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Job Polarisation: The Change of Nature of Task and Skill Needs

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Abstract: Job polarisation is the growth of high- and low-skilled employment relative to middle-skilled employment, typically in developed countries. Based on Khazanah Research Institute's (KRI) descriptive study in 2017, Malaysia's workforce experienced job polarisation over the last two decades. This study uses a different approach, i.e. multinomial logistic regression, to measure the probability of employment choice by different job categories to validate the presence of job polarisation in Malaysia. Unlike past research that used headcounts based on wage quantiles, this paper considers the individual and sectoral effects. This study confirms the job polarisation finding of KRI (2017) by comparing Malaysia's employment structure between 2011 and 2017. Technology changes the methods and skills required to perform the same tasks. Besides, the adoption of technology depends on the firm's or industry's foresight of how technology may change the productivity of the worker. If the investment cost of a technology is greater than the training cost, firms may not adopt the technology. If an industry has the foresight of how technology may change the performance of tasks, and recruit workers in tandem with upskilling programmes, the phenomenon of job polarisation will fade out eventually.

Keywords: Job polarisation, employment structure, skill-biased technological change, technological progression
JEL classification: J01, J21, J24

1. Introduction

Rapid industrialisation and diffusion of technologies in the production process have transformed the Malaysian economy from one that was agriculture and commodity-driven to manufacturing and services driven (Rasiah et al., 2015). Apart from changes in economic activities, the advancement of technologies also changes the way workers carry out their works. The emergence of Industrial Revolution 4.0 (IR4.0) has marked a milestone of what technologies can do in production activities and everyday life. These technologies include artificial intelligence (AI), Internet of Things (IoT), robotics and financial technologies. IR4.0 further enhances the function of automation. Taking AI

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as the leading IR4.0 technology, it employs machine learning and deep learning on big data to generate algorithms that make predictions or classification (Petropoulos, 2018).

Concerns on employment arise as Malaysia's economy continues to adopt IR4.0 technologies, in terms of the substitution between technology, capital and labour. This has brought up the widely discussed issue of job polarisation among the developed economies. Job polarisation is the phenomenon of an increase in growth of high-skilled and low-skilled employment, while there is a decrease in the growth of middle-skilled employment (Goos et al., 2014). Job polarisation is a result of the biasedness of technology towards skilled and non-routine workers as it is complementary to their skillsets, rather than routine workers who are replaceable by technology.

Figure 1 shows the distribution of Malaysia Standard Classification of Occupations (MASCO) 1-digit occupations in 2005 and 2020 in percentage. Based on Khazanah Research Institute (KRI) (2017), the classification of skills and occupations are as follows:

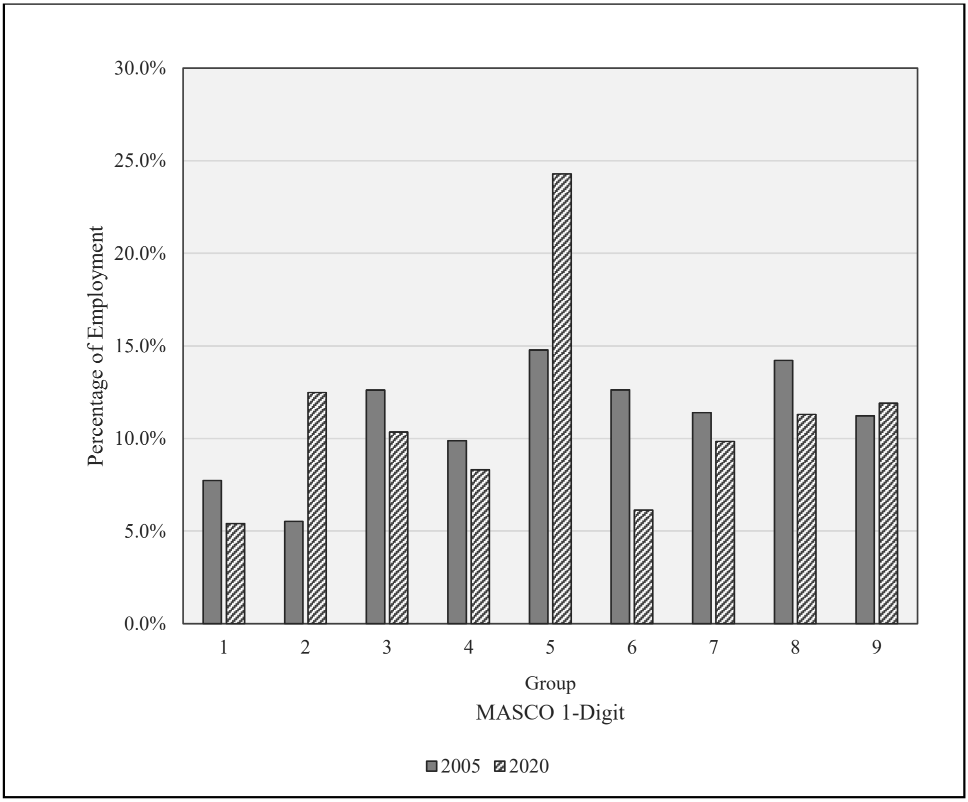

Figure 1. Malaysia: Distribution of MASCO 1-digit occupations, 2005 and 2020

Notes: MASCO 1-digit occupations consist of MASCO 1 – managers, MASCO 2 – professional, MASCO 3 – technician and associate professional, MASCO 4 – clerical support workers, MASCO 5 – service and sales workers, MASCO 6 – skilled agriculture, forestry, livestock and fishery workers, MASCO 7 – craft and related trades workers, MASCO 8 – plant and machine operators and assemblers and MASCO 9 – elementary workers.

Source: Ministry of Human Resources, 2020.

