Wage premiums in the digital economy: Evidence from Malaysia

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Abstract

The ongoing widespread adoption of digital technologies globally is leading to much interest in the relationship between technology and wages. This paper uses individual level information from the 2014 Household Income and Expenditure Survey (HIES) to examine the wage premiums in Malaysia that are attributable to technology. We find a wage premium of 12.75% from working in the ICT sector. This premium is present for medium- and high-skilled workers in the sector, and, interestingly, is higher for the former group of workers. We estimate the returns from an additional year of education and work experience to be approximately two and three times higher for an ICT worker compared to other sectors, respectively. Overall, the findings show that going forward, policy must focus on stimulating widespread adoption of digital technologies across other sectors through ICT educational and training policies. This will spur higher productivity and hence technology-induced wage increases to workers in non-ICT sectors.

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1. Introduction

In recent years, digital technologies have received widespread adoption by industries and consumers alike globally. The widespread adoption owes in part to lower costs, hence making their adoption more accessible. However, digital technologies can have both positive and negative effects on the economy. Consumers benefit from lower transactions costs and information asymmetries, but their jobs are potentially affected by the greater automation. Businesses benefit from lower barriers to entry, reduced operating costs and greater market reach, although incumbent firms may be disrupted by new entrants amidst a more uncertain operating environment.

This paper seeks to document the wage premium that workers earn from partaking in the digital economy and how this premium arises. We ask two key questions: First, do workers in ICT command a wage premium compared to workers in other sectors? Second, do we see a wage disparity between workers in the digital economy that is attributable to differing education and skill levels?

We use micro level data from the 2014 Household Income and Expenditure Survey (HIES) conducted by the Department of Statistics, Malaysia. Among others, this dataset contains detailed information on income, employment status, industry and occupational type for more than 200,000 individuals and 45,000 households. We estimate a Mincer equation which includes skill dummies of workers, while taking into account other determinants of wages such as years of education and working experience. We also use an ICT dummy to identify workers in this sector.

The effects of technology on wages are shown along three main dimensions. First, we find evidence for an average ICT wage premium of 12.75%. Second, premium for medium-skilled ICT workers is higher at 16.1%, but lower at 10.4% for high-skilled ICT workers. This finding is suggestive of the technology-induced labour supply changes in response to the ICT wage premium that leads to a greater share of university graduates working in the ICT sector, resulting in a more educated middle-skilled ICT segment. This in turn raises the productivity and wages of middle-skilled ICT workers. Third, within the ICT sector, there is a 32% wage premium for high-skilled workers. Empirical estimations by economic sector reveal that this wage premium can be attributed to the substantially higher returns to education and work experience in the ICT sector. However, the wage gaps between high-skilled and lower-skilled workers in non-ICT sectors are higher, ranging from 50% to 78%, which is a further evidence that technological changes are generally biased towards high-skilled workers (Autor, 2015).

The rest of the paper is organised as follows. Section 2 presents the landscape of the digital economy in Malaysia. Section 3 examines the literature on the link between digital economy and inequality. Section 4 explains the data and stylised facts while Section 5 describes the methodology adopted in this paper. Sections 6 and 7 discuss the results, and Section 8 explains the limitations and further areas of research. Section 9 concludes. Further technical and data specifications are provided in Appendix 1.

2. A macro view of digital economy and income inequality in Malaysia

This section provides the background on the digital economy and income inequality in Malaysia. In Malaysia, the number of internet users almost doubled from 12.5 million in 2005 to 21.0 million in 2016, while broadband penetration rate rose from 7.0% of households in 2005 to 81.5% in 2016. The percentage of smartphone users have also increased four-fold from 2010 to account for 53% of mobile phone users in 2015.

The Information and Communication Technology (ICT) Satellite Account by the Department of Statistics Malaysia (DOSM) provides the most comprehensive measure of the digital economy in Malaysia. The ICT Industry is defined as the sum of value added of the ICT industry and e-commerce. Based on this metric, digital related activities have contributed substantially to the Malaysian economy. In 2015, the ICT industry contributed RM206.1bil or 17.8% to GDP, up from RM135.6bil or 16.5% to GDP in 2010 (Figure 1). This represents an average annual growth rate of 8.8%, higher than nominal GDP growth of 7.1% during the same period.

Figure 1: Contribution of Malaysia ICT Industry to the Economy, 2010-2015

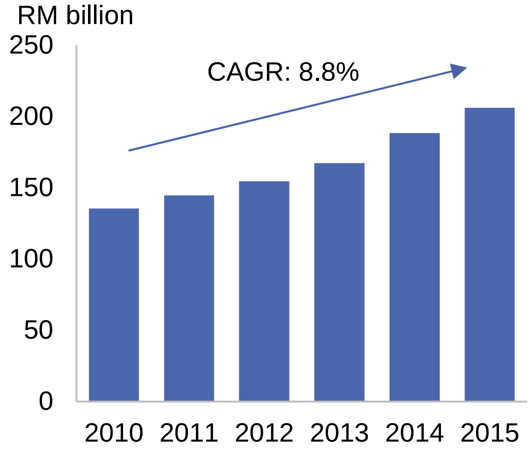


Figure 2: GDP Growth of ICT sectors, 2010-2015

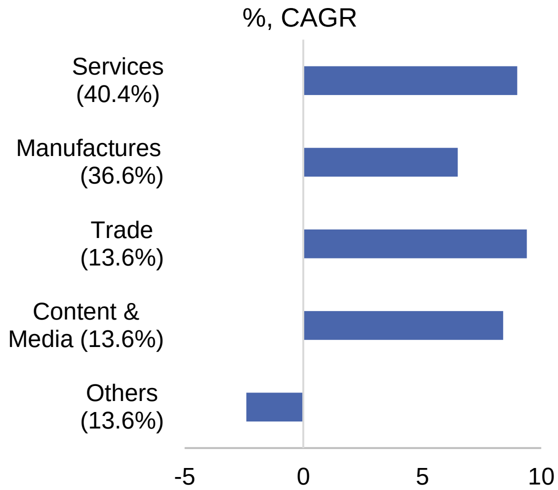


Figure 3: Employment share in ICT Industry by sector, 2015

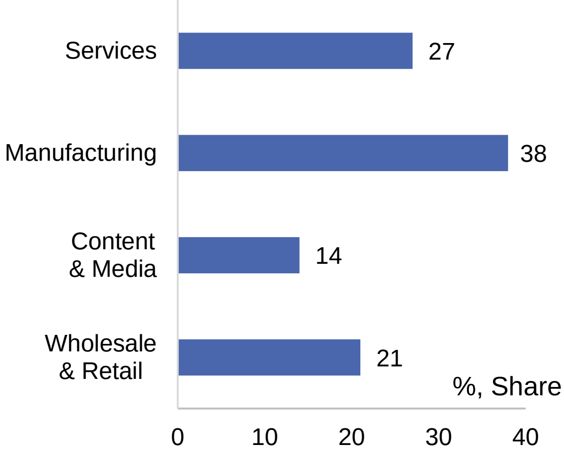
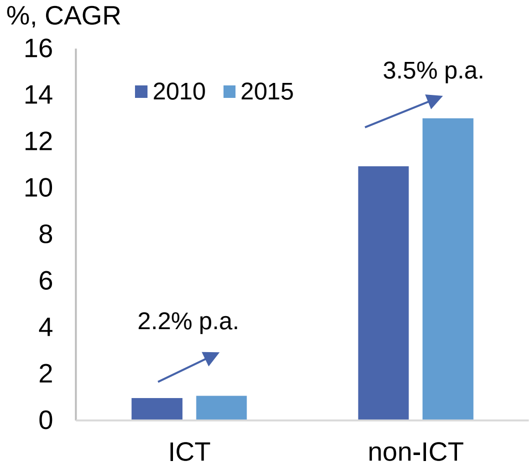


Figure 4: Employment growth of ICT vs non-ICT Industry, 2010-2015



Source: DOSM ICT Satellite Account, GDP by Income Approach, authors calculations

The services sector constitutes the bulk of the ICT industry (Figure 2). Taking ICT services, trade and content & media together, the services sector contributes about 60% to the ICT industry as at 2015. It also grew faster than ICT manufacturing between 2010 and 2015.

