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Labor Demand Forecasting: The Case of Cambodia

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Abstract

Labor demand forecasting is crucial for Cambodia's economic prosperity. This is because it enables the country to make well-informed decisions and implement effective policies that align with the changing dynamics of its labor market to promote sustainable economic progress. This study utilizes a demand-driven model; specifically, the autoregressive integrated moving average (ARIMA) model with a top-down approach to forecast Cambodia's labor demand from 2020 to 2025. By capturing current and future labor market trends, we can identify skill requirements and ensure high employment rates for sustainable development. With labor demand forecasting, Cambodia can proactively address skill gaps, optimize workforce planning, and foster an environment conducive to economic growth and stability.

JEL classification: C82, J21, J23.

Keywords: Labor demand, Employment forecasting, ARIMA, Top-down forecasting.

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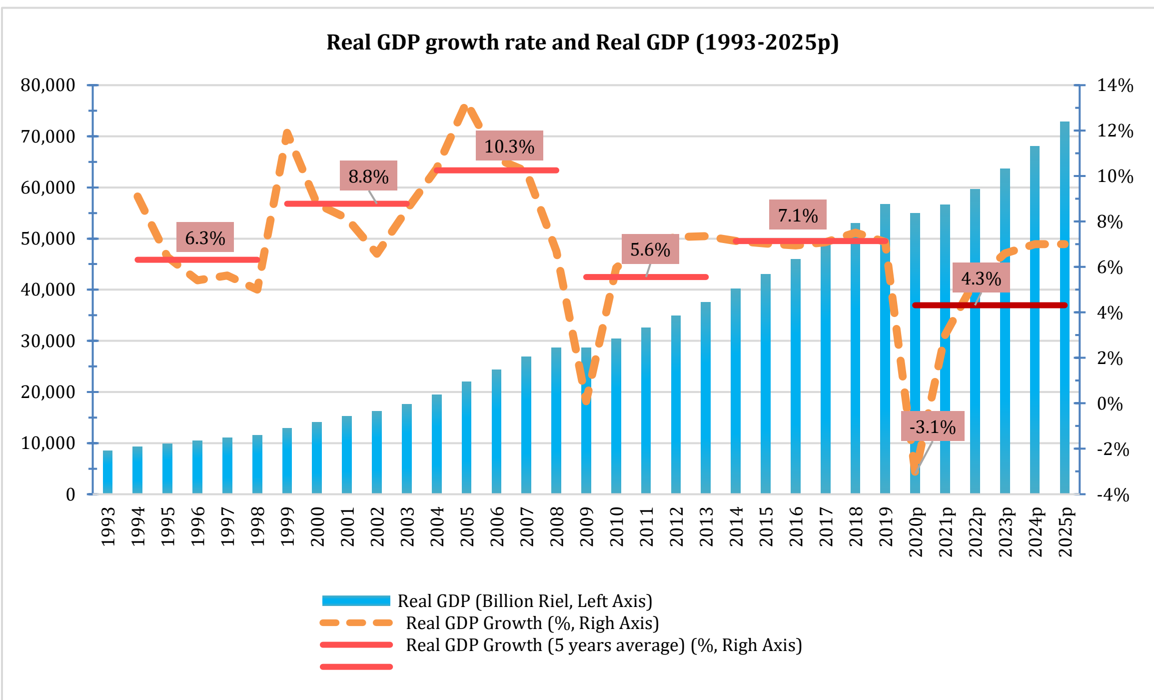
1 Introduction

Cambodia is a developing country in Southeast Asia with a population of over 15 million as of 2019 [1]. Notwithstanding its impressive growth rate, as shown in Figure 1, the Cambodian economy relies heavily on a limited number of sectors, namely garments, construction, trade, and tourism. As of 2019, the industrial sector contributed 35.6% of the country's GDP and employed 2.3 million individuals and the services sector accounted for 39.0% of the real GDP and employed 3.4 million people [2][3]. The labor market in Cambodia has undergone significant changes in recent years, with the country experiencing rapid economic growth, structural transformation, and shifting towards the industry and services sector. The country's resilient and adaptable workforce has attracted foreign investments and expanded export markets. However, low wages, poor working conditions, and social protection of workers remain critical issues. Therefore, policymakers and stakeholders must collaborate to create a more inclusive and sustainable labor market that benefits all Cambodian workers. These issues should be addressed promptly to ensure a better future for the country's labor force.

Notwithstanding Cambodia's efforts to develop its labor force, it faces challenges in addressing high-skill shortages and skills gaps. The country's education system needs to produce sufficient human capital with the required skills and competency levels [4]. However, the lack of infrastructure and the teacher quality problem, particularly in rural areas, continue to hinder the country's progress in expanding access to education. Overcoming these challenges is critical to ensure that all Cambodian students are afforded equal opportunities for quality education, which is vital for supporting the country's overall development goals, particularly its efforts to enhance its labor market.



Source: Author's calculations based on Cambodia's Ministry of Economy and Finance (MEF).

Figure 1: Real GDP growth rate and Real GDP (1993-2025p)

To find the key factors influencing labor market dynamics in Cambodia and how forecasting models and techniques can be utilized to accurately predict future labor market trends and inform effective policy interventions, forecasting labor demand is essential for Cambodia's economic success. It is imperative for economic planning, workforce development, addressing skill gaps, creating job opportunities, facilitating investment decisions, and ensuring optimal labor market functioning. By examining the unique factors and dynamics that influence labor demand in Cambodia, this research offers a localized perspective and contributes to a more comprehensive understanding of labor market forecasting. This allows researchers, policymakers, and practitioners to gain insights and make informed decisions and policies to meet the evolving demands of the labor market, thus contributing to sustainable economic progress. Therefore, this study aims to establish a forecasting employment model from 2020–2025 (a demand-driven model) by sector, occupation, and skill level to capture current and future labor market trends to identify the necessary skills and ensure high employment rates.

The remainder of this paper is structured as follows: literature review, methodology, result estimation, result interpretation, conclusion, and implications.

2 Literature Review

Employment forecasting is the process of estimating future employment trends in various industries and sectors of an economy. There are several approaches to employment forecasting, including time-series forecasting, bottom-up approach, top-down approach, and market signaling [5]. Time series forecasting uses statistical techniques to analyze past trends in employment data and forecast future employment levels, assuming that past trends will persist. The bottom-up approach estimates the employment demand at the company or industry level by examining individual job openings, employee turnover rates, and other factors that are aggregated to provide an accurate perspective of employment trends. The top-down approach estimates employment demand at the national or regional level based on economic indicators, such as GDP growth, inflation, and population growth, assuming that macroeconomic trends will drive employment trends. Market signaling involves analyzing job posts, hiring trends, and other labor demand indicators to estimate future employment trends. Employers often use this approach to determine and direct their training and recruitment efforts.