Table 1. Malaysia: Distribution of employment share across occupation groups, 1985 to 2020 (percentage)

Year	MASCO 1-digit occupations								
	1	2	3	4	5	6	7	8	9
1985	7.50	2.30	9.80	11.10	11.40	30.40	27.50	N/A	N/A
1990	7.80	2.20	9.80	11.30	11.40	26.20	31.30	N/A	N/A
1995	9.90	3.20	10.90	10.90	11.10	20.10	33.90	N/A	N/A
2000	11.00	4.20	10.90	11.30	12.80	16.90	32.80	9.00	N/A
2005	7.70	5.50	12.60	9.90	14.80	12.60	11.40	14.20	11.20
2010	7.20	6.20	14.30	9.90	16.50	11.60	10.30	12.60	11.40
2015	5.10	10.40	10.00	8.80	22.70	6.70	11.20	11.30	13.80
2020	5.40	12.50	10.30	8.30	24.30	6.10	9.80	11.30	11.90

Notes: MASCO 1-digit occupations consist of MASCO 1 – managers, MASCO 2 – professional, MASCO 3 – technician and associate professional, MASCO 4 – clerical support workers, MASCO 5 – service and sales workers, MASCO 6 – skilled agriculture, forestry, livestock and fishery workers, MASCO 7 – craft and related trades workers, MASCO 8 – plant and machine operators and assemblers and MASCO 9 – elementary workers. N/A – not available.

Source: Department of Statistics Malaysia, 2021.

MASCO 1, MASCO 2 and MASCO 3 are considered as high-skilled jobs, while MASCO 4, MASCO 5, MASCO 6, MASCO 7 and MASCO 8 are middle-skilled jobs and MASCO 9 is low-skilled job. Based on Figure 1, the proportion of occupations for MASCO 2, 5 and 9 has risen, highlighting the increasing employment of high-skilled and low-skilled workers. Meanwhile, MASCO 4, 6, 7 and 8 show a recognisable reduction in the proportion of employment. The reduction in these occupations is a symptom that illustrates the pervasiveness of job polarisation in Malaysia.

Given that 55% of the Malaysian total population have attained up to only secondary school education, a majority of them are middle-skilled (Department of Statistics Malaysia, 2021). The increasing adoption of technologies may pose risks among the middle-skilled workers. Hence, it is essential to unpack whether the symptom of job polarisation exists at the industrial level in Malaysia. The degree of readiness among the industries may differ according to the skillsets that each worker acquired. The unmatched skills and job requirement may bring about inefficiencies and jeopardise potential productivity; thus, it is important to understand the impact of technology on employment.

In general, the Malaysian economy shows an early sign of job polarisation. Past research shows that job polarisation is identified through complementary or substitution of use of technology. This study sheds some light on the impacts of technologies on how tasks are performed. The significance of job polarisation may indicate that the return of technology investment does not outweigh training costs. Firms may prefer to maintain low-skilled workers for cost effectiveness. The study by KRI (2017) compares data between two time periods with descriptive statistics, while our work employs wage quantile descriptive analysis and multinomial logistic regression model to analyse the likelihood of employment among different occupations based on the employed workers' characteristics between 2011 and 2017. Past research utilises wage quantile descriptive statistics on headcount, whereas this paper utilises multinomial logistic regression which considers the individual and sectoral effects of employment choice. This allows us to examine the likelihood of an individual being employed in a particular occupation category.

This paper proceeds in five sections. The next section provides an overview of the literature in job polarisation. Section 3 explains the data and research methodology used. Section 4 discusses the research findings and results. Section 5 proposes a set of policy recommendation. Section 6 is the conclusion.

2. Literature Review

The reviewed literature includes these two aspects: (i) skills, routine and task-biased technological change on employment; and (ii) measurement of job polarisation. The following subsections discuss how these aspects are studied in the literature.

2.1 Skill and Routine-Biased Technological Change on Employment

The impact of technological change onto employment skill changes has been widely discussed since the 1990s. The earlier studies have concrete explanation towards how technologies are skill-biased. Skill-biased technological change (SBTC) is a phenomenon where skilled labour is favoured over unskilled labour by increasing its relative productivity and its relative demand, which is dominantly caused by the adoption of new technologies (Violante, 2008). In general, SBTC separates labours into two groups, high-skilled and low-skilled. Card and DiNardo (2002) show in their study that the rising adoption of computer technology has brought about rising demand for labours who are likely to use computers in the United States. They provide further explanation that SBTC benefits the higher skilled workers as the new technology is complementary for them, while in return it results in low-skilled workers being substituted by technologies. This is in-line with the idea of Nelson and Phelps (1966) that more educated, able, or experienced labours are more likely to adapt to technological change as it is less costly for them to learn the additional knowledge needed to adopt new technology. In this case, workers no longer carry out routinised or specialised tasks, but they are responsible for a wider range of tasks (Violante, 2008).

Unlike developed countries, the evidence of SBTC for developing countries is relatively lesser, and its occurrence is considerably slower in developing countries (Maloney & Molina, 2019). Martins-Neto et al. (2023) state that the existing literature relates the lack of job polarisation in developing countries to low technology adoption and the offshoring of routine, middle-income jobs. In the case of Malaysia, Said and Haris (2008) find technological change to be the leading factor that explains the relative labour demand between 1984 and 1997 using micro-level data. They find that technological change increases the relative labour demand for middle-level education workers and decreases the demand for those with higher and lower levels of education. Marouani and Nilsson (2019) state that educational attainment among Malaysians has increased with continuous progression, which has brought about SBTC in Malaysia.

While SBTC explains the biasedness of technologies towards skilled labours and replacement of low-skilled labours, routine-biased technological change (RBTC) is discovered given the pervasive U-shape of employment distribution in the UK (Bennett, 2016; Goos et al., 2014), the United States (Autor & Dorn, 2013; Goos et al., 2014), and the European countries (Bennett, 2016). This type of distribution is also known as job polarisation.

Under the theory of RBTC, jobs are classified into routine manual, routine cognitive, non-routine manual and non-routine cognitive (Autor et al., 2003). Based on Acemoglu and Autor (2011), the distinction between routine cognitive and routine manual tasks is that routine cognitive tasks are more intensely used in clerical and sales occupations, while routine manual tasks are commonly found in production and operative positions. These tasks are considered substitutable by machines and technologies, since the core of these occupations follows precise, well-understood procedures. According to the arguments of Autor et al. (2003) and Goos et al. (2014), what determines the substitutability of an occupation by technologies is not solely the skills required to perform the job, but the amount of routine the work involves. Routine work consists of repetitive tasks that can be easily codified and programmed, which can be automated by inputting the algorithm into computers to conduct the activities independently.