In terms of employment, the ICT industry employed 1.06 million people in 2015, or 7.6% of 14.06 million workers in the country. As with output, the majority of ICT workers are in the services sector (Figure 3). Interestingly, the share of ICT workers was higher at 8.0% of total employment in 2010. The main reason for the decline in share of ICT workers is the lower employment growth particularly in ICT manufacturing. The ICT sector's workforce grew by an average of 2.2% annually, compared to non-ICT sector, by 3.5%. The economy as a whole employed 3.4% more workers on average per year (Figure 4).

What about wages? Are workers in ICT rewarded more compared to their non-ICT counterparts? In 2015, aggregate wages of ICT workers, as measured by compensation of employees, accounted for 14% of total wages, despite comprising 8% of employment. In growth terms, aggregate wages in ICT industry, has risen by the same pace of 9.1% as overall economy between 2010 and 2015. However, wages per worker in ICT has risen proportionately more during the same period. In 2010, an ICT employee earned RM36,300 per annum, compared to RM20,500 for non-ICT employee. By 2015, the average wage of ICT employee had risen to RM53,000 per annum, representing an average annual growth rate of 6.8%. In comparison, wages for a non-ICT worker increased by 5.4% per annum to reach RM26,600 in 2015 (table 1). Given the faster wage growth of workers in ICT, the gap in the average pay for ICT and non-ICT worker has risen – in 2015, ICT workers earned double non-ICT workers earn.

Table 1: Wage per worker of ICT vs non-ICT Industry

	2010	**2015**	**CAGR**
	RM per annum		**%**
ICT	38,274	53,097	6.8
non-ICT	20,478	26,628	5.4
ICT wages as a multiple for non-ICT wages	*1.87*	*1.99*	-

Source: DOSM ICT Satellite Account, GDP by Income Approach, authors calculations

There are two main takeaways that can be gleaned from the macro-level information from the ICT Satellite Account. Firstly, the robust growth in ICT sector in recent years has not resulted in proportionately more job creation in the ICT sector compared to non-ICT sector in Malaysia. In fact, employment growth in ICT sector has been slower, resulting in a smaller employment share of ICT workers in the country. Slower ICT job growth was particularly evident in the manufacturing sector. However, there is a lack of data to ascertain whether within the ICT sector itself, low-skilled jobs are being displaced by the technical ones. Secondly, workers in the ICT sector earned twice than their non-ICT counterparts, on average. Of significance, wage growth per ICT worker is higher than non-ICT workers. Should this pace continue, the wage disparity between an ICT worker and non-ICT worker will only widen over time.

The slow ICT employment growth amid higher wages suggests that digital advancements have increased productivity and rendered some labour-intensive and low-skilled jobs redundant. This is nonetheless a positive development from a macro perspective, given the aspiration of Malaysia towards a high income nation which relies on productivity as a source of growth. On the other hand, one could also argue that over time, as ICT plays a larger role in Malaysian economy, the nation will need fewer workers, and those who do not have the necessary skills risk being left behind.

3. Literature Review

3.1 The link between digital economy and inequality

In the last decade, there has been ample literature on the impending adverse effect of income inequality on the economy. High levels of inequality affects human capital and market efficiency negatively, therefore reducing demand for products and services in the economy. In addition, high inequality is often associated with political instability, a lack of social cohesion and limited social mobility (Laiglesia, 2011; Bhalla and Lapeyre; 2016). Dabla-Norris et al. (2015) find economic empowerment of the poor seems to be instrumental for growth, while increasing share for the rich stalls or reverses economic growth.

On these grounds, the digital economy is often viewed as a good equaliser. Prices of digital assets such as computers and peripherals, communications equipment and software have continued to decline over the years, leading to lower costs and higher efficiency, resulting in more competitive prices for products and services (Van Ark, 2016). Furthermore, technology serves to lower market barriers and information costs. For example, digital platforms for taxis (Uber), retail (Amazon) and accommodation (AirBnB) have lowered barriers to entry, providing many with opportunities to start their own small businesses. As a result, the unskilled have new income-generating opportunities and economic rents are being redistributed.

However, there are rising concerns that digital technology leads to greater inequality. With almost four billion of the world's population still not having any internet access and nearly two billion who do not have a mobile phone (World Bank, 2016), it is clear that many are not able to reap benefits from the digital revolution. Where access is not so much of an issue, particularly in developed countries, the divide is between the "haves" and the "have-mores" (Manyika et. al, 2015). While the "haves" struggle to cope with current with digital technologies, individuals, firms and sectors that "have-more" operate at the frontier of digital technologies and capture significant gains relative to the "haves" in terms of market share and income growth.

3.2 The link between wage inequality, wage premium and technological change

A large body of literature provides substantial definition of wage inequality (McCall, 2000; Moretti, 2013). According to the neoclassical model of Kuznets (1955), inequality increases alongside expanding incomes at early stages of development and decreases at higher levels of per capita income. As a result, most studies focuses on the differential gap between race, education, age and income levels (Anand and Kanbur, 1993; Feenberg and Poterba, 2000). However, there is also large portion of inequality occurring within these groups (McCall, 2000: Card and DiNardo, 2002; Moretti, 2013). A confluence of global factors (technological progress and outsourcing of non-routine and mid-skilled manufacturing jobs from advanced to emerging economies (IMF, 2017)), and local factors (greater dependence of less-educated foreign workforce (Bank Negara Malaysia, 2017)) do affect wage disparities between different educational attainment and skill groups.

Broadly, wage inequality is often measured as the dispersion of wages between skilled and unskilled workers within three comprehensive classes; an increase in the relative demand for skills caused by skill biased technological change, a slowdown in the growth of the supply of skilled workers and the erosion of labour market institutions, such as unions and the minimum wage that protect low-wage workers (Moretti, 2013). This study intends to focus on the related literature that investigates the effect of skill biased technical change (SBTC) on inequality.

In recent decades, there is growing number of literature explaining wage inequality and its link to SBTC (DiMaggio et al., 2004; Mishel et al., 2013; Dabla-Norris et al., 2015, Autor 2015). According to Card and DiNardo (2002), a significant portion of increase in wage inequality occurred during the 1990s, where technological innovation was at a rapid pace. The abovementioned study postulates that rising skill premiums are primarily dependent on the notion that the revolution of technology is heavily skill-biased, and this environment contributes to increases in inequality. Moreover, SBTC increases wage dispersion, as the spread of technology enhances computerization at industries such that the usage of internet and robots complemented by skilled workers replaces low skilled labour intensive tasks (Moore and Ranjan, 2005; Hutter and Weber, 2017).

The most prominent impact of technology is the increased premium it places on skills. Modern technologies substitute tasks that are traditionally performed by unskilled workers, while acting as a complement to skilled workers. Frey and Osborne (2017) identify a wide range of occupations likely to be affected by the automation of both routine and non-routine tasks. The abovementioned study concludes that low-skilled occupations such as factory, sales and service jobs are more susceptible to technology substitution compared to high-skilled jobs.