Numerous forecasting models have been developed to estimate the number of available jobs for various qualifications in specific sectors within a particular timeframe. Occupational forecasting is often based on fixed share or trend-extrapolated coefficients. A study conducted in Australia explored the application of computable general equilibrium (CGE) models to analyze the dynamics of labor markets and predict future trends [6]. The authors discussed the underlying theoretical framework and methodology of CGE modeling, emphasizing its relevance to labor market forecasting. They treated occupational share effects as a type of technical change and forecasted them by extrapolating historical trends in the occupational mix in each industry. The study comprehensively examined the practical implementation of general equilibrium modeling in labor market forecasting, emphasizing its significance in policy analyses and decision-making processes. In the late 1990s, the Bureau of Labor Statistics (BLS) used a demand-driven model to project occupational employment based on population growth, labor force participation rates, and macroeconomic trends in the United States. This approach remains unchanged [7]. In Cyprus, occupation forecasts were obtained by applying past occupational shares to future data on sectoral employment [7][8], while in Ireland, the occupational structure of employment was projected by considering past trends and expectations related to the evolution of skills and occupations [9]. In a study conducted in the Netherlands, a model was developed to explain the occupational structure using system dynamics OLS techniques to account for employment dynamics across 43 occupational groups and 13 industry sectors between 1988 and 2003 [10]. The findings of the study revealed long-term and short-term relationships between employment trends by occupation and sector and value-added, capital, and research and development (R&D) levels. The long-term relationship reflected the production technology specific to each sector. In Latvia, [11] instead utilizes many approaches, including the quantitative approach, employing various forecasting models and techniques to project the labor force demand and supply and identify potential mismatches. The authors analyze factors such as economic growth, demographic trends, and labor market indicators to develop their forecasts. This paper enhances our understanding of labor force dynamics and forecasting techniques specific to Latvia. In the case of data limitation, especially for developing countries, [12] demonstrates the application of the CGE model for labor market forecasting and conducts a decomposition analysis to identify the underlying factors that drive labor market changes. Applying the method to Vietnam's economy demonstrates its effectiveness in generating detailed labor market projections and highlighting the underlying factors shaping the forecasts. The authors highlight the importance of wages as indicators of economic value and scarcity, advocating for their central role in policymaking. They discuss the influence of technology and preferences on wage rates and stress the need for education policies to adapt to changing workforce needs. The decomposition approach enables a detailed examination of how different factors affect labor market forecasts, offering insights into the impact of policy interventions and the potential benefits of adjusting education policies.

In a previous study, different methodological frameworks and approaches for labor demand forecasting were explored and the E3ME macroeconomic model was concluded to be a widely used model [13] [14] [15] [16] [17]. The E3ME is a demand-driven model, that derives labor demand from economy- or sectoral-level output and disaggregates it by occupation and qualifications. In the study, two categories of demand were employed: expansion demand by occupation and qualifications, and replacement demand. The study was limited by its dependence on the availability, quality, and range of data; therefore, the authors suggested using country-specific data and information in the future to improve forecasting results. In Germany, [17] examines labor demand between 1996 and 2007 and applies the multisectoral macroeconomic model to forecast labor demand by sectors, occupations, and qualifications until 2025. They analyze the demand for labor by considering different factors such as industrial sector growth, technological advancements, changes in occupational structure, and skill requirements. The empirical results highlight sector-specific labor demand patterns and their applications to inform decision-making in workforce development and education policies in Germany.

Another study adopted the demand-driven model used by the Bureau of Labor Statistics of the United States to project the demand for skills in Cambodia’s labor market [18]. The study forecasted sectoral growth by considering production factors, productivity changes, international trends, industry composition data, and other macroeconomic factors. Employment coefficient was constructed for each sector and forecasted forward using the autoregressive model (AR1) for 19 sub-sectors and ten occupational levels for 2012–15. However, the variables used were limited to the lag and quadratic time trends selected for the study.

[19] presents a study on forecasting the construction labor market in Hong Kong using the Box-Jenkins approach. They utilize time series analysis techniques (ARIMA) and consider factors such as economic growth and government policies to develop forecast models. The empirical results of the study provide insight information on five major labor market indicators such as employment level, productivity, unemployment rate, underemployment rate, and real wage. A recent study conducted in the Saudi labor market also employed the ARIMA model to forecast job demands from 2021–2025 by analyzing historical job vacancy data from 2015 to 2020 [20]. The findings in the study could assist policymakers and business leaders in making well-informed decisions regarding workforce planning and employment. The study not only proved the effectiveness of the ARIMA model in accurately forecasting future job demands but also provided valuable insights into the practical application of ARIMA models in predicting labor market trends and informing policies and business strategies.

Several studies conducted in different countries have confirmed the efficacy of a top-down approach in forecasting labor demand. In this study, we combined two forecasting methods: time series projection (autoregressive integrated moving average, ARIMA) and a top-down approach. We aimed to extend the data coverage from 1993–2011 to 2019 and expand the model structure by including additional variables, such as the real GDP growth rate, investment per worker, wage, and energy price. These indicators helped to capture the relationship between macroeconomic factors and labor demand, enabling more accurate predictions of future workforce requirements.

3 Methodology

3.1 Framework

Two separate data were collected for this study: sectoral forecasts of real GDP and investments data from Cambodia's Ministry of Economics and Finance and employment and real wage estimates (1993–2019) from the Cambodian Social Economic Survey (see Appendix Table A2). The forecasting period is from 2020 to 2025, and we employed the method used by [18].

The employment forecasting model presented in this study comprises four main steps. First, employment by sector in the missing year was estimated by extrapolating the geometric growth model, interpolating between two different years available within each of the four major sectors (agriculture, garments, other industries excluding garments, and services between 1993–2019). This study categorized the industrial sector into two subsectors (garments, and other industries excluding garments). This is because the garment sector in Cambodia contributes significantly to economic and infrastructure development, employment growth, exports, poverty reduction, and foreign investment.

