in country c during the same period. The change in the employment share is expressed as the annualised percentage change relative to the midpoint of a cell's share of overall employment throughout the sample period, adjusted by winsorisation at the top and bottom 1%. The change in the wage distribution is measured as the annualised change in the within-country centile of the employment-weighted average wage for each occupation cell over the sample period.

The variable $X_{o,c}$ represents the potential exposure of occupation o units to AI, serving as an indicator for the probability of AI-enabled automation and its impact on employment share or relative wages. A positive (negative) β_c suggests that occupations with higher potential for AI automation experienced increasing (declining) employment shares or relative wages. Observations are weighted by the cells' average employment, and standard errors are clustered by sector. The variable D_c is a dummy variable indicating presence in country c , with Singapore used as the reference country. AI exposure scores from Webb (2019) are utilized to measure occupational exposure to AI.

The β_c coefficients in the employment and wage equations indicate the type of relationship between AI and jobs: complementarity, displacement, or reinstatement. A positive coefficient, β_c , in both equations denotes a complementarity relationship, where AI exposure is associated with increases in both employment shares and relative wages due to productivity gains from AI. On the other hand, negative β_c coefficients in both equations imply a displacement effect, where AI exposure reduces employment shares and wages. When one of the two coefficients is positive and the other is negative, it signifies a reinstatement effect, where AI automation eliminates certain tasks or jobs but also generates new ones within the same occupation category.

B. Data

This study assesses the impact of AI on the labour market by integrating labour data with a patent-based AI exposure measure, ensuring consistency across dimensions such as country, year, and occupations. The primary classification used is the two-digit ISCO framework. Labour data sources include the International Labour Organization (ILO) and the national statistics departments of Singapore and Malaysia.

AI exposure scores are based on Webb's (2019) methodology, which uses US Standard Occupational Classification (SOC) system occupations. Meanwhile, employment and wage data follow the ISCO-08 classification. Crosswalks at the four-digit ISCO level generate scores for two-digit occupations, assuming similar technology exposure in South-east Asia and the United States.

The analysis utilizes data from 2015 to 2020, with specific years for Brunei (2014-2020) and the Philippines (2017-2020) due to data availability constraints. AI exposure scores reflect AI advancements from 2015 to 2020, based on 2020 occupation descriptions, and are treated as time-invariant for this study.

III. Empirical Findings

A. Descriptive statistics

Panels A and B of [Figure 1](#) provide descriptive analysis on employment shares and average wage percentiles across ASEAN countries with respect to occupational AI exposure, highlighting the varied employment and wage structures based on different levels of AI exposure. Notably, while occupations with medium AI exposure generally constitute the majority of the labour force in most ASEAN countries, Myanmar is an exception with a predominant portion of its employment in high AI exposure occupations. This trend is evident even when compared to its more developed ASEAN counterparts like Singapore. This phenomenon is primarily attributed to a substantial segment of Myanmar's labour force categorized as "market-oriented skilled agricultural workers," which possess particularly high exposure scores due to extensive patenting activity in AI aimed at automating tasks within these specific job categories.

Wage percentiles also exhibit variation, with medium AI exposure occupations commanding the highest average wages in Cambodia, Indonesia, Myanmar, and Vietnam. In contrast, Singapore sees the highest wage percentiles in high AI exposure occupations. These disparities highlight distinct labour market dynamics across countries, indicating differential impacts of AI on employment regionally.

B. Main findings

B.I. Region and country results

The pooled regression analysis presented in [Table 1](#) evaluates the impact of artificial intelligence (AI) on employment share and wage percentile across the ASEAN region. The findings indicate a general displacement effect characterized by negative coefficients: specifically, a one-unit increase in the AI score correlates with a statistically significant reduction of 0.102 units in the employment share and a 0.459 unit decrease in the wage percentile, significant at the 1% and 10% levels respectively.

However, further country-level analysis ([Figure 2](#)) reveals varied effects. In five countries - Vietnam, Philippines, Myanmar, Malaysia, and Cambodia - AI exhibits reinstatement effects, positively impacting relative wages while negatively affecting employment shares. Contrarily,

in Malaysia, AI has a negative impact on relative wages, similar to the observations in Thailand and Indonesia. Notably, Malaysia experiences a positive effect on employment shares, largely attributable to the pronounced benefits AI provides to occupations with moderate exposure compared to those with low exposure.