The literature on the effects of digital economy on employment provides various insight into the issue. On the one hand, a set of empirical highlights the debate on whether the digital revolution has created more jobs than they have displaced. Nottebohm et. al (2012) suggests that the internet is a net job creator in both developed and developing economies while more recent studies suggest that the threat of automation is more real, as advancements in cognitive computing and artificial intelligence are replacing work related to decision-making (Davenport and Kirby, 2015; World Bank, 2016).

Another set of studies analyses job polarisation as a result of technology (Goos, Manning and Salomons, 2009; Mishel, Schmitt and Shierholz, 2013; Green and Sand, 2015). In contrast to skill-biased technological change, where employment shift from low-skilled toward high-skilled occupations, job polarisation suggest that there is growth in employment in both the highest-skilled and lowest-skilled occupations, with declining employment in the middle of the distribution (Goos and Manning, 2007; Green and Sand, 2015). This theory accentuates a shift away from middle-skilled occupations driven largely by technological change and provides a broad, cohesive explanation for changes in employment patterns. This scenario has contributed to stagnant median wages despite rising productivity and wealth, implying that a majority of people are worse off (Brynjolfsson and McAfee, 2014).

Interestingly, computerisation and changing technology has had significant impact on wage premium through the evolving composition of occupational employment in the last few decades (Mishel, Schmitt and Shierholz, 2013; Beaudry, Green, and Sand, 2016). The profound technological change has generated greater need for greater skills and education. Lindley and Machin (2014) and Beaudry, Green, and Sand (2016) emphasizes the importance of cognitive skills possessed by graduate degree holders to help maintain and expand their wage premium relative to those holding a basic college degree. Contrary to schools of polarisation, Yunus (2017) finds that the decline in returns for ICT workers with tertiary education is attributable to an increasing labour market mismatch in the ICT sector, resulting in a shift towards higher graduate employment in middle-skilled jobs. This in turn raises the productivity and wages of middle-skilled workers while suppressing wages of high-skilled workers. Lastly, although most other sectors are not technologically intensive, their high-skilled workers are still involved in problem-solving and abstract-oriented tasks that are complemented and aided by technology, consistent with the skill-biased technological changes that has occurred in most sectors (Autor, 2015).

The existing literature suggests that the advancement of technology, in particular digital technology, can exert a profound impact on the labour market. Although there are many studies suggesting that digital technologies contribute to wage inequality, there are also an increasing stream of literature emphasising the need for enhanced skills and education in generating wage premium across work clusters. However, most studies concentrate on developed countries, and only a few on developing countries. On this note, this paper seeks to contribute to the discussion, focusing on ICT and its impact wage premium in Malaysia in particular.

4. Data description and stylised facts

In this section we describe the dataset that we use for our empirical analysis and the basic stylized facts of Malaysia's households.

4.1 Data description and construction of variables

Our dataset is based on the 2014 Household Income and Expenditure Survey (HIES), conducted by the Department of Statistics Malaysia. The survey contains detailed information of more than 45,000 households and 200,000 individuals. Household characteristics include total income, geography and composition of household. Meanwhile, individual characteristics such as age, gender, educational attainment, and employment status, industrial and occupational type are also included in the survey. Detailed 2014 HIES Individual Level and Household Level data definitions can be found in Appendix 1.

We scale our dependent variable, monthly wages (RM) per worker by the number of household members that are in the labour force, as follows:

$$Y_i = \frac{Annual\ Household\ Income_i\ (RM)}{12} \times \frac{1}{N_i - x_i} \tag{1}$$

where Y_i is the monthly wages per worker in household *i*; Annual Household Income (RM) only reflects income earned via employment, while excluding income derived from household assets and transfers; N_i refers to the size of household *i*; and, x_i is defined as the number of all inactive household members in household *i*. Meanwhile, other variables of interest are also adjusted and rounded to reflect the contribution of active household members, which is denoted by:

$$Z_i = \sum_{j=1}^{N-x} z_{ij} \times \frac{1}{N_i - x_i}, \qquad Z_i \in S_i, X_i, L_i, M_i, H_i, ICT_i \tag{2}$$

where Z_i is the adjusted set of variables denoting years of education, S_i; years working experience, X_i; skill dummies L_i, M_i, H_i which corresponds to low, medium and high skill level dummies; and, ICT dummy, derived from the 2014 HIES dataset. The ICT dummy proxies for the information and communication sub-sector, which includes telecommunication, computer programming, consultancy, information and related activities, as well as content and media sub-sectors.

4.2 Stylised facts about households and analysis of data

We begin by undertaking a prima facie analysis between the estimated average monthly wages per worker and its determinants. Figures 5, 6 and 7 plot the wages against years of working experience, years of education and skill levels. Figure 5 shows an inverted U-shaped life cycle profile of wages, which is broadly in line with theoretical and cross-country empirical evidences (Qian et al, 2016, Rupert and Zanella, 2010, Lemieux, 2006 and Mincer, 1973). Wages typically accelerate sharply during early stages of career and declines steadily towards the end of the working age, with a peak around 25 to 30 years. The decline is attributed to the gradual transition of older workers into retirement by working progressively fewer hours and undertaking more part-time work in lieu of full-time employment. Rupert and Zanella (2010) identified health deterioration and grand-parenting responsibilites as the major factors in explaining the sudden drop in average hours worked beginning at age 50, thereby effectively reducing labour supply and wages earned beyond that age.

As observed by Mincer (1973), the expected convex relationship between wages and education is also seen in Figure 6. Education increases wages by various means of productivity-enhancing measures, be it through intrinsically augmenting capacity and skillset of workers (Becker, 1962; Schultz, 1961; and Mincer, 1973), or via signalling and "credential" channels (Spence, 1973). The exponential increase in wages between 14 and 16 years of education is consistent with the "credential" effects of education, in which the returns to tertiary education are systematically higher than primary and secondary levels of education. Workers are rewarded for both the additional productivity-enhancing contribution from tertiary education and for achieving a particular certification (Yunus, 2017, Belman and Heywood, 1997, and Hungerford and Solon, 1987).