The substitutability and complementarity of technologies with jobs differ according to the repetitiveness and complexity of the tasks. High-skilled jobs are complementary to computer and technologies (Autor et al., 2003); with the aid of technologies among the high-skilled workers, they are freed from performing the repetitive tasks, and able to utilise their time on other complex tasks. Meanwhile, low-skilled jobs are not directly affected by technology as the low-skilled tasks involved non-routine manual intensive tasks, which is relatively price inelastic (Autor & Dorn, 2013; Baumol, 1967). In addition, if the wage of the low-skilled workers is higher than the cost of investment or training cost, there is no incentive to replace them with technologies (Feng & Graetz, 2020). Hence, there is minimal incentive for firms to automate low-skilled jobs if labour cost is lower. The middle-skilled jobs are repetitive in nature, which can be easily codified, automated and done by machines. Hence, displacement of middle-skilled labours is more likely to happen. The differences in how technologies complement or substitute different types of labours contribute to the presence of job polarisation.

The described phenomenon typically happens in developed technology-leading countries. Few reasons may explain the difference in the impact of adoption of technology between developed and developing countries. Firstly, it is the scarcity of skilled labours in developing countries (Caselli & Coleman, 2006). Besides, shifting of routine jobs from developed to developing countries has exposed the developing countries to choose different sets of technologies and paths of technological change (Das & Hilgenstock, 2018; Lo Bello et al., 2019). Another reason could be the difference in the countries' labour market response to the same technological change (Caunedo & Keller, 2022). These differences comprise of training costs, demographics, and labour market frictions. Similar to the finding of Caunedo and Keller (2022), Feng and Graetz (2020) find that the training costs for employees to utilise the new technology are high. Hence, the technological adoption rate between developed and developing countries has a disparity.

2.2 Measurement of Job Polarisation

The measurement of job polarisation varies across studies. The unit of analysis and technique for measuring job polarisation may impact the investigation of job polarisation. Majority of the reviewed literature categorises occupations according to the International Standard Classification of Occupation (ISCO) code which is set by the International Labour Organisation (Autor et al., 2006; Fernandez-Macias, 2012; Goos & Manning, 2007; Hensvik et al., 2020; Jaimovich & Siu, 2019). The granularity of the jobs depends on whether 1-digit, 2- digit or 3-digit codes are employed. The codes provide broad definitions of skillsets that are required for the employed workers to carry out. Once the categorisation of occupations is done, the occupations are further ranked according to either wage pay or job nature.

Using labour force survey and new earnings survey data, Goos and Manning (2003) and Goos and Manning (2007) rank occupations based on wage pay, and further classifies the occupations into three big groups. The changes in employment hours were observed to measure the changes in demand for jobs. Wage pay does not fully reflect the skills in demand, as some jobs may reward higher wage to compensate for working in dangerous or dirty conditions, or the wage paid to jobs of the same nature may vary according to firm size.

The classification of job occupations by job nature is widely used. Instead of measuring the changes based on wage categorisation, many studies have grouped the occupations based on job characteristics. The characteristics are defined according to job repetitiveness and the level of cognition required. The basis of this classification is done by tagging Routine Task Index based on job description (Adermon & Gustavsson, 2015; Haslberger, 2021; Hershbein & Kahn, 2018).

Majority of the existing literature examines job polarisation with statistical analysis, or by tracing the changes in number of employed hours, employment or wage changes across time using panel data. Besides, Goos and Manning (2007) also employ simple regression, incorporating wage in quadratic form by modelling the change in employment in a job as the dependent variable, and the initial median wage of the job as the independent variable.

This study fills several research gaps. Firstly, most of the existing studies are done on developed nations as they are technology leading countries which first experience the impact of technologies on employment structure. However, studies of developing countries on job polarisation are scarce. Hence, an exploration of job polarisation in Malaysia can fill the research gap. Secondly, most studies use headcounts of labours as the unit of job polarisation analysis, while probability studies are more suitable to confirm the presence of job polarisation in developing countries. This may validate whether Malaysia experiences the same type of employment change as the other countries.

3. Data and Methodology

3.1 Data

This research employs the data from the Salaries and Wages Survey conducted by the Department of Statistics Malaysia (DOSM). The survey collects individual level data. The reason for using this data is the absence of longitudinal tracing at the individual level. This data is used as there is lack of availability of longitudinal firm-level data. The data provides information on individuals' characteristics, sector employed and occupations.

The data frame available is the 2011 and 2017 data and they are used to demonstrate the changes in employment distribution and measurement of job polarisation. The unweighted number of observations for 2011 is 50,529 and 2017 is 84,681. Our study includes only full-time Malaysian workers.

The classification of occupations is based on the existing literature. Table 2 displays the classification of the task's nature associated with Malaysia MASCO 1-digit occupations.

Table 2. Classification of occupational typology

Repetitiveness / Complexity	Manual	Cognitive
Routine	Middle skill (Assembly-line) • Controlling machines and processes • Spend time making repetitive motions	Middle skill (Clerical and sales) • Organizing • Retrieving • Manipulating information
Non-routine	Low skill (Personal services and security) • Situational adaptability • Visual and language recognition • In-person interactions	High skill (Managerial and creative) • Problem-solving • Intuition • Persuasion • Creativity

Source: Acemoglu & Autor, 2011; Autor et al., 2003; Kuriakose & Iyer, 2020.

The variable of interest is the occupational choice of the employed workers, which is defined according to MASCO 1-digit classification. The explanatory variables are shown in Table 3.

3.2 Methodology

The conceptual framework to measure job polarisation is built on the assumption that the adoption of technologies in the production process replaces the middle-skilled workers who perform routine works, enhances the work carried out by high-skilled workers, and induces more demand for low-skilled workers to be employed.