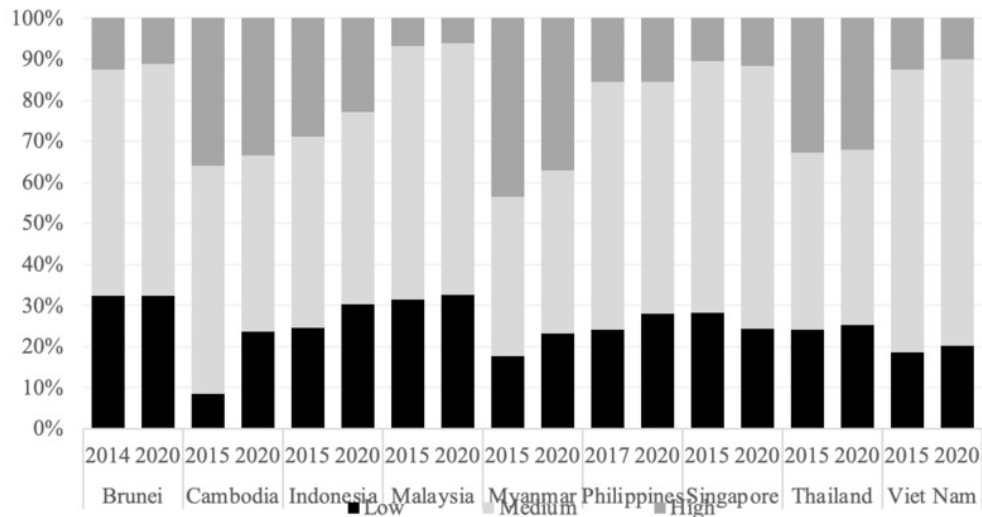
Singapore uniquely demonstrates a complementarity effect, where AI positively influences job availability. Meanwhile, only Indonesia and Thailand exhibit the expected displacement effect, with AI negatively impacting both employment and wages, consistent with the regional aggregate trends. This dichotomy, particularly given Indonesia and Thailand's demographic significance within ASEAN, underscores the necessity for nuanced national strategies that address the diverse impacts of AI on labour markets across different countries, sectors, and occupations.

B.II. Exploring country variation in structural features

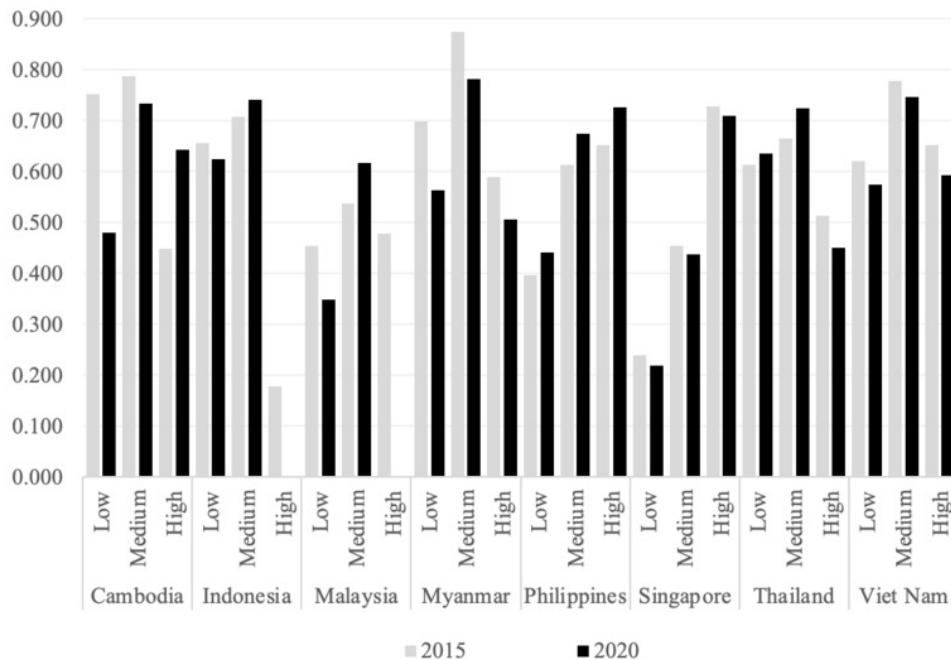
The divergence in correlations between AI exposure and employment and wages across countries may reflect varying extents of technology adoption and dissemination, influencing the actual exposure of occupations to technology. The unique structural characteristics of each country could also affect technology uptake and dispersion, as well as labour market responses to new technology integration. To explore the influence of these structural factors on our country-specific estimates, we analyse the Pearson correlations between these estimates and indicators of technology adoption and structural attributes of the ASEAN countries in our sample, presented in [Table 2](#).