Figure 5: Average Monthly Wages per Worker by Working Experience, 2014

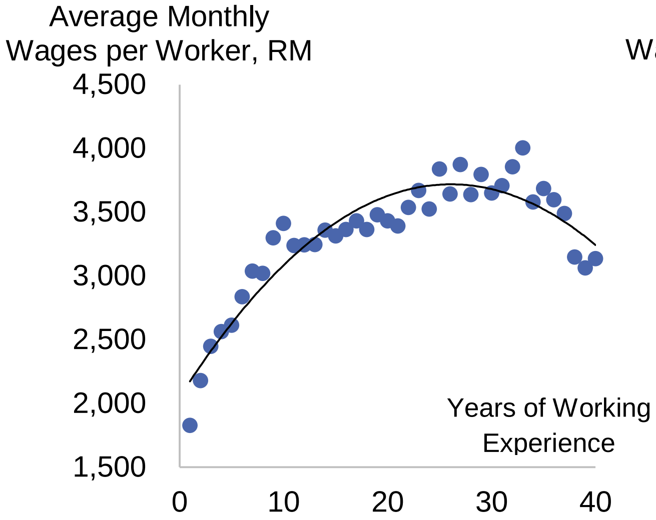


Figure 6: Average Monthly Wages per Worker by Years of Education, 2014

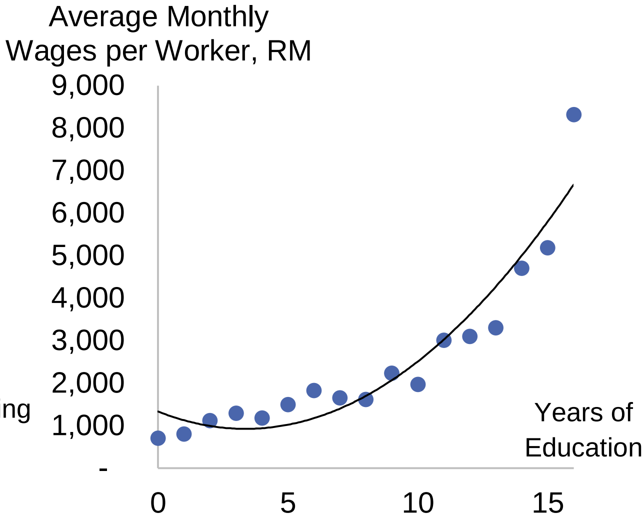
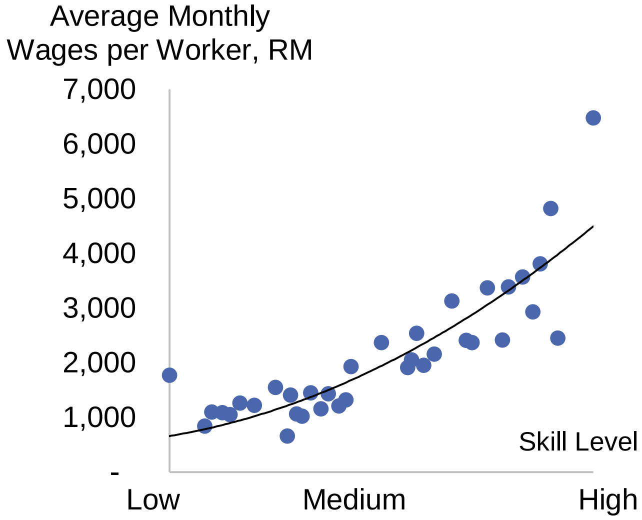


Figure 7: Average Monthly Wages per Worker by Skill Level, 2014

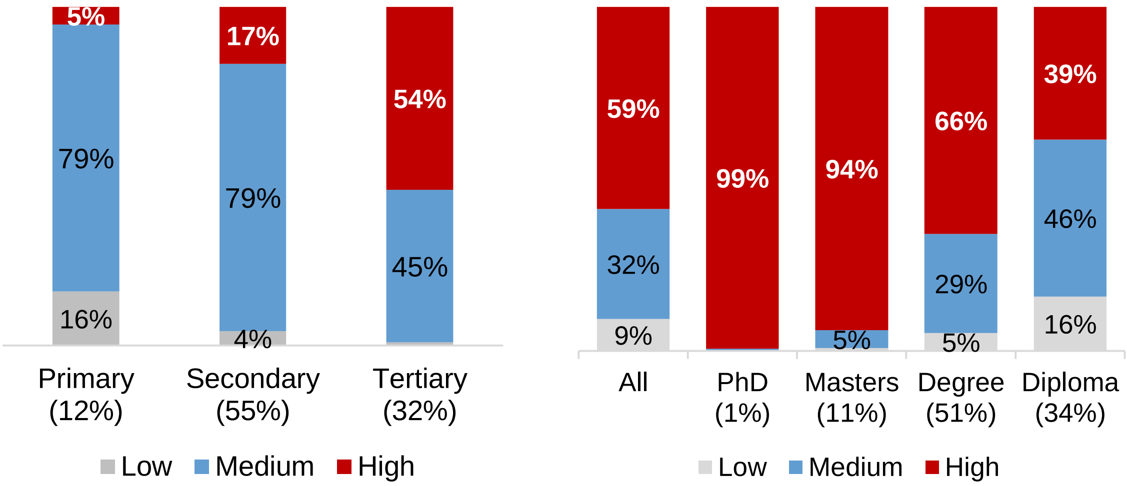


Source: staff estimates, DOSM 2014 HIES

The returns to skill profile in Figure 7 bears similar resemblances to Figure 6, as exhibited by the upward sloping trend. Higher-skilled workers tend to earn higher wages than workers of lower skill groups. However, the returns to skill are distinct from returns to education for several reasons. Skills are shown to be more affected by shifts in demand towards more high-skilled workers within and across industries (Juhn et al, 1993), owing in part to technology advancements in the workplace that complement jobs performed by high-skilled workers - tasks that involves problem-solving, logical reasoning and communication, but which substitute for routine-based and non-complex tasks performed by medium-skilled workers (Autor, 2015). Workers' skills also reflect important productivity attributes such as quality of education, on-the-job training and firm competitiveness, which are distinct from both years of education and working experience (Hanushek et al, 2013). Such differences are notable in the Korean experience, which shows marked performance in the PISA (Programme for International Student Assessment) that measures performances attributable to educational attainment, while fares poorly in the skill-based PIAAC (Survey of Adult Skills) assessment (Lee and Wie, 2017).

The charts in Figure 8 provide further evidence on this heterogeneity. On the left, while most fresh graduates (less than two years of working experience) are employed in high-skilled jobs, a large segment is also employed in medium-skilled jobs. These findings are broadly in line with 2014 Graduate Tracer Study published by Ministry of Higher Education, Malaysia. This difference, however, becomes less pronounced for post-graduate qualifications.

Figure 8: Composition of Skill Level by Level of Education for Fresh Graduates, 2014