The second step of this model is to estimate the employment coefficient of each sector i^{th} in period t, which is given as:

$$C_{it} = \frac{E_{it}}{Y_{it}}$$

- where E_{it} is the total employment in the sector i^{th} in period t, and Y_{it} is the total real GDP of the sector i^{th} in period t

Third, we performed an autoregressive integrated moving average (ARIMA) estimation for the natural log transformation of the employment coefficient at time t, which are:

$$ln\ (\hat{C}_{i,t}) = F_i\left(t, t^2, \varphi_{i,t}\right)$$

- where t is the time trend and $\varphi_{i,t}$ denotes the set information available for the sector i^{th} up to time t , such as the real GDP growth rate, investment per worker, real wage, unemployment rate, oil price, and dummy variables (for various years:1997–98, 2008, and 2020).
- The employment coefficient is worker per million-riels output produced.
- The real GDP growth rate is the growth rate of the adjusted GDP at 2000 constant price.
- Investment per worker is the adjusted investment stock with a depreciation rate.
- Real wage is the adjusted nominal wage with the GDP deflator at a 2000 constant price.
- The unemployment rate is the total number of unemployed people divided by the total labor force. Unemployed is defined as an individual who is actively seeking employment but is currently without a job (see NIS, 2019).
- Oil price is the adjusted oil price per barrel in the local currency with the GDP deflator at the 2000 constant price.

If the input data are not available, they are forecasted using the ARIMA model and a dummy variable for the remaining forecasting period (2020–2025). For each variable, a series of tests was performed, such as a stationary test, autocorrelation (ACs), and partial autocorrelation (PACs). Using the Akaike information criterion (AIC) and Bayesian information criterion (BIC), we determined the lag length of the time series and compared the models for the best results (see Appendix Table A1). The selected models were tested for white noise, and the AR parameters satisfied the stability condition with all eigenvalues inside the unit circle.

Finally, employment forecasts were made using each sector's employment coefficients estimated from the previous equation.

$$\hat{E}_{i,t+s} = \hat{C}_{i,t+s} \times \hat{Y}_{i,t+s}$$

- Where $\hat{E}_{i,t+s}$ is forecasted employment of sector i at time $t + s$,
- $\hat{C}_{i,t+s}$ is the employment coefficient of sector i in period t,

Occupational share forecasting was performed using the ARIMA model and a dummy variable and then rescaled back to a 100% share. The composition of the occupation share throughout the period was rigid.

3.2 Estimation Result

The table below presents the results of the forecasted model for the employment coefficient (workers per million riels) in Cambodia. The estimation reveals a negative relationship between time and the employment coefficient, indicating that, as time progresses, the employment requirements to produce the same level of output decrease. This could be attributed to several factors, such as introducing new technology; automation that reduces the need for manual labor; changes in market demand that lead to decreased production; or a decline in employment necessary to produce the same output level. However, the extent of the negative relationship varies across sectors. The highest was observed in other industries (excluding the garment sector) (-0.028), followed by agriculture (-0.025) and services (-0.012). In contrast, the quadratic form of time showed a positive relationship with the employment coefficient. This relationship suggests that there may be an optimal point at which employment per output is maximized before the diminishing returns are set. However, the magnitude was relatively small given the significance level. Time and its quadratic form did not affect the garment sector.

The negative relationship between the real GDP growth rate and employment per output suggests that as the economy grows, it becomes more efficient and productive and requires less labor to produce the same output. With a 1.0% increase in the real GDP growth rate, the employment coefficient decreased by 1.0 units in the garment sector, 0.9 units in the other industries sector, and 1.1 units in the services sector. This relationship is supported by [17] as economies develop and become more productive, Cambodia may experience reduced employment growth even during periods of positive GDP growth. In Germany, job losses are expected in highly productive sectors such as the industry and services sector.

The investment per worker and employment coefficient changes exhibits an inverse relationship with a 1% significance level. A 1.0% increase in investment per worker is associated with a 0.5% decrease in the employment coefficient in the agriculture sector, 0.3% decrease in the garment sector, 0.6% decrease in other industries, and 0.5% decrease in the services sector. Overall, this suggests that as investment per worker increases, the number of workers required to produce each output decreases. Thus, it is a significant factor to consider when analyzing the change in workers per unit output.

The change in wages and the employment coefficient has a mixed relationship; however, only the change in wages in other industries is statistically significant and has a positive relationship with the employment coefficient. Specifically, a 1% increase in wages is associated with a 0.22% increase in the employment coefficient. This implies that higher wages may increase the demand for labor, which in turn may increase the employment coefficient. This relationship is similar to [12]; higher wage expands employment across qualifications. For higher-value-added industries, wage increases may positively impact employment, as firms rely on skilled labor and quality service provision to expand their operations.

The estimation table suggests a negative relationship between the unemployment rate and the employment coefficient. The coefficient of -0.107 in the agricultural sector indicates a one percent increase in the employment coefficient for every 0.1% decrease in the unemployment rate.

The change in the energy price (oil price per barrel) has an inverse relationship with the employment coefficient. A 1% increase in energy prices results in a 0.1% decrease in the employment coefficient in other industries and a 0.05% decrease in the services sector. This relationship suggests that as energy prices increase, firms may reduce their production output, which could reduce the number of workers needed to produce one million riels of output.

However, the dummy variable is statistically significant only in other industries and has a negative effect on the employment coefficient, with a negative coefficient of -0.164. The dummy variable for different years (1997–98, 2008, and 2020) negatively affects the employment coefficient in other industries.