The jobs or tasks are classified according to cognitive, routine and manual tasks, which can also be classified correspondingly to high-skilled, middle-skilled and low-skilled. Taking Autor et al.'s (2006) job polarisation model, the economy's aggregate output is given by the Cobb-Douglas production function:

$$Y = C^{\alpha} R^{\beta} M^{\gamma} \tag{1}$$

whereby, C, R and M represent cognitive, routine and manual tasks, for α, β, $\gamma \in (0,1)$ and $\alpha + \beta + \gamma = 1$.

Table 3. Description for the dependent and independent variables

Dependent variable	Categorical classification of dependent variable
Y: MASCO occupation	1 = Managers 2 = Professionals 3 = Technician and associate professionals 4 = Clerical support workers 5 = Service and sales workers 6 = Skilled agricultural, forestry, livestock and fishery workers 7 = Craft and related trades workers 8 = Plant and machine operations and assemblers 9 = Elementary occupations
Independent variables	Classification of independent variables
X1: Gender	0 = Female (reference group) 1 = Male
X2: Age	Continuous
X3: Highest educational status	1 = No PMR 2 = PMR 3 = SPM 4 = Pre-University (including Foundation programme, Matriculations, STPM and Diploma programme) (reference group) 5 = Tertiary
X4: Industry (MSIC)	A: Agriculture, forestry and fishing B: Mining and quarrying C: Manufacturing D: Electricity, gas, steam and air conditioning supply E: Water supply; Sewerage, waste management and remediation activities F: Construction G: Wholesale and retail trade; Repair of motor vehicles and motorcycles H: Transportation and storage I: Accommodation and food service activities J: Information and communication K: Financial and insurance / Takaful activities L: Real estate activities M: Professional, scientific and technical activities N: Administrative and support service activities O: Public administration and defence; Compulsory social security P: Education Q: Human health and social work activities R: Arts, entertainment and recreation (reference group) S: Other service activities
X5: Salary	Continuous

Cognitive tasks can only be done by workers who supply the labour inputs of L_C. Routine tasks can be performed by either workers who supply the labour inputs of L_R or by computer capital, K, measured in efficiency units. Hence, L_R and K are perfect substitutes. Manual tasks can be performed by either workers who supply the labour inputs of L_M or displaced routine workers, which makes them L_M after they engage manual tasks. The assumption is that technological capital is perfectly elastic to routine tasks at price ρ per efficiency unit as the technological capital is assumed to be exogenous and continuously declining.

The economy comprises of workers who are endowed with a vector of three skills:

$$S_i = (c_i, r_i, m_i) \tag{2}$$

where i represents each individual worker, and the lower-case letters denote i's skill endowment for the three production tasks. This study differs from Autor et al. (2006) in that it assumes there are three types of workers, which include Low or No skilled (L), Middle-skilled (M), and High-skilled (H) while they categorise workers into two groups only. The distribution of L is $\theta_L \in (0,1)$, M is $\theta_M \in (0,1)$, and H is $1 - \theta_L - \theta_M \in (0,1)$.

For simplicity, we assume that all the high-skilled workers are homogenous in their skills endowment. Each of them is endowed with one efficiency unit of cognitive skill: $s^H(c,r,m) = (1,1,1)$. The labour supply of each high-skilled worker is $L^H = (1,1,1)$.

Middle-skilled workers perform routine tasks heterogeneously, while they are equally skilled for carrying out manual tasks. Hence, the skill endowment for middle-skilled worker i is $s^M(c,r,m) = (0,n_i,1)$, whereby n is a continuous variable distributed on the unit interval with positive probability mass at all point $n \in (0,1)$. The labour supply for each middle-skilled worker i is $L^M(c,r,m) = (0,\lambda_i n_i,(1-\lambda_i))$, where $\lambda_i \in [0,1]$. λ_i is the choice for the worker to maximise earnings. If λ_i is high for middle-skilled worker i, they will choose to engage in routine work, if not then otherwise.

Workers with no or low skills are equally skilled for manual tasks, and their skill endowment is $s^L(c,r,m) = (0,0,1)$. The labour supply for each none or low-skilled worker is $L^L = (0,0,1)$.

Based on the conceptual framework which matches the skills and job tasks between employed workers and occupation, the study employs multinomial logistic regression for analysis. The fundamental framework is built on random utility model. Let U_{ij} denote labour i's utility from choosing an occupation, j. Every labour maximises their utility, hence labour i chooses occupation j if $U_{ij} > U_{ik}$, for all $k \neq j$.

The given choices are nine types of MASCO 1-digit occupations. Assume that a labour's utility is:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{3}$$

whereby V_{ij} is the deterministic component of the utility and ε_{ij} is the random component that cannot be observed in our labour utility function, and that every ε_{ij} is independent.

The log likelihood ratio for the occupational choice j would be:

$$\begin{aligned} \ln\frac{\Pr(Y_i = j)}{\Pr(Y_i = K)} &= V_{ij} \\ &= \alpha_j + \beta_m Gender_{mi} + \beta_n Age_i + \beta_o Education_{oi} + \beta_p MSIC_{pi} + \beta_q Salary_i \end{aligned} \tag{4}$$

The chosen reference occupational group, K, is MASCO 3. MASCO 3 is chosen as the occupation consists of technicians, and it is well noted that every business or industry requires technicians. α_j represents the coefficient for intercept, the variable with subscript m represents gender category (whereby female is the reference group), o represents highest educational attainment category (whereby Pre-U is the reference group), and p represents MSIC industry category (whereby R is the reference group). The variables with subscripts n and q are continuous variables representing age and salary respectively.

The results of the multinomial logistic regression are presented in odd ratios. Multinomial logistic regression coefficients must always be interpreted as effects between pairs of categories.