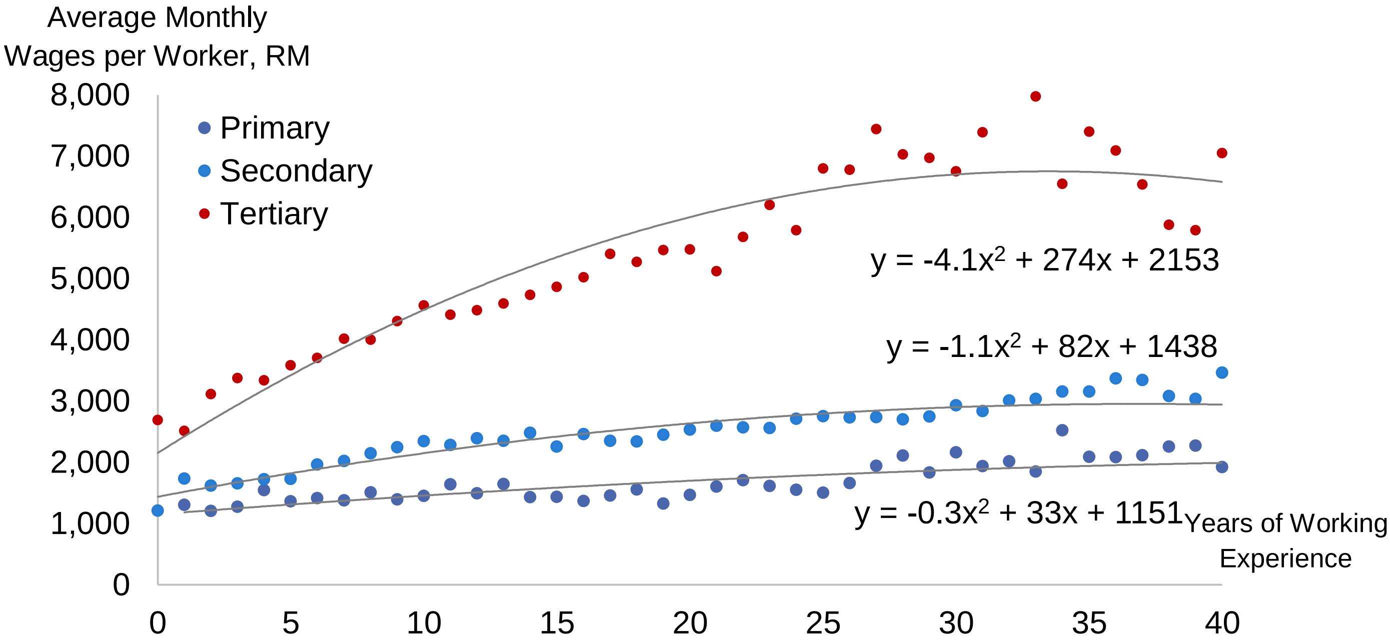


Source: staff estimates

Source: MOHE Graduate Tracer Study, 2014

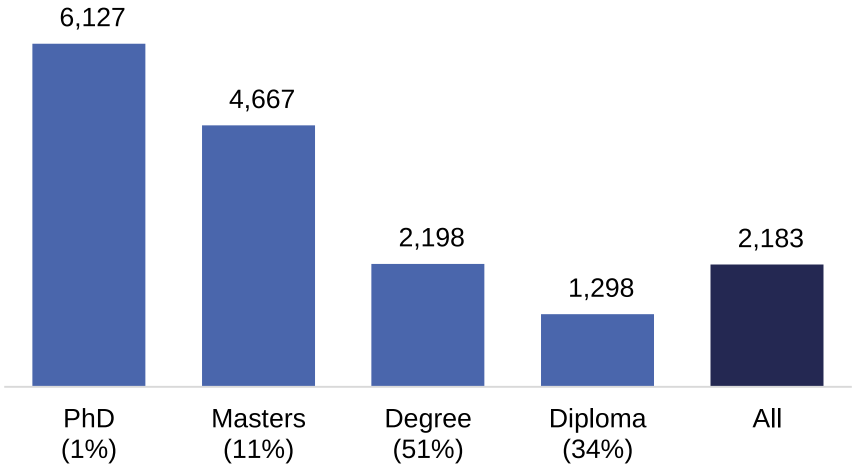
Figure 9 reproduces the wage profile for different education groups. Wages for workers with tertiary education are higher and increases with years of working experience. Based on the fitted polynomial trend for wages of workers with tertiary education, it can be observed that the estimated starting pay for a fresh graduate with no working experience (y-intercept) is roughly RM2,150. This estimate is also in line with the 2014 Graduate Tracer Study, which shows an average monthly wages of RM2,183 for all fresh graduates (Figure 10). Meanwhile, the equivalent starting pay for workers with secondary and primary education are RM1,438 and RM1,151 respectively. These findings are also in line with the experiences of the US labor market (Lemieux, 2006 and Mincer, 1973).

Figure 9: Average Monthly Wages per Worker by Working Experience for Different Educational Attainment, 2014



Source: staff estimates

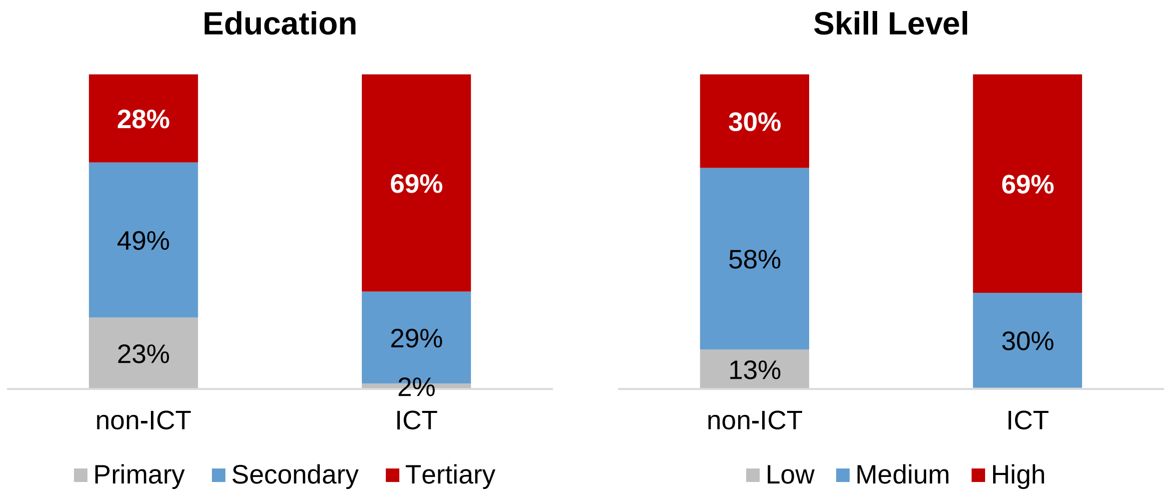
Figure 10: Average Monthly Wages of Fresh Graduates (RM), 2014



Source: MOHE Graduate Tracer Study, 2014

Figure 11 compares educational attainment and skill levels between ICT and non-ICT workers. The ICT sector is shown to have greater share of workers with tertiary education and high skill level vis-a-vis non-ICT sectors. Technology sectors have a higher share high-skilled and educated workers who are more adept in utilising new technologies (Aghion et al, 1998, and Aghion, et al, 1999).

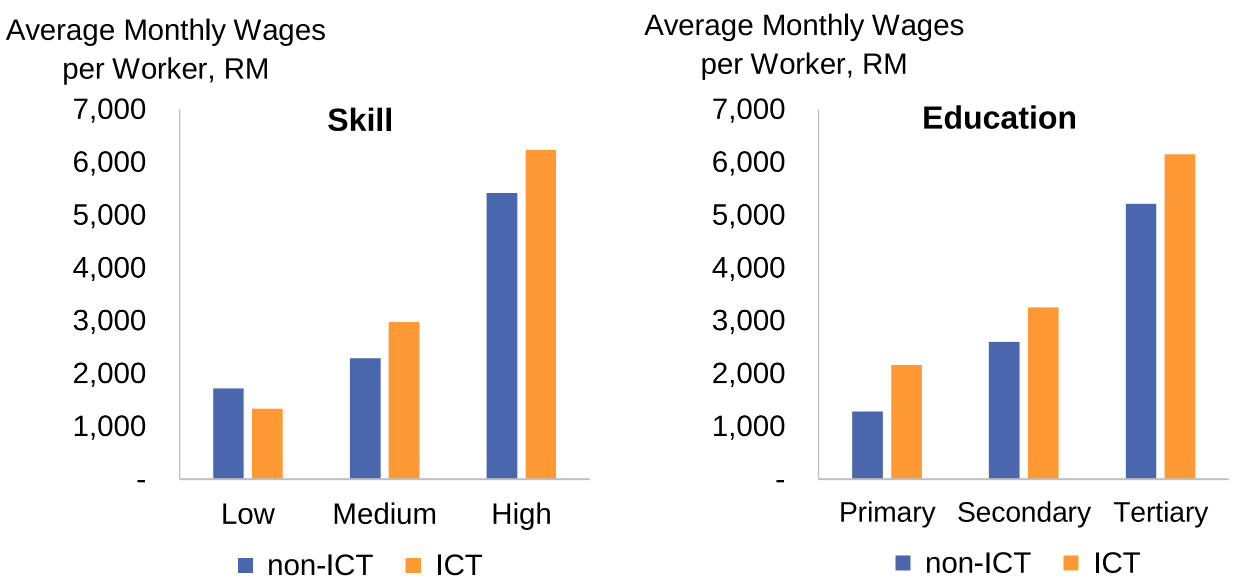
Figure 11: Share of Non-ICT and ICT Workers by Educational Attainment and Skill Level (%), 2014



Source: staff estimates

Consistent with the macroeconomic findings in Section 2, Figure 12 also shows ICT workers commanding a wage premium, particularly in middle- and high-skilled segment. Although the opposite was observed for low-skilled ICT workers, a small sample size in this segment limits further interpretation. Nevertheless, ICT workers have higher wages across all education groups.