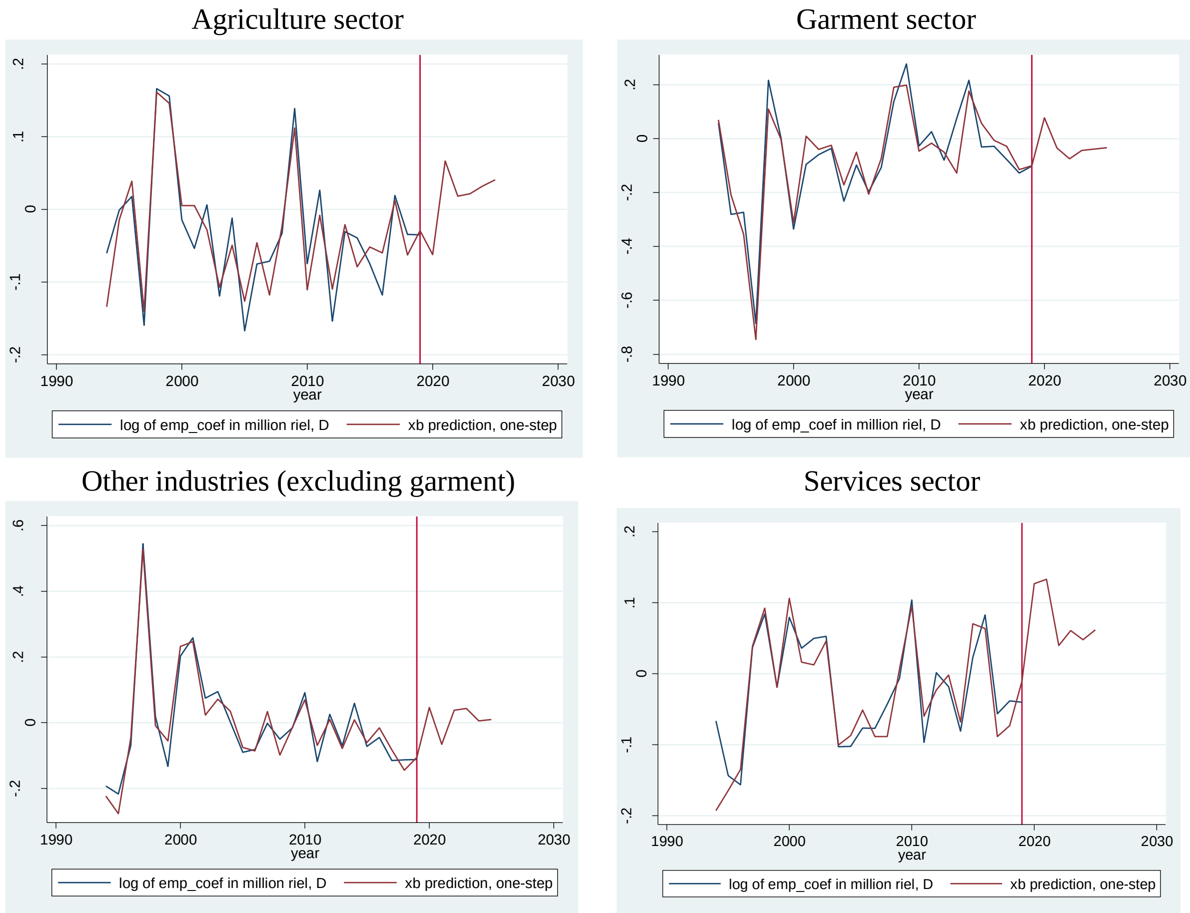
Finally, the constant term in this model is statistically significant across all four sectors and has a positive relationship with the dependent variable. The positive sign of the constant term suggests a baseline level of the employment coefficient (workers per million riels) that is not accounted for by the other independent variables included in the model.

Table 1: Estimation result

Dependent variable: Employment coefficient (workers per million riels output) (ln, d1)				
Sector	Agriculture	Garment	Other industries excluding garment	Services
Time	-0.025***	-0.039	-0.028***	-0.012***
	(0.008)	(0.05)	(0.004)	(0.003)
$Time^2$	0.001**	0.001	0.001***	0.000***
	(0.000)	(0.002)	(0.000)	(0.000)
Real GDP Growth Rate	-0.016	-1.007***	-0.915***	-1.123***
	(0.235)	(0.154)	(0.117)	(0.229)
Investment per worker	-0.530***	-0.353***	-0.583***	-0.510***
(ln, d1)	(0.123)	(0.096)	(0.032)	(0.040)
Wage	0.021	-0.012	0.220***	-0.087
(ln, d1)	(0.085)	(0.109)	(0.067)	(0.070)
Unemployment rate	-0.107***	-0.088	0.020	-0.013
	(0.029)	(0.084)	(0.023)	(0.041)
Oil price per barrel	-0.032	0.041	-0.126***	-0.046**
(ln, d1)	(0.041)	(0.082)	(0.032)	(0.023)
Dummy	0.022	0.076	-0.164***	-0.010
	(0.055)	(0.064)	(0.034)	(0.028)
Constant	0.304***	0.629*	0.386***	0.246***
	(0.069)	(0.334)	(0.027)	(0.027)
AR (lag1)	-0.566**	0.597*	-0.918***	-0.985***
	(0.242)	(0.319)	(0.256)	(0.231)
AR (lag2)			-0.562***	-0.756***
			(0.197)	(0.161)
/sigma	0.033***	0.065***	0.033***	0.027***
	(0.008)	(0.012)	(0.008)	(0.007)
Log likelihood	51.833	33.793	51.122	55.569
Wald chi2	98.12	359.57	889.37	444.67
Prob > chi2	***	***	***	***
Sample:	1994 - 2019			
Out of sample forecast:	2020-2025			
*Standard deviation is in parentheses. * p<0.10, ** p<0.05, *** p<0.01*				
(ln, d1) indicate variable with natural log and first difference.				

Source: Author's estimation.

The following graph illustrates the log of the employment coefficient (workers per million riels output) compared with the forecast results for each sector. The estimated results are similar to the data owing to the same input data.



Source: Author's estimation.

Figure 2: Estimation result by sector

3.3 Result Interpretation

This study employs the top-down approach; therefore, capturing the overall trend, share, and real GDP growth rate in the selected sectors is essential. Over the past decades, Cambodia has experienced rapid economic growth with an average real gross domestic product of 7.6% between 1993 and 2019. Cambodia's economy is driven by four key sectors: agriculture, garments, other industries (excluding garments), and services.

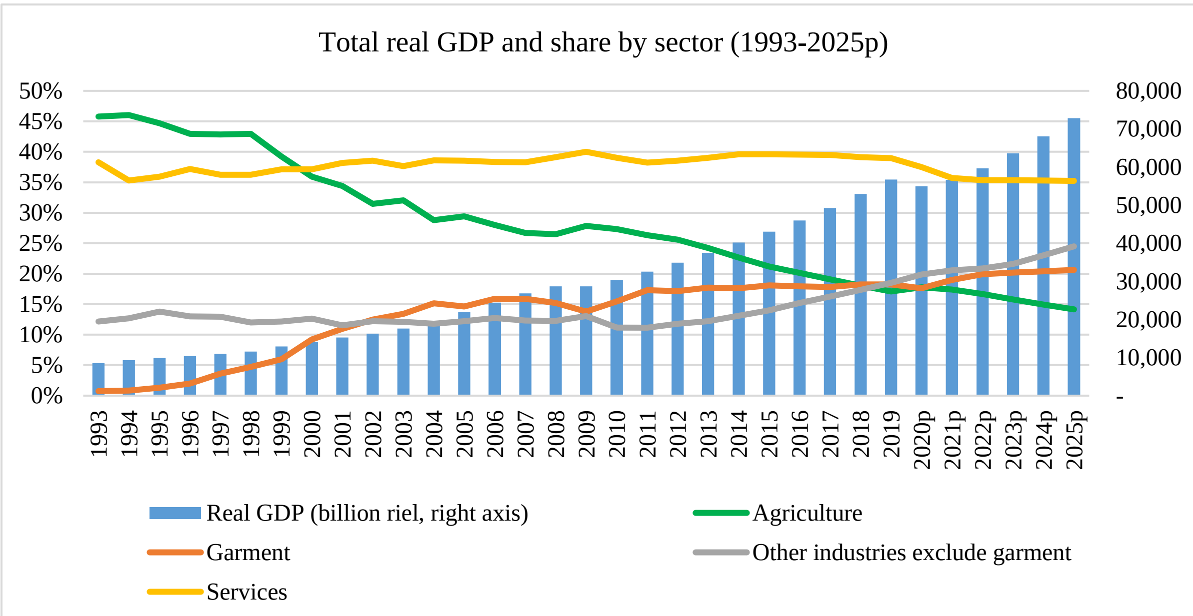
The agricultural sector was a significant contributor to GDP in the early stages of the country's development; however, it declined over time. The sector contributed 45.8% of the GDP in 1993, 35.9% in 2000, and 17.1% in 2019. It is expected to contribute 14.2% in 2025. In terms of growth rate, the agriculture sector is experiencing a downward trend: 4.5% between 1993–2009 to 2.0% between 2010–2019 and is expected to increase by 1.0% between 2020 and 2025.