Initially, we utilise the Cisco Digital Readiness Index to evaluate a country's preparedness for the digital era across seven key pillars. These pillars generally show high positive correlations with employment share but exhibit little correlation with wages. The "Ease of Doing Business" pillar strongly correlates positively with employment (0.917), suggesting that a conducive business environment boosts employment, but correlates negatively with wages (-0.556), implying that job creation does not necessarily translate into higher wages. Similarly, the "Basic Needs" pillar positively correlates with employment (0.804) but negatively with wages (-0.382), indicating that basic service improvements increase employment but do not necessarily lead to higher wages.

Additionally, we employ the ASEAN Digital Integration Index, created by the ASEAN Coordinating Committee on Electronic Commerce (ACCEC), to assess ASEAN member countries' readiness for the digital economy across several key dimensions. Similar to the Cisco index, all pillars exhibit high positive correlations with employment but negative correlations with wages. Notably, the "Innovation & Entrepreneurship" pillar shows the highest positive correlation with employment (0.825), indicating that countries with a strong culture of innovation and entrepreneurship tend to have higher employment levels, yet it also displays one of the highest negative correlations with wages (-0.343).



Panel A: Employment shares



Panel B: Wage percentiles

Figure 1. Occupational exposure of AI versus employment shares and wage percentiles, by country

Notes: Figure 1 presents data on the distribution of employment shares and wage percentiles across different levels of occupational exposure to AI in ASEAN countries. Panel A illustrates employment shares for occupations classified into three categories based on their level of AI exposure: low (black bars), medium (light gray bars), and high (dark gray bars). These shares are shown for two different years to provide a comparative view of labour market changes over time. Panel B displays wage percentiles corresponding to low-, medium-, and high-AI exposure occupations for 2015 (or 2017 for the Philippines) and 2020. Wage percentiles are presented on a scale from 0 to 1, with higher values indicating relatively higher wages within each country's labor market.

Furthermore, we examine the impact of the World Bank Worldwide Governance Indicators (WGI) on country estimates. The WGI assesses public governance quality across six dimensions. Most dimensions demonstrate strong positive correlations with AI's effects on employment and slight negative correlations with wages. The "Rule of Law" dimension shows the strongest positive correlation with employment (0.860), suggesting robust rule of law correlates with higher employment shares.

Finally, we analyse correlations between country estimates and key educational pillars of the OECD's Programme for International Student Assessment (PISA), which assesses 15-year-old students' competencies in reading, mathematics, and science triennially. All educational aspects show strong positive correlations with both employment and wage estimates, with Mathematics showing the highest correlations (0.787 and 0.457, respectively). This suggests that education, particularly in Mathematics,

Table 1. Pooled linear regression of annualised changes in employment and wages against occupational AI exposure, 2015-2020

	Employment share	Wage percentile
AI score	-0.102*** (-4.406)	-0.459* (-1.842)
Intercept	0.044*** (4.494)	0.206 (1.731)
Dummy_Cambodia	0.014*** (4.823)	0.077*** (4.359)
Dummy_Myanmar	0.012*** (4.161)	-0.032 (-1.859)
Dummy_Vietnam	0.006*** (3.887)	0.007 (1.788)
Dummy_Indonesia	0.008*** (4.058)	-0.010 (-1.514)
Dummy_Singapore	0.004*** (3.650)	NA NA
Dummy_Philippines	0.002** (3.058)	0.040*** (11.001)
Dummy_Thailand	0.009*** (4.037)	-0.035** (-2.988)
Dummy_Malaysia	0.003*** (3.476)	-0.017*** (-4.356)
R-squared	0.140	0.254
No of observations	295	254