Figure 12: Average Monthly Wages per Worker of ICT and non-ICT Sectors by Skill Level, 2014



Source: staff estimates

5. Methodology

In this section, we provide the empirical framework to examine the validity of the stylised facts presented in the earlier section. We estimate a model of wages that is based on the standard Mincer equation (Mincer, 1974; Chiswick, 2006; and Polachek, 2006), with wages estimated as a function of education, working experience and the squared term of working experience. Similar empirical studies by Pereira and Martin (2000) and Akerman et al (2013) also assessed wage inequality via different modifications of the Mincer equation. The baseline standard Mincer model takes the following form:

$$Log\ Y_i = c + \alpha S_i + \beta X_i + \delta {X_i}^2 + \varepsilon_i \tag{3}$$

where *Log* Y_i is the logged average monthly wages (RM) per worker of household *i*; *c* is a constant term, S_i, X_i and ${X_i}^2$ are the corresponding years of education, working experience and the squared term of working experience; and ε_i is the error term. Motivated by the stylised facts presented earlier, we include skill level dummies into the Mincer equation model. Equation (4) shows the extended Mincer model:

$$Log\ Y_i = c + \alpha S_i + \beta X_i + \delta {X_i}^2 + Z_i + \varepsilon_i \tag{4}$$

where Z_i is a vector of skill dummies which take value 1 and zero otherwise for workers of medium and high skill levels respectively (Low skilled occupation group as control). Hur et al (2003) also used skill dummies to examine wage inequality in Korea. Lastly, Equation (5) includes the ICT dummy, which takes value 1 if an individual *i* works in the ICT sector, and zero otherwise, and its interaction with the skill dummies.

$$Log\ Y_i = c + \alpha S_i + \beta X_i + \delta {X_i}^2 + ICT_i\,.Z_i + \varepsilon_i \tag{5}$$

6. Empirical findings

Table 3 presents the regression results based on the methodology discussed, estimated using ordinary least squares (OLS) with robust standard errors. The results are presented first in its basic form and the subsequent adjustments are shown thereafter.

The baseline model is estimated based on the standard Mincer equation in Equation (3), which contains the years of education and years of working experience and its squared term as initial determinants. Although the adjusted R^2 of 0.297 is considerably low, it is broadly in line with the overall fit of the Mincer equations in Yunus (2017). Coefficients for education is positive and statistically significant, indicating that an additional year of schooling increases monthly wages by approximately 11.25% for each additional year of education, which is in accordance with the estimates for Malaysia by Yunus (2017) and Kenayathulla (2013). However, the working experience and its squared terms are not only insignificant, they also exhibit opposite signs with each other, albeit at an extremely small magnitude, respectively. These findings represent significant departure from the literature. Nevertheless, we may consider the standard Mincer equation to be inadequate based on the stylised facts presented earlier, as well as its poorer fit for data in recent decades than it did in the past (Lemieux, 2006).

Table 3: Determinants of Wages

	(1)	(2)	(3)	(4)
VARIABLES	Base	Base with skill	Base with skill and ICT	Base with interactions
Education	0.1125***	0.0690***	0.0686***	0.0686***
	(0.0010)	(0.0011)	(0.0011)	(0.0011)
Work	-0.0011	0.0070***	0.0072***	0.0072***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
$Work^2$	0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Medium_skill		0.1510***	0.1504***	0.1497***
		(0.0105)	(0.0105)	(0.0105)
High_skill		0.7281***	0.7245***	0.7249***
		(0.0121)	(0.0122)	(0.0122)
ICT			0.1275***	-0.1507
			(0.0166)	(0.1362)
ICT*Medium_skill				0.3090**
				(0.1394)
ICT*High_skill				0.2660*
				(0.1377)
Constant	6.6252***	6.6573***	6.6580***	6.6584***
	(0.0143)	(0.0148)	(0.0148)	(0.0148)
Observations	46,741	46,741	46,741	46,741
R^2	0.2968	0.4001	0.4007	0.4007

Robust standard errors in parentheses
***, ** and * indicate significance at 1%, 5% and 10% levels respectively

Model 2 estimates an extended Mincer equation with skill dummies as specified in Equation (4). Both skill dummies are statistically significant and indicate that average wages do differ across skills. Medium- and high-skilled workers earn an average 15.1% and 72.8% more than their low-skilled counterparts. As posited in literature, we consider these sizable wage differentials to be attributable to skill-biased technological changes in the workplace which predominantly increases productivity of high-skilled workers (Autor, 2015). In addition, the working experience variables now show the correct signs and magnitudes, which captures the diminishing wage profile with older age. Also, the returns to education is nearly halved once skill levels are taken into account, which is broadly in line with the notion that occupational-based skills are intrinsically distinct, although not mutually exclusive, from productivity-augmenting capabilities obtained from formal schooling. Furthermore, the model shows a marked improvement in fit.

As specified in Equation (5), Models 3 and 4 introduce the ICT sector dummy and its interaction with skills respectively. In Model 3, the ICT dummy is significant, implying that workers in the ICT sector enjoy an average wage premium of 12.75% in comparison to their non-ICT counterparts. Model 4 shows that the ICT premium is as large as 30.9% and 26.6% for medium- and high skilled ICT workers respectively. However, this finding is in contrast to the literature as we expect high-skilled ICT workers to benefit more from technological changes. We proceed to assess the effects of ICT for each skill level separately for robustness purposes.

In Table 4, we estimate the ICT premium while allowing returns to education and work to vary across different skill segments. Consistent with our stylised facts presented earlier, the education and work variables are positively associated with the level of worker's skill. The returns from an additional year of education are shown to increase from 4.1% to 6.1% and 10.9% for low-, medium- and high-skilled workers respectively. However, we observe a wider disparity for returns to years of working experience. An additional year of working experience for high-skilled workers returns nearly 10 and 5 times more than medium- and low-skilled workers respectively. Compared to the results in Model 4, the ICT premia of 16.1% and 10.4% are shown to be lower for medium- and high-skilled workers. Nevertheless, the outperformance of the medium-skilled ICT premium remains in line with estimates from Model 4.

Table 4: Determinants of Wages by Skill Level

	(5)	(6)	(7)
VARIABLES	Low	Medium	High
Education	0.0410***	0.0616***	0.1091***
	(0.0035)	(0.0013)	(0.0028)
Work	0.0057**	0.0027***	0.0260***
	(0.0025)	(0.0009)	(0.0020)
$Work^2$	-0.0001**	-0.0000**	-0.0003***
	(0.0000)	(0.0000)	(0.0000)
ICT	-0.1628	0.1614***	0.1039***
	(0.1516)	(0.0299)	(0.0188)
Constant	6.9155***	6.9401***	6.5667***
	(0.0269)	(0.0146)	(0.0503)
Observations	3,017	28,498	15,226
R^2	0.0851	0.1138	0.2374

Robust standard errors in parentheses
***, ** and * indicate significance at 1%, 5% and 10% levels respectively

The results from Table 3 and 4 show that medium-skilled ICT workers have benefited more from technological advances, and hence is suggestive of a lower wage gap within the ICT sector. We test this notion more formally. In Table 5, we estimate and compare the wage gap between high-skilled and other workers separately for each sector, denoted by the high-skilled dummies. The ICT sector's wage gap of 31.9% is the lowest, while it ranges from 50% to 78% for other sectors. The results also show that returns to education and work experiences of workers in the ICT sector is higher than all other sectors.