The garment sector experienced its first significant growth in contribution to real GDP in 1996 at 2.0%. It experienced an increase in 2000 (9.2%) and in 2019 (18.2%). Moreover, further is expected in 2025 (20.6%). For the growth rate, the garment sector exhibited an upward trend between 1993–2009 at a rate of 32.0% and maintained a favorable growth of 10.2% between 2009–2019. Growth projection for 2020–2025 is estimated at 6.6%. The influx of foreign investment and preferential trade agreements has driven rapid growth in this sector over the past two decades.

The industrial sector (excluding the garment sector) experienced stable growth in the past decades, contributing approximately 12.4% between 1993 and 2009. In 2019, the sector experienced significant growth, contributing 18.5% to real GDP. The future projection for 2025 is estimated at 24.5%. The significant increase in the country's investment in manufacturing and construction and the growing infrastructure demand can be attributed to this growth.

The services sector, unlike the other sectors, has had an all-time high share of real GDP since 2000, contributing an average of 38.2% between 1993–2019. The sector is expected to experience a continuous upward trend and contribute 35.7% to GDP from 2020 to 2025. The expansion of tourism, trade, and financial services has driven the growth of the service sector, in addition to the government's quick response to the pandemic.

Cambodia's real GDP growth has been driven by four major sectors. Over the years, growth has shifted from agriculture to industrial and services sectors. While the garment sector has played a significant role in this growth, focus is now being placed on other industries and services.



Source: Author's calculations based on Cambodia's Ministry of Economy and Finance (MEF).

Figure 3: Total real GDP and share by sector (1993–2025p)

Table 2: Average Real GDP Growth Rate (billion riels, yearly)

Sector	Average Real GDP Growth Rate (billion riels, yearly)							
	1993-2019		1993-2009		2010-2019		2020p-2025p	
	Abs. Value	%	Abs. Value	%	Abs. Value	%	Abs. Value	%
Total Real GDP	1,854	7.6%	1,261	7.9%	2,803	7.1%	2,684	4.3%
Agriculture	223	3.6%	256	4.7%	171	2.0%	100	1.0%
Industry	760	12.2%	413	13.2%	1,315	10.5%	1,997	7.9%
Garment	396	23.6%	244	32.0%	638	10.2%	779	6.6%
Other industries excluding garment	364	9.5%	169	8.5%	676	11.1%	1,222	9.3%
Services	725	7.7%	513	8.3%	1,062	6.8%	593	2.7%

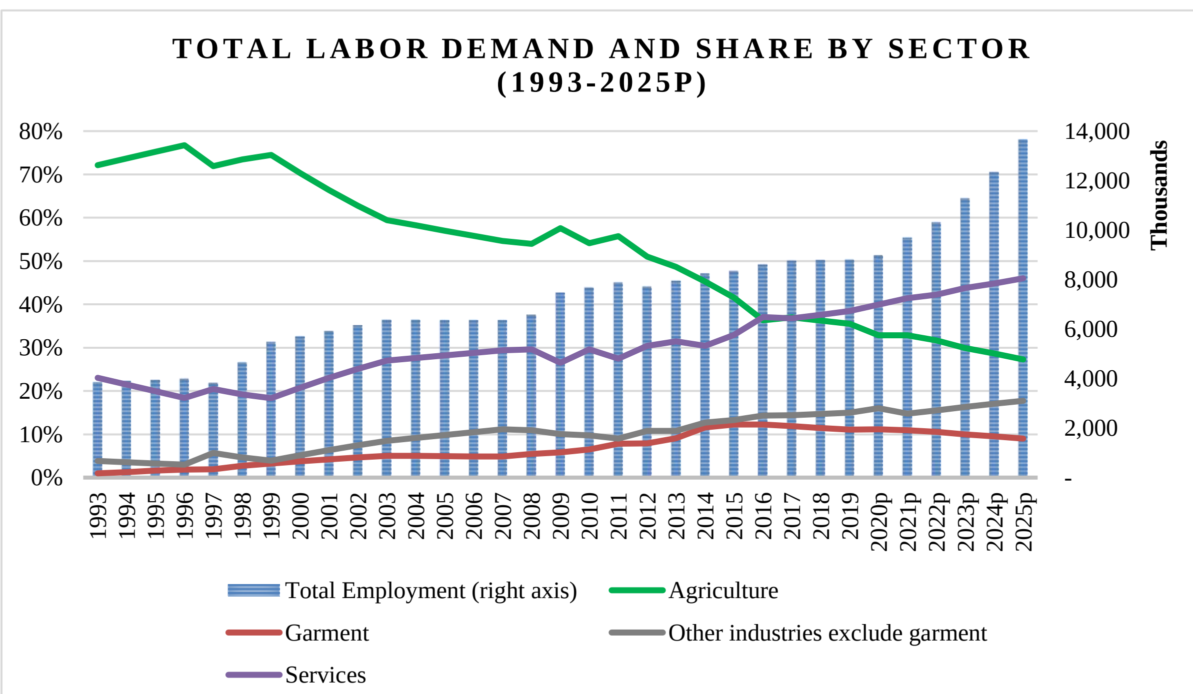
Source: Author's calculations based on Cambodia's Ministry of Economy and Finance (MEF).

