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

Lee, King Fuei

Schroder Investment Management

March 2024

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LEE King Fuei[1]
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Forthcoming in Asian Economics Letters

Abstract

The surge in artificial intelligence (AI) has significantly impacted industries and job roles, raising concerns about its effects on labour markets. This study examines AI's influence on employment and wages within the ASEAN region, using a patent-based measure of AI exposure. Findings indicate that while AI generally displaces jobs, the impact varies by country. Most ASEAN countries experienced a reinstatement effect, except Indonesia and Thailand where displacement occurred. Singapore showed a complementarity effect. Education emerges as a key policy tool to counteract AI's negative labour market impacts, encouraging job complementarity.

JEL Classification: E24, J24, J62, J64, O33
Keywords: ASEAN, Southeast Asia, artificial intelligence, automation, employment, wages, labour market

[1] Lee King Fuei, Schroder Investment Management, 138 Market Street #23-01 CapitaGreen Singapore 048946, Tel: (+65) 6800 7000, Email: king.lee@schroders.com

1. Introduction

Over the last decade, the technological landscape has undergone significant transformation, primarily driven by advancements in a broad spectrum of automation technologies. While the initial automation discourse was focused on robotics and software, the swift rise of ChatGPT has thrust artificial intelligence (AI) into the limelight, catalysing a competitive pursuit for AI dominance, particularly within Silicon Valley. AI's capability to automate complex tasks and perform advanced cognitive functions signals a potential overhaul of industry structures, job roles, and workforce dynamics, raising global concerns about its impact on employment and wages.

The burgeoning interest in the labour market implications of artificial intelligence (AI) has led to an expansion of research in this area. Economists have developed various models to analyse AI's effects, yet these models frequently amalgamate AI with other forms of automation, such as robotic process automation, neglecting AI's distinct predictive enhancements. Certainly a core attribute of automation technology is its capacity to broaden the scope of tasks that can be executed by capital, thus elevating capital's task share at the expense of labour. This shift induces a displacement effect, where capital supplants tasks formerly undertaken by labour, diminishing labour demand and applying downward pressure on employment and wages. Concurrently, this displacement effect, by augmenting output, lowers labour's share of national income and decouples wage growth from productivity advancements.

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

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

Due to this theoretical ambiguity, researchers have shifted towards empirical studies to gauge AI-enabled automation's real-world effects. This however necessitates accurate AI measure. Earlier research used a task-based approach to assess AI, examining the automatability of various jobs and their tasks. Autor, Levy, and Murnane (2003) suggested that computers could replace routine tasks, using US Department of Labour data to evaluate automatability. Frey and Osborne (2017) extended this model to consider recent technological advancements, predicting that nearly half of US jobs face high automation risk using the ONET database and expert opinions. Arntz, Gregory, and Zierahn (2016) refined this approach by evaluating automatability of individual jobs, not just broad occupations, revealing a lower job automation risk and highlighting task variability within occupations.

The task-based approach to measuring AI's impact on labour markets, despite its meticulousness, faces critique for its ad hoc nature and the subjective judgment it requires, often demanding extensive technical knowledge difficult to obtain for emerging technologies. Webb (2019) addressed these limitations by introducing an objective, patent-based methodology leveraging natural language processing to link detailed patent information with occupational data, thereby objectively assessing technology's workplace impact. By analysing verb-noun pairs from patents and job descriptions, Webb's method quantifies occupational exposure to automation, indicating that higher education roles are more vulnerable to AI, while lower-skilled jobs face greater risks from robotics and software. This approach also correlates increased AI exposure with employment and wage declines. Extending this methodology to European labour markets, Albanesi et al. (2023) found a positive relationship between AI automation and employment shares, highlighting a contrasting impact of AI on employment in Europe versus the US.

This study assesses AI's impact on employment in ASEAN countries from 2015 to 2020 using Webb's (2019) patent-based AI measures. The results show varied AI effects on employment and wages, with a general trend towards the displacement effect in the ASEAN region. Country-specific analyses show reinstatement effects in most countries, displacement effects in Indonesia and Thailand, and a complementarity effect in Singapore. Correlations with technology adoption and structural attributes indicators mostly relate to reinstatement effects, positively affecting employment but negatively affecting wages. Education, especially in Mathematics, is found to be a key policy response to counter AI's labour market impact.