We consider four potential reasons for these findings. First, ICT workers in general have benefitted from education that better matches the skill demands of ICT firms. From Model 8, the returns to education for the ICT sector is shown to be nearly twice as large as workers in other sectors. Second, on-the-job learning and training in the ICT sector yields almost three-fold returns than non-ICT services sectors. As the workforce in the ICT sector is largely composed of medium- and high-skilled workers, the returns from on-the-job training would be proportionally higher for a given amount invested compared to other sectors with lower shares of skilled workers. Third, labour supply and demand dynamics can also exert considerable influence on the wages of the ICT workers. Yunus (2017) argues that the decline in returns for ICT workers with tertiary education between 2002 and 2007 is attributable to an increasing labor market mismatch in the ICT sector, resulting from a shift towards higher graduate employment in middle-skilled jobs. This in turn raises the productivity and wages of middle-skilled workers while suppressing wages of high-skilled workers. Lastly, although most other sectors are not technologically intensive, their high-skilled workers are still involved in problem-solving and abstract-oriented tasks that are complemented and aided by technology, consistent with the skill-biased technological changes that has occurred in most sectors (Autor, 2015). In short, effective education and training have reduced the ICT wage premium by skill, which is further narrowed with greater educational attainment among middle-skilled ICT workers. Meanwhile, the gap is higher in all other sectors, which is in line with literature.

Table 5: Determinants of Wages by Sector

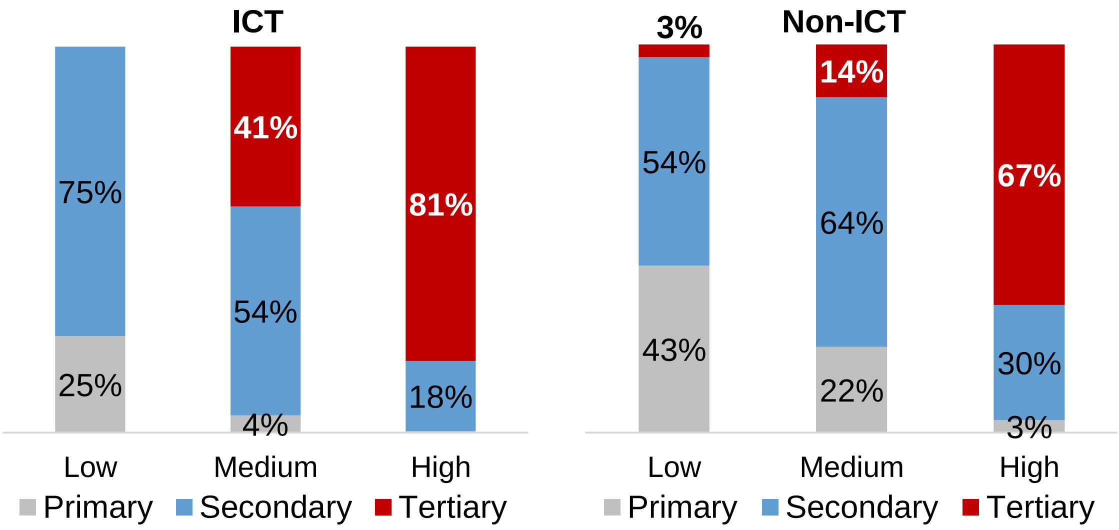
	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	ICT	Non-ICT services	Manufacturing	Agriculture	Mining	Construction
Education	0.1415***	0.0779***	0.0714***	0.0490***	0.0877***	0.0626***
	(0.0117)	(0.0014)	(0.0024)	(0.0024)	(0.0097)	(0.0027)
Work	0.0277***	0.0092***	0.0031	-0.0059***	-0.0001	-0.0105***
	(0.0069)	(0.0011)	(0.0019)	(0.0017)	(0.0083)	(0.0025)
$Work^2$	-0.0002	-0.0001***	0.0000	0.0001***	0.0002	0.0003***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0001)
High	0.3188***	0.5014***	0.5709***	0.6664***	0.6117***	0.7870***
	(0.0477)	(0.0079)	(0.0125)	(0.0295)	(0.0497)	(0.0184)
Constant	5.8453***	6.6809***	6.7190***	6.8473***	6.8667***	6.9031***
	(0.1762)	(0.0193)	(0.0306)	(0.0189)	(0.1468)	(0.0295)
Observations	1,040	33,050	9,877	8,201	784	6,398
R^2	0.4626	0.3758	0.4030	0.1864	0.4301	0.4442

Robust standard errors in parentheses

***, ** and * indicate significance at 1%, 5% and 10% levels respectively

Additional evidences of this trend can be seen in Figure 13. 41% of medium-skilled jobs in the ICT sector are filled by tertiary educated workers, compared to 14% in the non-ICT sector. Meanwhile, we also see a higher proportion of high-skilled jobs filled by university graduates in the ICT sector vis-à-vis non-ICT sectors.

Figure 13: Distribution of ICT and non-ICT Workers by Educational Attainment and Skill Level (%), 2014



Source: staff estimates

7. Discussion

The lower wage gap in the ICT and in the services sector is an interesting finding. This suggests that compared to other sectors, the services sector, and in particular the ICT sector, the gap in productivity is more modest across skill levels, resulting in the narrower wage gap. One reason, as explained above, could be because mid-skilled workers in ICT has tertiary education and this is reflected in their wages. However, we could also interpret the narrow wage gap as an indication that technology is adopted in a more widespread manner in the ICT and services sectors.

Indeed over the last two decades, the services sector has undergone significant structural changes. We saw a rapid increase in adoption of the internet, smartphones, cloud computing, data centres, big data analytics, social media applications, sharing economy and fintech. Workstations are equipped with better computers, and many companies move from traditional computers to handheld devices. There is also more interactive multimedia content, riding on the boom in mobile technology.

What is more important is that these technological changes are increasingly adopted across all types of workers, with positive impact on productivity and wages. The digitalisation in retail, hotels and airlines, banking, media & advertising and healthcare industries, for example, has transformed the way business is conducted in the services sector. Not only are managers and professionals benefitting from technological advancement, mid-and low-skilled staff such as receptionists, cashiers, waiters, salespersons, courier delivery persons, clerks and drivers, are also benefitting from technology induced productivity advancements via adoption of personal computers and related technologies to fulfil their duties.

The adoption of technology is also gaining more traction in the manufacturing sector in recent years, particularly with the advent of the Industry 4.0 revolution in Malaysia, with more manufacturers moving into full or partial automation in their production processes in order to further improve efficiency, enhance productivity and reduce costs. This has consequently led to less reliance on low-skilled labour, particularly unskilled foreign worker, in routine manufacturing operations. The Government is playing a big role in encouraging industrial automation by providing funding schemes to small and medium manufacturers (SMEs) - more than 400 companies have obtained financing amounting to RM1.5 billion since 2007 to modernise their production lines.

The upskilling and reskilling of graduates through industry-driven training programmes have managed to partially address the skill mismatch between local academic curriculum and the industry requirements. This is particularly evident in the electronics and electrical (E&E) industry, where past industry-led training programmes such as Expert-led Industry-driven Talent-enhanced (ELITE), Northern Industrial Technical Enhancement Scheme and the current Upgrading Skills Programme by E&E Strategic Council have produced batches of graduate trainees with better employability and technical skills that meet the demand of the industry. These were achieved through collaboration and joint-funding between the Government, the industry and the academia.