The shift in Cambodia's leading sector from agriculture to industry and services has caused significant changes in the labor market. There has been a gradual increase in employment in the industry and services sectors and a drastic decline in the agricultural sector. The overall trend of labor demand derived from the employment coefficient is expanding notwithstanding the setbacks caused by the pandemic in 2020. Labor demand in the agricultural sector experienced a downward trend from 2011 to 2020, and an upward trend in 2021. Agriculture remains an essential source of employment for many Cambodians, particularly those living in rural areas. However, its share of total employment has decreased over time because of a shift towards the industrial and service sectors. This trend is continuing as the country develops its manufacturing and service sectors.

Over the past two decades, the garment industry has become a major source of employment in Cambodia. It is currently the largest sector, employing over 900,000 people in 2019, and is expected to be over 1.2 million by 2025. However, the sector faces challenges such as rising labor costs and increased competition from other low-cost manufacturing countries. Consequently, labor demand decreased from 9.1% between 2010–2019 to 3.9% between 2020–2025.

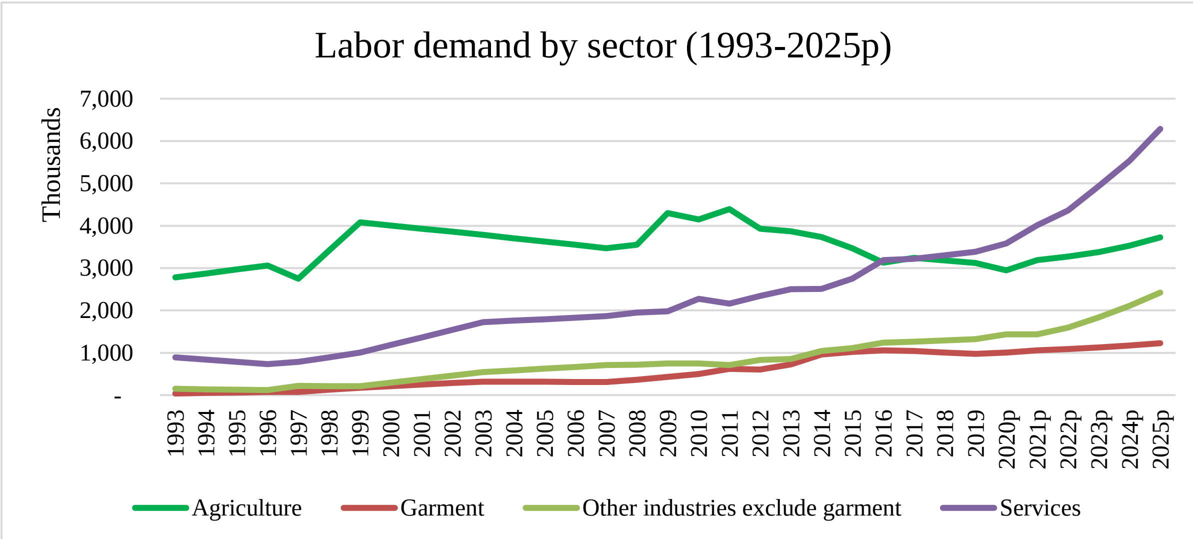
Industries other than the garment sector experienced significant growth. The average growth rate of labor demand was 6.1% between 2010 and 2019 and is expected to increase to 10.8% for the forecasted period. The increase in labor demand is accompanied by the government's efforts to attract foreign investment through various policies, including expanding infrastructure (e.g., developing special economic zones), favorable tax incentives, and better bureaucratic procedures.

Cambodia's services sector has the largest share of labor demand. The average growth rate of labor demand in the services sector has been stable, given its prominent share (5.7% between 2010–2019). However, it is expected to double in the forecasted period (10.9% between 2020–2025). Such growth is driven by the expansion of trade, tourism, and financial services, the spillover effects of industry expansion, and quick recovery from the pandemic.



Source: Author's estimation.

Figure 4: Total labor demand and share by sector (1993–2025p)



Source: Author's estimation.

Figure 5: Labor demand by sector (1993-2025p)

Table 3: Average Labor Demand Growth Rate (yearly)

Age 15-64	Average Labor Demand Growth Rate (yearly)							
	1993-2019		1993-2009		2010-2019		2020p-2025p	
	Abs. Value	%	Abs. Value	%	Abs. Value	%	Abs. Value	%
Total Employment	190,273	3.4%	225,873	4.4%	133,313	1.7%	810,084	7.6%
Agriculture	13,108	0.8%	95,068	3.2%	(118,029)	-3.0%	100,696	3.1%
Industry	81,206	10.7%	62,518	12.9%	111,108	7.1%	225,376	8.1%
Garment	36,060	14.4%	24,748	17.8%	54,159	9.1%	41,950	3.9%
Other industries excluding garment	45,146	10.0%	37,770	12.4%	56,949	6.1%	183,427	10.8%
Services	95,959	5.5%	68,287	5.4%	140,234	5.7%	484,011	10.9%

Source: Author's estimation.