3.3 Reliability Tests

Pseudo R-squared is computed as the reliability test by measuring the goodness-of-fit for the specification of the multinomial logistic regression model. This paper employs McFadden's, and Cox and Snell's pseudo R-squared measurement. McFadden's pseudo R-squared is calculated as:

$$R^2 = 1 - \frac{\ln \hat{L}(M_{Full})}{\ln \hat{L}(M_{Intercept})} \tag{5}$$

This approach measures how much the model explains the variability of data and compares the goodness of fit between the null and fitted model (McFadden, 1977). McFadden (1977) recommends that models with good fit should have pseudo R-squared values ranging from 0.2 to 0.4, and values above this range indicate excellent fit.

Cox and Snell's pseudo R-squared can be calculated as:

$$R^2 = 1 - \{\frac{L(M_{Intercept})}{L(M_{Full})}\}^{2/N} \tag{6}$$

Cox and Snell's (1989) ratio of the likelihoods takes into account the improvement of the full model over the intercept model. The closer the range of Cox and Snell's pseudo R-squared to 1, the better the fit is.

4. Findings

4.1 Descriptive Statistics

The descriptive statistics are shown in Table 4 and Table 5 while Figure 2 compares the distribution of employment within the same industries between 2011 and 2017. Firstly, some occupations are sectoral specific, with MASCO 2 dominating in services sector, MASCO 7 construction sector, and MASCO 8 manufacturing sector. Secondly, changes in the distribution of occupation within sectors can be seen prominently in the construction sector, particularly the drop in MASCO 7 employment. In addition, mining and quarrying, services, and utilities sectors experience increased employment of MASCO 2.

Table 4. Descriptive statistics for employment data in 2011 (n = 50529)

Variables	Description	Mean	SD	Median	Min	Max
Age	Age of labour	35.34	10.87	34	15	64
Salary (RM per month)	Salary includes overtime pay	1894.00	1593.02	1500.00	30.00	35000.00
		n		%		
Gender	Female	19881		39.35		
	Male	30648		60.65		
Education	No PMR	6847		13.55		
	PMR	6503		12.87		
	SPM	21243		42.04		
	Pre-U	9595		18.99		
	Tertiary	6341		12.55		
MSIC	A	1382		2.74		
	B	404		0.80		
	C	9671		19.14		
	D	341		0.67		
	E	370		0.73		
	F	4076		8.07		
	G	7434		14.71		
	H	2574		5.09		
	I	2996		5.93		
	J	723		1.43		
	K	1437		2.84		
	L	185		0.37		
	M	1296		2.56		
	N	2461		4.87		
	O	6423		12.71		
	P	5689		11.26		
	Q	2062		4.08		
	R	411		0.81		
	S	594		1.18		

Notes: MSIC consists of MSIC A – agriculture, forestry and fishing, MSIC B – mining and quarrying, MSIC C – manufacturing, MSIC D – electricity, gas, steam and air conditioning supply, MSIC E – water supply; sewerage, waste management and remediation activities, MSIC F – construction, MSIC G – wholesale and retail trade; repair of motor vehicles and motorcycles, MSIC H – transportation and storage, MSIC I – accommodation and food service activities, MSIC J – information and communication, MSIC K – financial and insurance/takaful activities, MSIC L – real estate activities, MSIC M – professional, scientific and technical activities, MSIC N – administrative and support service, MSIC O – public administration and defence; compulsory and social security, MSIC P – education, MSIC Q – human health and social work activities, MSIC R – arts, entertainment and recreation and MSIC S – other service activities.

Table 5. Descriptive statistics for employment data in 2017 (n = 84681)

Variables	Description	Mean	SD	Median	Min	Max
Age	Age of labour	36.54	11.18	35	15	64
Salary (RM per month)	Salary includes overtime pay	2760.00	3355.63	2145.00	45.00	98000.00
			n		%	
Gender	Female		34072		40.24	
	Male		50609		59.76	
Education	No PMR		8309		9.81	
	PMR		9377		11.07	
	SPM		36944		43.63	
	Pre-U		16498		19.48	
	Tertiary		13553		16.00	
MSIC	A		2500		2.95	
	B		892		1.05	
	C		15222		17.98	
	D		653		0.77	
	E		696		0.82	
	F		6491		7.67	
	G		12757		15.06	
	H		4450		5.26	
	I		5955		7.03	
	J		1180		1.39	
	K		2257		2.67	
	L		461		0.54	
	M		2013		2.38	
	N		5187		6.13	
	O		8982		10.61	
	P		9452		11.16	
	Q		3915		4.62	
	R		558		0.66	
	S		1060		1.25	

Notes: MSIC consists of MSIC A – agriculture, forestry and fishing, MSIC B – mining and quarrying, MSIC C – manufacturing, MSIC D – electricity, gas, steam and air conditioning supply, MSIC E – water supply; sewerage, waste management and remediation activities, MSIC F – construction, MSIC G – wholesale and retail trade; repair of motor vehicles and motorcycles, MSIC H – transportation and storage, MSIC I – accommodation and food service activities, MSIC J – information and communication, MSIC K – financial and insurance/takaful activities, MSIC L – real estate activities, MSIC M – professional, scientific and technical activities, MSIC N – administrative and support service, MSIC O – public administration and defence; compulsory and social security, MSIC P – education, MSIC Q – human health and social work activities, MSIC R – arts, entertainment and recreation and MSIC S – other service activities.