Notes: We estimate the relationships between AI and employment and wages by using the coefficients β_c in the following regression:

$$y_{o,c} = \alpha_c + \alpha_o + \beta_c X_{o,c} + \beta_d D_c + \epsilon_{o,c}$$

where the dependent variable $y_{o,c}$ represent either the change in the employment share of occupation o in country c , or the change in the wage distribution position of occupation o in country c over the period of 2014-2020. $(X_{o,c})$ is the measure of potential exposure of occupation o units to AI calculated by Webb (2020). D_c is the dummy variable that takes the value of 1 when the observation is in country c and takes the value of 0 otherwise. Singapore is used as the reference benchmark country. Observations are weighted by the cells' average employment, and standard errors are sector clustered. t-statistics for the are shown in parentheses. Significance levels: ***, **, and * denotes statistical significance at 1%, 5%, and 10% levels, respectively.

serves as an effective policy response to mitigate AI's impact on employment and wages.

IV. Conclusion

This study empirically examines the impact of artificial intelligence (AI) on employment and wages within the ASEAN region, using a patent-based measure of AI for objectivity. The analysis reveals an overall displacement effect in ASEAN, characterized by job losses and decreased wages, primarily driven by developments in Thailand and Indonesia. However, country-specific analyses indicate a reinstatement effect in other ASEAN countries, with Singapore uniquely demonstrating a complementarity effect where AI enhances both employment and wages.

Our research underscores the necessity of a nuanced understanding of AI's impact on labour markets, suggesting that structural characteristics such as digital readiness, governance, and education levels, particularly education, play a critical role in mitigating AI's adverse effects. The findings advocate for policy measures focused on enhanc-

ing education to maximise AI's benefits while addressing its challenges in labour markets.

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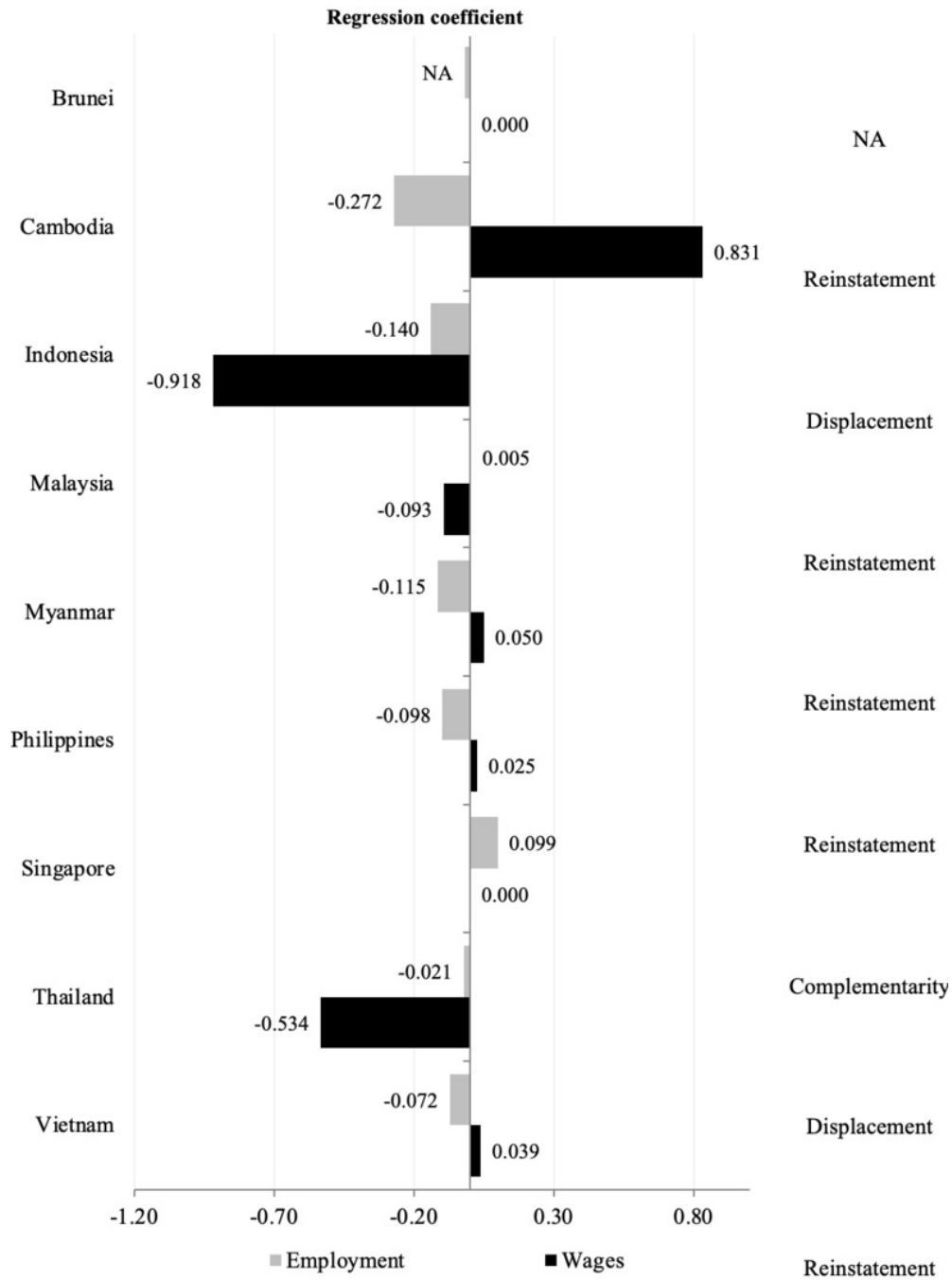