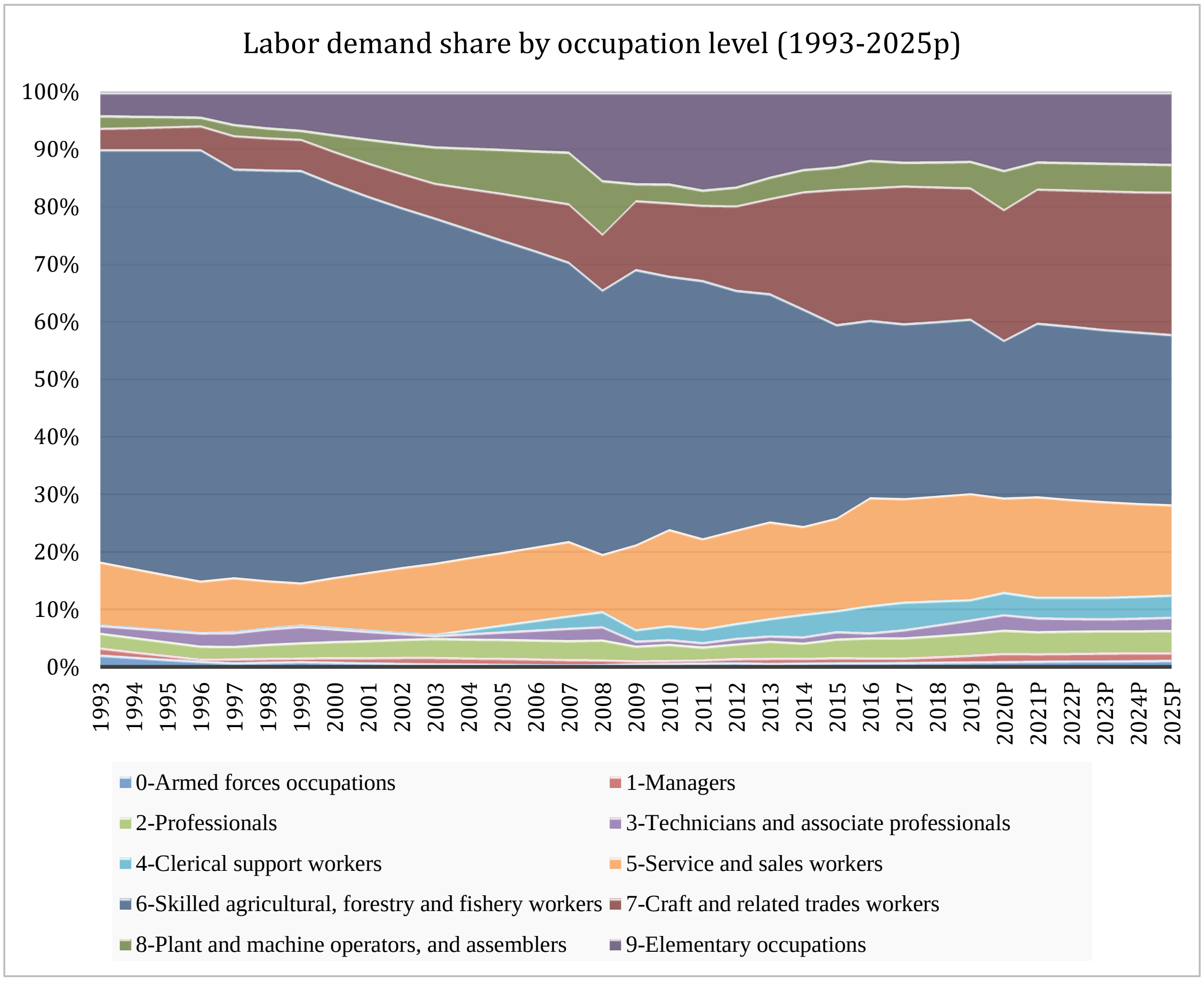
Table 4 presents the expected growth rate of labor demand and output by sector. It highlights the expansion and contraction of the overall performance of Cambodia's economy; thus, the country's ability to generate new jobs, given the expected growth. In the industrial sector, the non-garment sector generates more employment than the garment sector. During the early stages of the pandemic in 2020, Cambodia's service sector faced a decline in real GDP growth. However, the sector has maintained its contribution to employment growth and is currently demonstrating a promising trajectory with substantial employment and real GDP growth. This may be attributed to the emergence of new forms of e-commerce, including online platforms, delivery services, and digital marketplaces. Cambodia's labor demand is closely linked to its real GDP growth across various sectors. As a country undergoes structural changes and endeavors to diversify its economy, labor demand is expected to shift further toward the industry and services sectors. This shift reflects Cambodia's efforts to adapt and develop a robust and diverse economic landscape.

Table 4: Growth rate of labor demand and real GDP in the forecasted year (2020p–2025p)

Sector	Labor Demand Growth Rate					
	2020p	2021p	2022p	2023p	2024p	2025p
Overall	2.0%	8.0%	6.4%	9.4%	9.4%	10.7%
Agriculture	-5.6%	8.1%	2.5%	3.3%	4.6%	5.5%
Industry	6.3%	2.1%	7.8%	10.4%	10.5%	11.3%
Garment	2.8%	5.5%	2.9%	3.6%	4.0%	4.6%
Other industries excluding garment	8.9%	-0.4%	11.4%	15.1%	14.5%	15.0%
Services	5.9%	12.0%	8.5%	13.3%	12.1%	13.6%
	Real GDP Growth Rate					
Overall	-3.1%	3.0%	5.4%	6.6%	7.0%	7.0%
Agriculture	0.5%	1.1%	0.7%	1.1%	1.3%	1.3%
Industry	-1.2%	8.5%	8.9%	9.2%	11.1%	11.1%
Garment	-6.4%	10.8%	10.8%	8.1%	8.1%	8.1%
Other industries excluding garment	4.0%	6.4%	7.2%	10.3%	13.9%	13.9%
Services	-6.7%	-1.9%	4.3%	6.6%	6.8%	6.8%

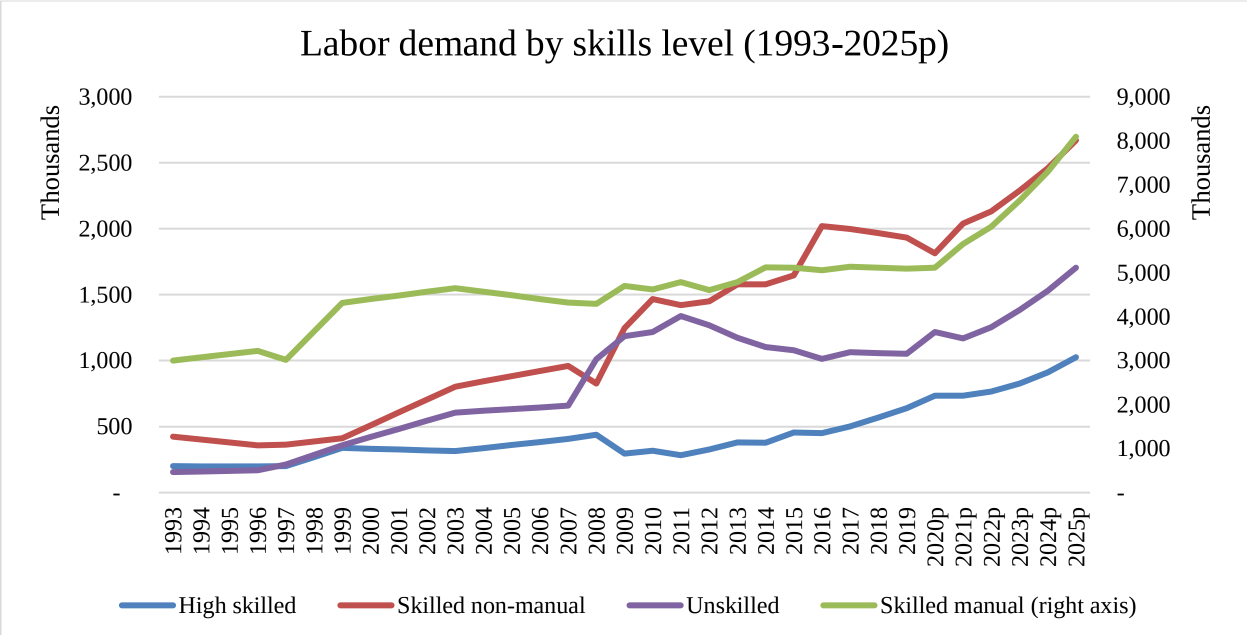
Source: Author's estimation.