This study has several motivations. First it aims to illuminate the impact of AI on labour markets in Southeast Asia, an area not extensively explored, employing a novel patent-based methodology. It seeks to fill a research void by shedding light on the region's economic dynamics as influenced by AI, and how these effects vary across different countries, underscoring the importance of national contexts. Education is highlighted as a pivotal mechanism for mitigating AI's adverse labour market impacts, providing a foundation for informed policy-making in the face of rapid digitalization.

This paper's structure is as follows: Section 2 outlines the research methodology and data used for analysis. Section 3 presents the empirical results. Section 4 concludes the paper, summarising the main findings and implications.

2. Methodology and Data

2.1 Empirical model

To investigate the relationship between the occupational exposure of AI to changes in employment shares and relative wages, we follow the methodology of Albanesi et al. (2023) by estimating these relationships using the coefficients βc in the following regression:

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

where the dependent variable $y_{o,c}$ represents either the change in the employment share of occupation o in country c during the sample time 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 overall the sample time period, winsorised 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 time period.

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

The β_c coefficients in the employment and wage equations indicate the nature of the AI-jobs relationship as complementarity, displacement, or reinstatement.. A positive β_c in both equations signifies a complementarity relationship, where AI exposure correlates with increases in both employment shares and relative wages, reflecting productivity gains from AI. Conversely, negative β_c coefficients in both equations suggest a displacement effect, with AI exposure reducing employment shares and wages. In instances where one of the two coefficients is positive and the other negative, it indicates a reinstatement effect, where AI automation destroys certain tasks or jobs, but also creates new ones within the same occupation cell.

2.2 Data

This study evaluates AI's labour market impact by integrating labour data with a patent-based AI exposure measure, ensuring alignment across dimensions like country, year, and occupations, primarily using the two-digit ISCO classification. Labour data comes from the ILO and the national statistics departments of Singapore and Malaysia.

AI exposure scores, based on Webb (2019), are derived from US SOC system occupations, while employment and wage data use the ISCO-08. Crosswalks at the four-digit ISCO level are used, with scores calculated for two-digit occupations assuming similar technology exposure in Southeast Asia and the US.

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

3. Empirical Findings

3.1 Descriptive evidence

Descriptive analysis in panels A and B of Figure 1, detailing employment shares and average wage percentiles across ASEAN countries by occupational AI exposure, reveals significant diversity in employment and wage structures by AI exposure levels. Notably, while occupations with medium AI exposure generally dominate the labour force across most ASEAN countries, Myanmar stands out with a majority of its employment in high AI exposure occupations, even compared to its more developed ASEAN counterparts like Singapore. This phenomenon can be attributed primarily to a significant portion of the labour force in Myanmar who are being categorized as "market-oriented skilled agricultural workers." These occupations have particularly high exposure scores, reflecting the extensive patenting activity in AI aimed at automating tasks within these specific job categories. Wage percentiles also vary, with medium AI exposure occupations commanding the highest average wages in Cambodia, Indonesia, Myanmar, and Vietnam, in contrast to Singapore where high AI exposure occupations enjoy the highest wage percentile. These disparities highlight the distinct labour market dynamics across countries, indicating differential impacts of AI on jobs regionally.

3.2 Empirical analysis

3.2.1 Region and country results

The pooled regression analysis, as shown in Table 1, examines the impact of AI on employment share and wage percentile across the ASEAN region, indicating a general displacement effect with negative coefficients: a one-unit increase in the AI score is associated with a statistically significant decrease 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

Yet, detailed analysis at the country level (Figure 2) reveals varied effects. In five countries - Vietnam, Philippines, Myanmar, Malaysia, and Cambodia – AI exhibit reinstatement effects, with relative wages being positively impacted by AI while exerting a negative impact on employment shares. For Malaysia, it is the opposite. Particularly, Malaysia experiences a negative impact of AI on relative wages akin to that observed in Thailand and Indonesia. Nonetheless, the observed positive impact on employment shares is largely attributable to the more pronounced benefits AI provides to occupations with moderate exposure, compared to those with low exposure. Singapore uniquely demonstrates a complementarity effect with AI positively influencing jobs. Only Indonesia and Thailand exhibit the anticipated displacement effect, with AI negatively impacting both employment and wages, aligning with the regional aggregate. This dichotomy, especially given Indonesia and Thailand's demographic weight in ASEAN, underscores the need for nuanced national strategies that consider the diverse impacts of AI on labour markets across different countries, sectors, and occupations.