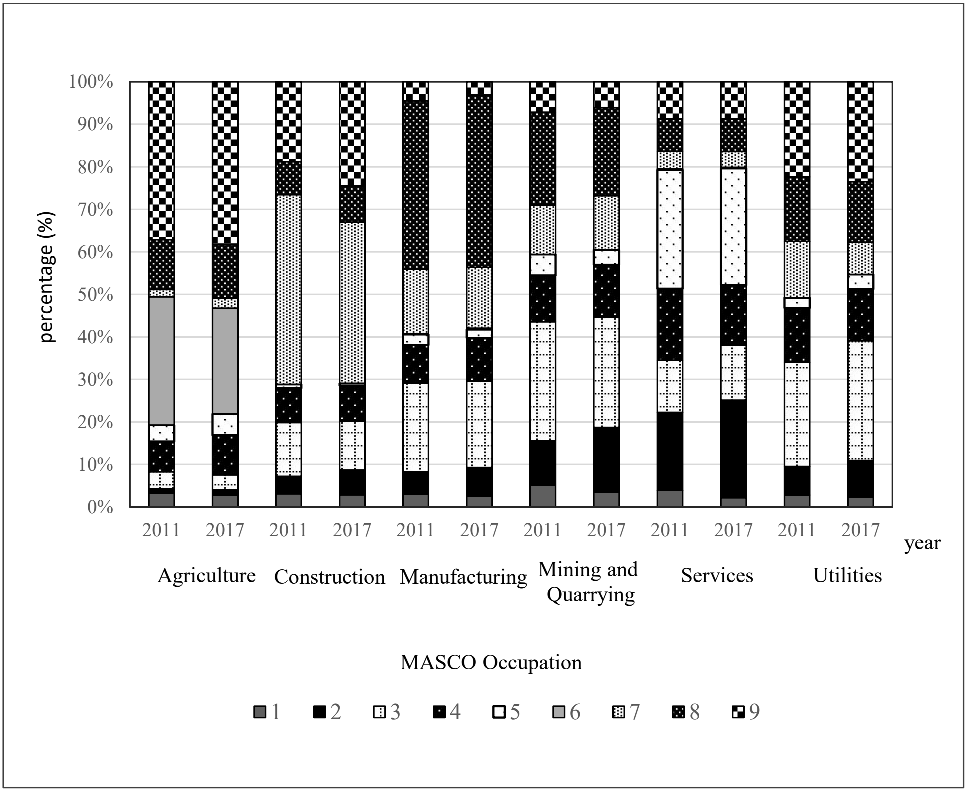

Figure 2. Occupation distribution by aggregated sectors (2011 and 2017)

Notes: MASCO 1-digit occupations consist of MASCO 1 – managers, MASCO 2 – professional, MASCO 3 – technician and associate professional, MASCO 4 – clerical support workers, MASCO 5 – service and sales workers, MASCO 6 – skilled agriculture, forestry, livestock and fishery workers, MASCO 7 –craft and related trades workers, MASCO 8 – plant and machine operators and assemblers and MASCO 9 – elementary workers.

Table 6 shows that the distribution of employment across sectors did not experience any drastic change between 2011 and 2017. Hence, our data shows no structural change in employment during this period in Malaysia.

Table 6. Employment distribution by aggregated sectors

Sector	Agriculture		Construction		Manufac-turing		Mining and Quarrying		Services		Utilities	
Year	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017
No. of employment	1382	2500	4076	6491	9671	15222	404	892	34285	58227	711	1349
Proportion by year (%)	3	3	8	8	19	18	1	1	68	69	1	2

4.2 Multinomial Logistic Regression Output

This section examines the likelihood of employment by occupation using multinomial logistic regression method for two time periods, 2011 and 2017. The pseudo R-squared values are reported in Table 7 as validity tests. Both the models for 2011 and 2017 have pseudo R-squared values that fall under the range of good fit and the models are reliable.

Table 7. Pseudo R-squared values

Models	McFadden	Cox and Snell
2011	0.4065	0.8103
2017	0.3945	0.7957

Based on Table 8, the log odds of a male being employed in occupations MASCO 1, 2, 4, and 5 relative to MASCO 3 are lower than that of a female in both years. However, male workers are more likely to be employed in MASCO 6, 7, and 8 relative to MASCO 3 compared to female workers.

With a year increase in age, the log odds of a worker being employed in MASCO 1 and MASCO 2 increase relative to being employed in MASCO 3 for both 2011 and 2017. An increase in age by a year, the log odds of a worker being employed in middle-skilled (MASCO 4, 5, 6, 7 and 8) and low-skilled (MASCO 9) decrease relative to being employed in MASCO 3. This may be explained by the nature of lower skilled jobs that are manual intensive and physically exhaustive, which requires workers to be physically adept. As explained by Takala and Seitsamo (2015), work ability declines with age especially for the work that is physically demanding.

As for the education variable, Malaysia's employed labour force exhibits a positive relationship between education and salary. Table 7 shows that high-skilled workers (MASCO 1, 2 and 3) require at least tertiary or pre-university education, while the others receive relatively lower salary compared to the high-skilled workers. This shows the accumulation of human capital as an investment decision, whereby an individual gives up a proportion of their current income during the period of education or training in expectation of increased future earnings (Blundell et al., 1999; Psacharopoulos & Patrinos, 2018).

High-skilled workers involved in non-routine cognitive jobs, MASCO 2, are more likely to be employed in the service industry, such as MSIC K, O and Q, as compared to the manufacturing industry in 2017. This can be explained by the increased adoption of technologies in the high-skilled service industry. These occupations are complementary to computer and technologies (Autor et al., 2003; Card & DiNardo, 2002). Hence, this drives the increment in demand for high-skilled workers who are equipped with cognitive abilities and adaptive skills. MASCO 1, however, shows a reduction in likelihood of employment. This may be explained by MASCO 2 that is able to cover a wide range of tasks with the complement of technology to replace MASCO 1 (Violante, 2008).

MASCO 4 and 5 are routine cognitive occupations. Based on Table 8, the log odds of a worker being employed in MASCO 4 relative to MASCO 3 increase for most of the

Table 8. Multinomial logistic regression output – Choices of occupation for the year 2011 and 2017