8. Limitations and Further Research

There are several limitations in the empirical analysis. First, the analysis utilises cross-section data from HIES conducted in 2014, which means the effects of technology across different time periods or cohorts are not examined. Second, despite the official definition of ICT sector as explained in the earlier part of this paper, the lack of a more detailed breakdown of industries in the data inhibits us to fully adhere to this official definition. Instead, the ICT sector is proxied by the information and communication subsector under the services sector, while the non-ICT is generally defined as the rest of the economy (or services sector). Given this limitation, other sectors that have a high adoption of technology are not included as the ICT sector. Third, we also do not account for firm characteristics such as the regulatory environment, firm size, age, seniority of management, ownership type or innovative capabilities due to data limitations. This may matter because wage inequality across firms has been found to matter more than within-firm pay gaps (Song et al, 2016). Fourth, the Mincer model can also be fine-tuned to account for the signalling effects of tertiary education (Spence, 1973), which allows for the returns to tertiary education and certification to be quantified. Finally, we do not account for technology effects on inequality via wealth accumulation, which Piketty and Goldhammer (2014) show to be a key source of inequality.

9. Concluding Remarks

This paper examines the role of ICT in affecting wages in Malaysia based on the 2014 Household Income and Expenditure Survey (HIES). The effects of technology on wages can be summarised in three key findings. First, we find evidence for an average ICT wage premium of 12.75%. Second, premium for medium-skilled ICT workers is higher at 16.1%, but lower at 10.4% for high-skilled ICT workers. This finding is suggestive of the technology-induced labour supply changes in response to the ICT wage premium that leads to a greater share of university graduates working in the ICT sector, resulting in a more educated middle-skilled ICT segment. This in turn raises the productivity and wages of middle-skilled ICT workers. Third, within the ICT sector, there is a 32% wage premium for high-skilled workers. Empirical estimations by economic sector reveal that this wage premium can be attributed to the substantially higher returns to education and work experience in the ICT sector. However, the wage gaps between high-skilled and lower-skilled workers in non-ICT sectors are higher, ranging from 50% to 78%, which is a further evidence that technological changes are generally biased towards high-skilled workers (Autor, 2015).

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Appendix 1: 2014 HIES Individual Level and Household Level data definitions

Table A1 below describes the selected individual level dataset used in the construction of variables for our study. For parsimonious reasons, we do not include other characteristics such as gender, marital status, nationality, geography and ethnicity in our analysis.

Table A1: Individual characteristics obtained from HIES 2014

No.	Individual Level
1	Educational attainment
2	Age
3	Employment status
4	Occupational type
5	Industry type
6	Household ID

Guided by literature[2], we use information regarding age and educational attainment to construct years of education and working experience for each individual in the workforce. The years of education variable is constructed based on the individual's highest level of certification obtained, which we describe in Table A2 below. Meanwhile, years of working experience is obtained by deducting years of education (and minus seven) from age. This formula is consistent with Malaysia's education policy in requiring mandatory schooling attendance for children aged seven and above. We assume each individual enters the workforce immediately upon achieving one's highest level of educational attainment. Data limitations also prohibit further differentiation for higher levels of tertiary education, i.e.: Masters, PhDs or multiple degree holders.

Table A2: Years of schooling by level of certification obtained

No.	Level of certification	Years of Schooling
1	Bachelors/Degree	16
2	Diploma	14
3	STPM / Pre-University	12
4	SPM	11
5	PMR	9
6	Primary	6
7	None	0

Source: Yunus (2017) MOHE (2010), Department of Statistics, Malaysia

[2] As posited by Mincer (1974), income was shown to vary linearly with years of schooling and work experience. Recent empirical studies also show that individuals with higher educational attainment also tend to earn higher wages (M Yunus 2017 and Liu, Belfield, & Trimble, 2015).

Next, we make the following data augmentations. Employment status of individuals, which is made up of 11 broad categories, are redefined as a binary variable to only denote an individual's general participation in the workforce. It takes value 1 if an individual is either an employer, employee in the private sector or public sector, or self employed, and zero otherwise. This is shown in table A3. We also reclassify the 9 occupational groups which correspond to the one-digit occupational code in the Malaysia Standard Classification of Occupations (MASCO) code 2008 into either Low, Middle or High skilled workers in Table A4.

Table A3: Employment status of individuals

No.	Types of Employment	Employment status
1	Employer	1
2	Employee in private sector	1
3	Employee in public sector	1
4	Self-employed	1
5	Unpaid family member	0
6	Unemployed	0
7	Housewife	0
8	Student	0
9	Retiree	0
10	Others	0
11	Unschooled children	0

Source: Department of Statistics, Malaysia

Table A4: Skill level of individuals

No.	Major Occupational Groups	Skill Level
1	Managers	High
2	Professionals	High
3	Technicians and Associate Professionals	High
4	Clerical Support Workers	Medium
5	Services and Sales Workers	Medium
6	Skilled Agricultural, Forestry and Fishery Workers	Medium
7	Craft and Related Trade Workers	Medium
8	Plant and Machine-operators and Assemblers	Medium
9	Elementary Occupations	Low

Source: MASCO 2008 Classification

Finally, we classify the industry that an individual works in using the Malaysia Standard Industrial Classification 2008 (MSIC 2008) at the 1-digit level. This allows for the identification of individuals working in the ICT services sub-sector. Due to data constraint, we assume Information and Communication is representative of the ICT sector. Although ICT industry cuts across various industries, including manufacturing, and wholesale and retail trade (see Figure 2), information and communication sub-sector constitute about 45% of the ICT sector. This sub-sector includes telecommunication, computer programming, consultancy, information and related activities, as well as content and media. It takes value 1 if an individual is working in the ICT services sub-sector and zero otherwise. Complete details of this classification is provided in table A5 below.

Table A5: Industrial Classification based on MSCI 2008

No.	Industrial Classification
1	Agriculture, Forestry and Fishing
2	Mining and Quarrying
3	Manufacturing
4	Electricity, Gas, Steam and Air Conditioning Supply
5	Water, sewerage and waste management
6	Construction
7	Wholesale and Retail Trade; Repair of motor vehicles and motorcycles
8	Transport and Storage
9	Accomodation and Food service activities
10	Information & Communication
11	Finance and Insurance/Takaful activities
12	Real Estates and Business Services
13	Professional, scientific and technical activities
14	Administrative and support service activities
15	Public administration and defence, social security
16	Education
17	Human health and social work activities
18	Arts, Entertainment and recreation
19	Other Services
20	Activities of household
21	Activities of extraterritorial organisations

Source: MSIC 2008 Classification

Table A6 below describes the selected household level dataset used.

Table A6: Household characteristics available from HIES 2014

No.	Household Level
1	Household ID
2	Total annual income (RM) of all household members
3	Size of households

A limitation of the survey is that income data is only collected at the household level. Most studies define household income and other characteristics based on the profile of the head of household (Yunus, 2017, Soh et al, 2017 and Murughasu, 2013). For our study, however, we also take into account characteristics of other household members. This is because characteristics of the head of household become less reflective of the household as the number of household members increases. Measurement errors are introduced, for instance, when households are classified as inactive based solely on the observation of an inactive head of household, while other household members are employed. A similar argument holds for other indicators of interest such as age, industrial and skill level, years of education and working experience. To partly address this data limitation and measurement issue, we define household characteristics using information from all household members, which are identified, merged and then averaged based on the matching household IDs. Hence, salient features of other household members are adequately accounted for. Nevertheless, we recognise that measurement errors still remain under this approach.

Another limitation of our approach is the omission of within-household heterogeneity from our analysis. Household dynamics and intergenerational dependencies among household members are thus not accounted for. For instance, studies have shown that educational attainment and wage levels of parents are also strong predictors of children's' future wage levels, (Erola et al, 2016 and Jencks, 1972). Our study instead focuses solely on the cross-sectional heterogeneity to understand how wage levels are determined based on a set of controls and the role of digitisation.