3.2.2 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.

We first use use 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 little correlation with wages. The "Ease of Doing Business" pillar strongly correlates positively with employment (0.917), suggesting a conducive business environment boosts employment, but negatively with wages (-0.556), implying job creation does not necessarily mean higher wages. Similarly, the "Basic Needs" pillar positively correlates with employment (0.804) but negatively with wages (-0.382), indicating that while basic service improvements increase employment, they don't necessarily lead to higher wages.

We also use the ASEAN Digital Integration Index which is 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 the pillars are highly positively correlated to employment. However, they are also all negatively related to wages. Indeed, the “Innovation & Entrepreneurship” has 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. However, it also shows one of the highest negative correlation with wages (-0.343).

We next examine the World Bank Worldwide Governance Indicators (WGI) impact on country estimates. The WGI assesses public governance quality across six dimensions. Most dimensions show 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 that employment shares in countries with robust rule of law.

Finally, we analyse correlations between country estimates and key educational pillars of the OECD's 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, especially in Mathematics, is a potent policy response to mitigate AI's impact on jobs.

4. Conclusions

This study empirically examines the impact of AI on employment and wages within the ASEAN region, utilizing a patent-based measure of AI for its objectivity. The analysis indicates an aggregate displacement effect in ASEAN, characterized by job losses and reduced wages, predominantly influenced by Thailand and Indonesia. However, country-specific analyses reveal a reinstatement effect in other ASEAN countries, with Singapore uniquely showing a complementarity effect where AI enhances both employment and wages.

Our research highlights the necessity of a nuanced approach to understanding AI's impact on labour markets, suggesting that structural characteristics such as digital readiness, governance, and education levels play a significant role, especially education, in mitigating AI's adverse effects. The findings advocate for policy measures focused on education enhancement to leverage AI's benefits while addressing its challenges in labour markets.