Cambodia's labor demand by occupation level is characterized by a high proportion of low-skilled workers. As of 2019, the largest share of employment constituted unskilled labor (57.8%) (see skill classification in the Appendix), which consists of agricultural, forestry, and fishery workers (30.4%), craft and related trade workers (22.9%), and plant and machine operators and assemblers (4.6%). The second largest share of employment constituted skilled non-manual labour (21.9%), which consists of two occupation levels: clerical support workers (3.5%) and service and sales workers (18.4%). Highly skilled workers, including managers, professionals, technicians, and associate professionals account for the smallest share of employment. Although Cambodia has shifted toward more advanced sectors, unskilled labour remains the largest share of employment, raising concerns about the development of human resources. This is because a significant portion of the population is employed in low-productivity agriculture, which does not require advanced skills. However, with the country's transition to more sophisticated industries and services, the need for skilled workers to meet the demands of these industries has become apparent.



Source: Author's estimation.

Figure 6: Labor demand share by occupation level (1993–2025p)



Source: Author's estimation.

Figure 7: Labor demand by skills level (1993–2025p)

4 Conclusion and Implication

Forecasting labor market trends in Cambodia is crucial for policymakers, researchers, and labor market stakeholders. Over the past decades, Cambodia has experienced significant economic growth, leading to an increase in employment opportunities. However, the labor market is still characterized by skill shortages and imbalances, low education levels, and inadequate infrastructure.

Owing to this, labor market forecasting is critical for developing policies and programs to address the country's skill gaps and shortages. As the economy continues to grow and diversify, there is a need to ensure that the workforce has the necessary skills and competencies to meet the demands of the labor market. This requires investment in education and training programs, particularly in rural areas, which are characterized by inadequate infrastructure and teacher quality problems. Particularly strengthening the existing technical and vocational education training (TVET) program to address the skills gap by promoting collaboration between educational institutions and industries to align curriculum with the evolving needs of the workforce. In addition, create a robust labor market information system that offers precise and current data on job openings, skill requirements, and career progression. Build online platforms and portals to streamline the process of connecting job seekers with suitable employment opportunities which will enhance the transparency in the labor market and improve job-matching effectiveness.

Another crucial implication is the importance of fostering inclusive economic growth and tackling issues associated with informal employment, which is a significant challenge in Cambodia. Implementing policies and initiatives that encourage formal employment and offer social protection for workers can reduce poverty and inequality and foster sustainable economic development. Addressing this challenge requires close coordination and collaboration among government agencies, the private sector, organizations, and civil society, thereby improving the enforcement of labor regulations to protect the rights of vulnerable workers.

Using the ARIMA and AR models in forecasting provides valuable information on labor market dynamics, including how economic and demographic factors shape employment patterns and occupational trends. These models enable stakeholders to make well-informed decisions regarding labor market policies, education policies, and investments in infrastructure. Therefore, continuous monitoring of labor market indicators, such as the unemployment rate, wages, and GDP growth rate, is essential to identify emerging trends and challenges in the Cambodian labor market.

Accurately predicting labor demand in Cambodia is challenging due to limited access to reliable data sources. This can impact the effectiveness of forecasting models, which rely on high-quality data. Existing data sources may not provide a complete picture of the labor market, particularly for informal and self-employed workers. The lack of long-term time series data and data gaps can hinder models' ability to forecast future labor demand accurately. Overall, the limitations related to data availability, quality, representativeness, and consistency pose challenges to labor forecasting models in Cambodia.

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Appendix

Table A1: Model selection

Sector/Model	**df**	**AIC**	**BIC**	**Selection/Reasons**
Agriculture				
arima100	11	-81.67	-67.83	Selected model
arima101	11	-94.59	-80.75	MA (lag) is not significant
arima102	12	-101.45	-86.36	Both MA (lag) are not significant
Garment				
arima100	11	-45.59	-31.75	Selected model
arima101	12	-46.38	-31.28	ARMA (lags) are not significant
arima102	12	-49.77	-34.68	ARMA (lags) are not significant
Other industries excluding garment				
arima100	11	-73.28	-59.44	AR (lag) is not significant
arima101	11	-87.58	-73.74	ARMA (lags) are not significant
arima102	12	-97.08	-81.98	ARMA (lags) are not significant
arima200	12	-78.24	-63.15	Selected model
arima201	12	-90.52	-75.42	MA (lag) is not significant
Services				
arima100	11	-78.89	-65.05	AR (lag) is not significant
arima101	11	-91.89	-78.06	MA (lag) is not significant
arima102	12	-101.03	-85.94	ARMA (lags) are not significant
arima200	12	-87.14	-72.04	Selected model
arima201	12	-98.48	-83.38	MA (lag) is not significant

Table A2: Data sources

No	Indicators	Source	Data range
1	Employment	Cambodia Socio-Economic Survey (CSES)	1993-2019
2	Real GDP	Ministry of Economic and Finance (MEF)	1993-2019 2020e-2025p
3	Investment	MEF	1993-2019 2020e-2025p
4	Wage	CSES	1993-2019
5	Unemployment rate	CSES	1993-2019
6	Oil price	http://www.bp.com/statisticalreview	up to 2021

Note: e-estimation, p-prediction.

To highlight education and skill levels, under the International Standard Classification of Occupations (ISCO), the nine major occupational groups were grouped into four broad occupational groups, as shown in the table below.

Table A3: ISCO classification

Broad occupation group	ISCO major group	Skill level
High skilled	ISCO_1: Managers	Tertiary (ISCED 5-6)
	ISCO_2: Professionals	
	ISCO_3: Technician and associated professionals	
Skilled non-manual	ISCO_4: Clerical support workers	Secondary (ISCED 2-4)
	ISCO_5: Service and sale workers	
Skilled manual	ISCO_6: Skilled agricultural, forestry, and fishery workers	
	ISCO_7: Craft and related trades workers	
	ISCO_8: Plant and machine operators and assemblers	
Unskilled	ISCO_9: Elementary occupations	Primary (ISCED 1)

Source: International Labour Organization. 2008. “International Standard Classification of Occupations (ISCO-08) – Conceptual Framework,” www.ilo.org/public/english/bureau/stat/isco/docs/annex1.doc.