Figure 2. Regression coefficients from regressions of annualized changes in employment shares and wage percentiles for Southeast Asian countries

Notes: The regression coefficients indicate how employment (gray bars) and wages (black bars) have responded to AI-related labor market shifts over time. The x-axis represents the magnitude of the regression coefficients, with negative values indicating a decline and positive values representing an increase in employment or wages. The rightmost column categorizes the effect of AI in each country as either displacement, reinstatement, or complementarity, depending on whether AI adoption has led to job losses, job recoveries, or wage increases without major employment shifts.

Table 2. Correlations between country estimates and institutions

Indicators	Pillars	Correlation	
		Employment	Wages
Cisco Digital Readiness Index	Basic Needs	0.804	-0.382
	Business & Government Investment	0.735	0.011
	Ease of Doing Business	0.917	-0.556
	Human Capital	0.557	0.037
	Start-Up Environment	0.688	0.052
	Technology Adoption	0.701	0.023
	Technology Infrastructure	0.716	-0.060
Asean Digital Integration Index	Digital Trade & Logistics	0.699	-0.322
	Data Protection & Cybersecurity	0.734	-0.616
	Digital Payments & Identity	0.747	-0.355
	Digital Skills & Talent	0.636	-0.194
	Innovation & Entrepreneurship	0.825	-0.343
	Institutional & Infrastructural Readiness	0.819	-0.214
World Bank Worldwide Governance Indicators	Control of Corruption: Estimate	0.843	-0.158
	Government Effectiveness	0.785	-0.197
	Political Stability and Absence of Violence/ Terrorism	0.584	0.088
	Regulatory Quality	0.825	-0.224
	Rule of Law: Estimate	0.860	-0.214
	Voice and Accountability	0.383	-0.595
OECD Programme for International Student Assessment (PISA)	Mean performance on the mathematics scale	0.787	0.457
	Mean performance on the reading scale	0.679	0.464
	Mean performance on the science scale	0.604	0.435

Notes: This table presents the correlation coefficients between various structural institutional indicators and country-level estimates of employment and wages. The indicators are grouped under four main indices: the Cisco Digital Readiness Index, the ASEAN Digital Integration Index, the World Bank Worldwide Governance Indicators, and the OECD Programme for International Student Assessment (PISA). Correlation values indicate the strength and direction of relationships between these institutional pillars and employment or wage trends.



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