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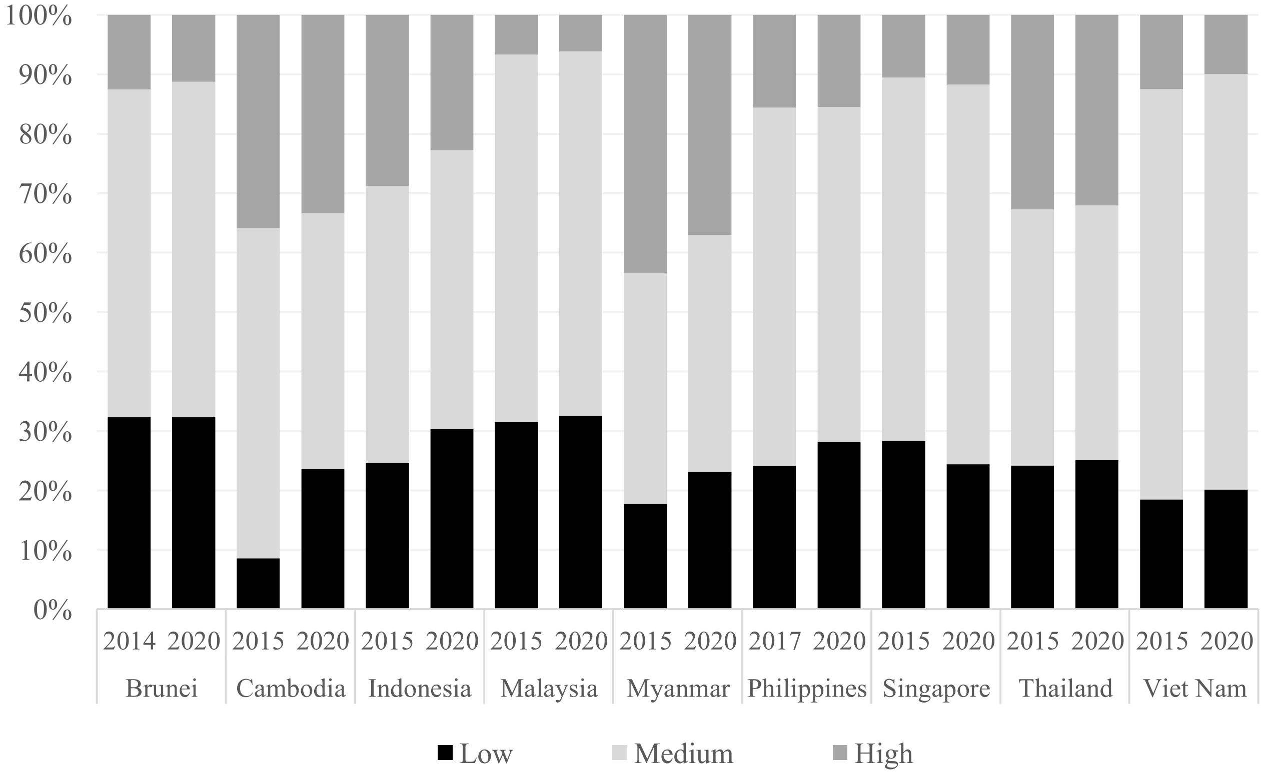
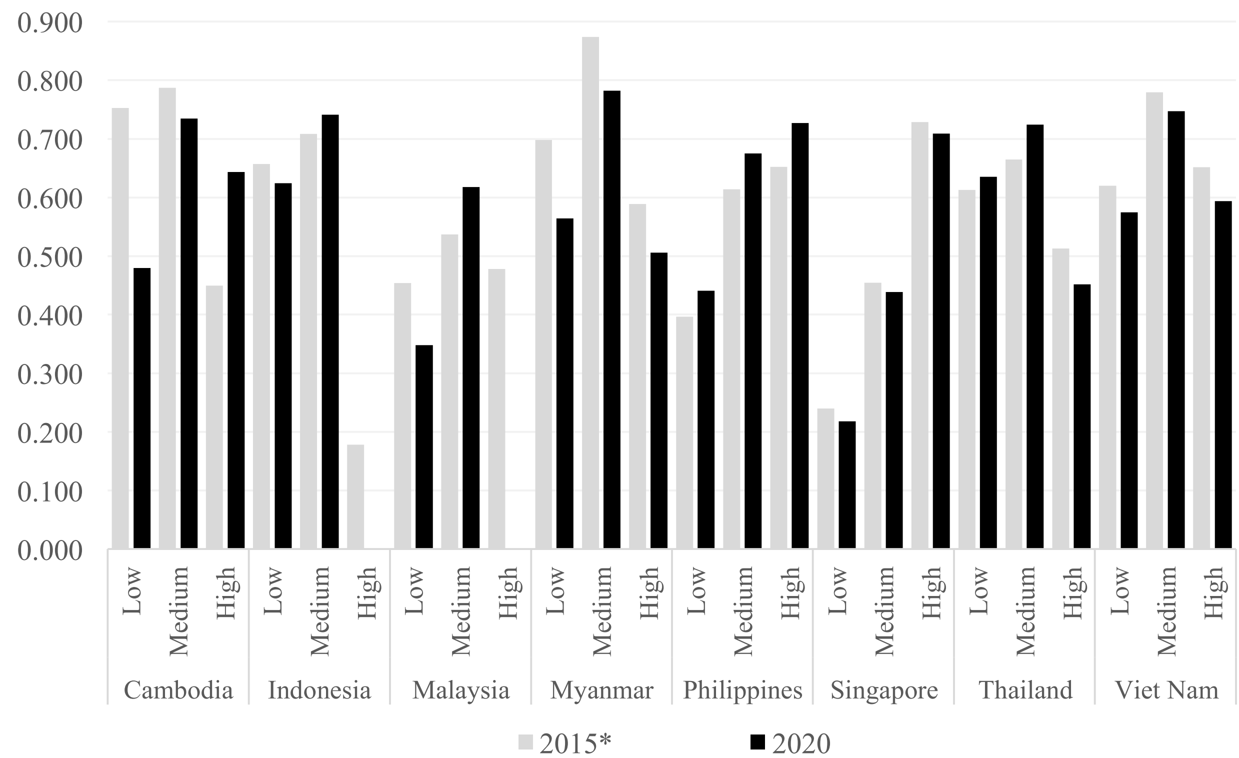
Figure 1: Occupational exposure of AI versus employment shares and wage percentiles, by country

Panel A: Employment shares



Panel B: Wage percentiles



* The starting year for Philippines is 2017.