MASCO		1		2		4		5		6		7		8		9	
Year		2011	2017	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017
Intercept		-3.346***	-4.627***	-1.119***	-1.216***	1.725***	0.775***	1.186***	1.375***	-4.077***	-3.653***	-3.231***	-3.177***	-3.689***	-3.399***	-0.140***	-1.056***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	Male	-0.593***	-0.192***	-0.841***	-0.697***	-1.912***	-1.902***	-0.403***	-0.362***	0.390***	0.162***	1.466***	1.347***	0.344***	0.594***	0.218***	-0.050***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age		0.038***	0.067***	-0.003*	0.011***	0.004**	0.001	-0.020***	-0.019***	0.002	-0.006***	-0.020***	-0.011***	-0.006***	-0.002*	-0.001	-0.002*
		(0.000)	(0.000)	(0.015)	(0.000)	(0.001)	(0.354)	(0.000)	(0.000)	(0.261)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0112)	(0.261)	(0.035)
Education	No PMR	-0.044***	-0.494***	-0.216***	-5.920***	-0.196***	-0.687***	2.672***	2.566***	2.094***	2.430***	2.896***	2.932***	3.243***	3.118***	3.659***	3.652***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	PMR	-0.228***	-0.924***	-0.959***	-4.471***	0.105***	0.041***	2.251***	1.927***	1.152***	1.368***	2.273***	2.116***	2.851***	2.584***	3.031***	2.937***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	SPM	-0.219***	-0.494***	-0.528***	-1.569***	0.879***	0.529***	1.753***	1.278***	0.958***	0.622***	1.346***	1.094***	2.018***	1.769***	2.157***	1.789***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Tertiary	1.761***	2.227***	2.001***	2.137***	-0.094***	0.429***	-0.308***	0.210***	0.396***	1.411***	-0.090***	0.228***	0.785***	-0.030***	0.272***	0.667***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Salary		0.000***	0.000***	0.000***	0.000***	-0.001***	0.000***	-0.001***	-0.001***	-0.001***	0.000***	-0.001***	0.000***	-0.001***	-0.001***	-0.002***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MSIC	A	1.143***	1.328***	0.044***	-0.595***	0.542***	1.361***	-1.329***	-0.596***	5.550***	4.211***	1.281***	1.049***	3.537***	3.135***	1.526***	2.631***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	B	-1.952***	-0.951***	-0.815***	-0.089***	-0.163***	1.075***	-1.717***	-1.223***	-0.772***	-1.521***	2.256***	2.372***	3.600***	3.291***	-0.097***	0.939***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	C	-0.953***	-0.454***	-0.602***	-0.332***	-1.513***	-0.220***	-3.135***	-2.515***	-0.224***	-0.549***	2.310***	2.320***	3.678***	3.668***	-1.404***	-0.315***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	D	-1.714***	-1.269***	-0.530***	-0.072***	-0.138***	0.687***	-2.392***	-1.378***	-0.770***	-1.155***	2.721***	1.804***	3.307***	2.702***	-0.108***	1.216***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	E	-1.015***	-0.585***	-0.385***	-0.382***	-0.404***	0.341***	-2.980***	-2.072***	-1.261***	-1.653***	1.383***	1.126***	2.568***	2.529***	0.873***	2.346***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	F	-0.475***	0.146***	-0.366***	0.204***	-0.438***	0.800***	-3.975***	-2.549***	-0.337***	-1.120***	3.464***	3.478***	2.422***	2.304***	0.461***	2.237***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 8. Continued

MASCO	1		2		4		5		6		7		8		9	
Year	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017	2011	2017
G	0.561***	0.229***	-0.725***	-1.081***	0.019	0.598***	1.039***	0.951***	0.286***	-1.036***	2.998***	2.630***	3.084***	2.558***	-0.460***	0.152***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.134)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
H	0.027***	0.239***	0.502***	0.601***	1.307***	2.103***	-0.867***	-0.456***	0.161***	-0.388***	1.277***	1.125***	5.058***	4.866***	0.621***	1.719***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
I	1.717***	1.815***	0.104***	-0.089***	-0.122***	1.081***	2.097***	2.663***	0.021***	0.828***	1.305***	1.461***	1.676***	2.000***	1.063***	2.652***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
J	-0.417***	0.391***	0.077***	0.920***	-0.459***	0.498***	-2.326***	-1.158***	-0.764***	0.116***	1.206***	1.208***	1.655***	0.659***	-1.646***	0.068***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
K	-0.131***	0.307***	-0.201***	0.712***	1.102***	1.694***	-2.103***	-1.685***	0.204***	-0.393***	0.073***	0.179***	1.621***	1.095***	-0.316***	-0.090***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L	-0.541***	-0.305***	-0.665***	-0.251***	-0.179***	0.798***	-1.511***	-2.350***	-0.794***	-1.787***	0.080***	-1.398***	1.502***	0.817***	-1.102***	-1.159***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
M	-0.675***	-0.165***	0.722***	1.234***	0.136***	1.370***	-2.755***	-2.698***	0.921***	-0.293***	1.010***	0.900***	1.257***	1.014***	-0.699***	0.734***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	0.090***	0.197***	-0.320***	-0.074***	-0.019***	0.781***	1.035***	1.413***	0.191***	1.711***	1.796***	1.461***	2.526***	2.149***	1.243***	3.032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
O	-0.706***	-1.111***	-0.290***	1.155***	0.959***	1.316***	0.838***	0.454***	2.499***	-0.336***	0.671***	0.342***	2.901***	1.967***	1.489***	2.180***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
P	-0.216***	0.472***	3.160***	3.618***	-0.012	1.493***	-0.288***	1.056***	1.497***	1.879***	1.295***	2.314***	2.750***	2.626***	1.037***	2.269***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.132)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q	-3.377***	-2.016***	-1.147***	0.252***	-2.176***	-1.249***	-1.187***	-0.817***	0.086***	-1.449***	-0.648***	-0.534***	1.335***	1.298***	-0.557***	0.139***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S	0.213***	0.201***	0.510***	1.138***	-0.259***	0.471***	0.869***	0.835***	-0.941***	-0.798***	2.945***	2.671***	2.234***	1.809***	0.375***	0.898***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Values in parentheses are p-values. Age and salary are continuous variables. Gender, education and MSIC are categorical variables. Gender consists of female and male, whereby female is the reference group. Education consists of No PMR, PMR, SPM, Pre-U and tertiary, whereby Pre-U is the reference group. MSIC consists of MSIC A – agriculture, forestry and fishing, MSIC B – mining and quarrying, MSIC C – manufacturing, MSIC D – electricity, gas, steam and air conditioning supply, MSIC E – water supply; sewerage, waste management and remediation activities, MSIC F – construction, MSIC G – wholesale and retail trade; repair of motor vehicles and motorcycles, MSIC H – transportation and storage, MSIC I – accommodation and food service activities, MSIC J – information and communication, MSIC K – financial and insurance/takaful activities, MSIC L – real estate activities, MSIC M – professional, scientific and technical activities, MSIC N – administrative and support service, MSIC O – public administration and defence; compulsory and social security, MSIC P – education, MSIC Q – human health and social work activities, MSIC R – arts, entertainment and recreation and MSIC S – other service activities, whereby MSIC R is the reference group.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