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

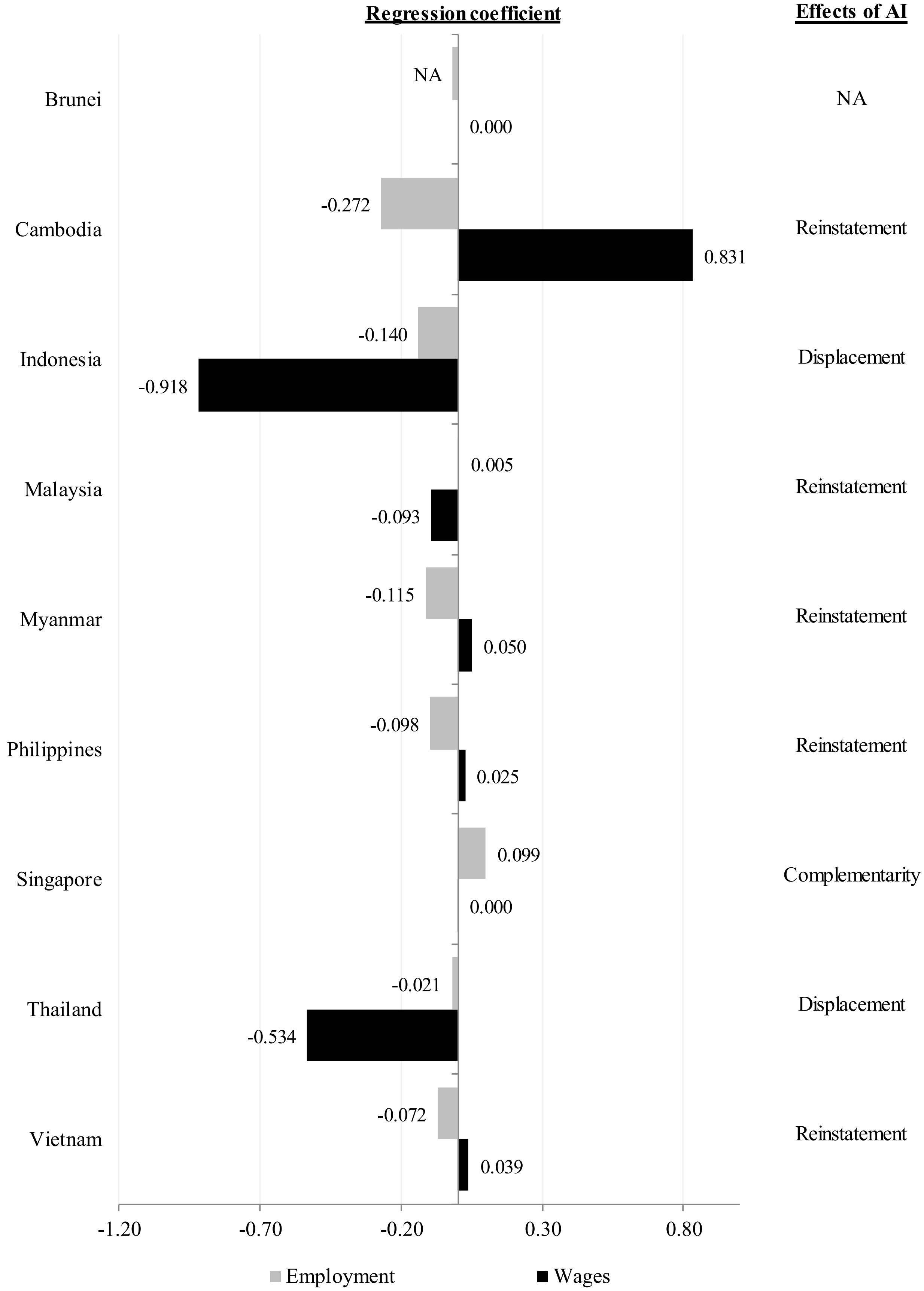


Table 1: Pooled linear regression of annualised changes in employment and wages against occupational AI exposure, 2015-2020

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 pver 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: *** = 1%, ** = 5%, * = 10%.

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

Table 2: Correlations between country estimates and structural 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 & Identitie	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 Givernance 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