sectors. However, the likelihood of a worker to be employed in MASCO 4 is lesser in MSIC C and Q, which represents the manufacturing, and human health and social work activities sectors. This perhaps may explain the limited feasibility of automation and differing initial occupational distribution in Malaysia compared to developed countries (Maloney & Molina, 2019). The routine cognitive occupation is still in demand for workers as substitution for it is yet to occur.

MASCO 5 occupations represent service and sales work. A worker is more likely to be employed in MASCO 5 than in MASCO 3 for most of the services sectors. However, the likelihood of a worker to be employed in MASCO 5 in MSIC G, wholesale and retail trade, and repair of vehicles and motorcycles sector, reduced between 2011 and 2017. MSIC I, accommodation and food services, rose relatively in its likelihood of employment for MASCO 5. This may be explained by a few reasons, these jobs are cognitive in nature and require human intervention. For example, the accommodation and food services sector require the interaction of human and customers to provide 5-star service. Liu et al. (2019) also mentions that self-service technology cannot replace all human staff, and hotels should maintain an ideal balance between high technology and human interaction. In addition, the slowness in adoption of technologies may be due to high investment or training costs that would incur when adopting new technologies.

MASCO 6, 7, and 8 represent routine manual occupations. MASCO 6 is skill specific towards the agriculture sector. Although the log odds of a worker being employed in MASCO 6 in MSIC A is higher than that of MASCO 3, the likelihood decreases from 5.550 to 4.211. The lower likelihood indicates a decrease in demand for MASCO 6. Perhaps, MASCO 6 skills are no longer in demand but others such as MASCO 1 are.

MASCO 7 and 8, routine manual occupations, are specific to construction, manufacturing, mining and quarrying, and utilities sectors. MSIC B, C and F show an increase in log odds of a worker being employed in MASCO 7 relative to MASCO 3. However, it decreases for the utilities industry represented by MSIC D and E. The log odds of a worker being employed in MASCO 8 decrease for the mentioned sectors, except for MSIC D. This is different from Maloney and Molina's (2019) finding whereby developing countries experience relative growth in machine operators and assemblers, with the evidence that job polarisation is yet to occur in developing countries. Hence, Malaysia shows the symptom of job polarisation.

MASCO 9 represents non-routine non-cognitive employment that are low-skilled. In general, the log odds of a worker being employed in MASCO 9 relative to MASCO 3 increase between 2011 and 2017 across all the industries compared to the MSIC R industry. There are a few possible reasons to explain why this is the experience of Malaysia's low-skilled employment. Firstly, these workers are generally receiving lower wages as compared to the other two types of workers, and the cost of training is also lower as no high levels of expertise are needed. As mentioned by Baumol (1967), and Autor and Dorn (2013), the tasks performed by low-skilled workers are manual-intensive, which is relatively price inelastic. The cost of recruiting or training may be higher than the investment of technologies to replace these workers, since their salary is the lowest in the economy. Hence, there is no or low incentive to introduce technologies to complement or automate elementary jobs, if these workers are, by default cheap to recruit. The cost of investment outweighs the return of investment. Another justification would be the increased consumption of low-skilled work as they are relatively income elastic (Mazzorali & Ragusa, 2013). As the employment and income for high-skilled workers increase, the consumption for low-skilled work service also increases especially by higher income groups that outsource domestic work.

5. Conclusion and Policy Implications

Malaysia's current employment structure experiences SBTC that is specific to occupations and sectors, which shows the symptom of job polarisation. Through the statistical analysis using multinomial logistic regression, there are a few key findings to conclude.

High-skilled workers experience an increase in the likelihood of employment among the high-skilled services sectors. Middle-skilled occupations, specifically the routine cognitive occupations, show relatively high likelihood of employment among most of the services sectors. Routine non-cognitive employment, MASCO 7 and 8, show different likelihood of employment. While MASCO 7 shows an increase in the likelihood of employment, MASCO 8 exhibits the contrary. This indicates a change in the task content for MASCO 8, which is task automation. MASCO 9, low-skilled workers are more likely to be employed across all industries. This projects a similar pattern as that of the developed countries in job polarisation. The wages of low-skilled workers are still lower than the cost of technology investment and training cost. Hence, there is no incentive to automate these jobs.

Technologies bring about changes in the ways jobs are performed in Malaysia rather than complement or substitute workers of different occupations. Most of the occupations require certain degree of technologies or tools to perform the tasks. Hence, when there are new technologies introduced, upskilling of labours should be done to ensure the match between skills and technologies. However, if firms are reluctant to adopt new technologies due to their low return of investment, upskilling might not happen, and employment in these occupations continue to rise.

The difference in employment demand between Malaysia and the developed countries highlights the lack of readiness for Malaysia to adopt new technologies in the production process. The relatively higher investment and training costs obstruct the adoption of technologies in Malaysia. In addition, the difference in job tasks content between developed and developing countries causes a difference in the demand for certain technologies used in the same occupation between these two groups of countries.

The policy implications drawn from this study are relevant for firms, government and education institutions in spurring the adoption of technologies in Malaysia. Firms may explore the long-run sustainable benefits that may be brought about by technologies in the production process and equip the workers with training to enhance productivity. If firms have the foresight of how technologies could change the ways tasks are performed, the phenomenon of job polarisation will reduce in the future. Governments should provide firms subsidies for training costs to reduce the burden that firms bear when adopting new technologies. Education institutions may design hands-on programmes for current and future workforce to equip them the knowledge in technology utilisation.

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