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Impact of Technology on Wages and Productivity in Singapore

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[Reviewed by Chaipat Poonpatpibul, and approved by Hoe Ee Khor]

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Abstract

The rise of digital technologies is generating renewed interest in the relationship between technology and the labor market. In this paper, I evaluate the impact of technology adoption on monthly wages and productivity in Singapore. The effects of technology on wages and real productivity can be summarized in three key findings. Firstly, results from the panel analysis show that an additional 1% spent on ICT per year leads to a 0.074% increase in average monthly wages, and the effect is more pronounced in the services sector. Secondly, the impact of ICT utilization on the real productivity growth rate is positive and significant, whereby an additional 1% spent on ICT per year leads to a 0.058% increase in the average real productivity growth rate. Thirdly, cross-sectional analysis of wages by skill levels show that higher skilled workers benefitted more from greater ICT utilization, while it is less evident for low-skilled workers. These findings corroborate literature on the differential impact of technology according to the skill level of workers.

JEL classification: E23, E25, O30, O40

Keywords: Technological change, wages, skills, ICT

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Executive Summary

Technological advances have been key in raising sustainable income levels over the longer-term, but their potential adverse distributional effects in relation to wage growth and employment prospects can be a cause for concern. More recently, the ongoing adoption of digital technologies globally is garnering much renewed interest in the relationship between technology and the labor market. Unlike the past, the scale and speed of their adoption have been unprecedented. While policymakers are considerably optimistic regarding their macroeconomic prospects, they are also particularly concerned about their potential adverse distributional effects. Studies show that the impact of these new technologies on the labor market are uneven, and can persist over prolonged periods (Autor and Dorn, 2013). Inasmuch technology increases job prospects, productivity and wages of skilled workers, they also displace labor in tasks made redundant by these changes.

The purpose of this study is to examine the impact of technology on monthly wages and productivity in Singapore. Research shows that technological advances led to higher productivity and wage improvements, but gains can be uneven across workers of different skills. This paper examines whether wages and productivity have indeed increased because of greater technological adoption in Singapore, and secondly, analyze the distributional effects of technology on wages.

The role of technology is jointly examined with other wage and labour productivity determinants via a human capital model framework à la Mincer (1973) estimated using the Generalised Least Squared (GLS) estimator. This paper seeks to examine the degree to which ICT utilization per worker – the total value of software, computer, electronic equipment, programming, information and telecommunication services utilized, affected wages and productivity at the sectorial level. Together with other wage and productivity determinants, the empirical model is based on the panel Mincer equation popularized by Card (2001) estimated using the Generalised Least Squared (GLS) estimator to account for both within- and cross-sector correlation. The panel data ranges from 1995 to 2016. Second, the impact of ICT investment on the 25th, 50th and 75th wage quantiles for all sectors is also assessed using cross-sectional data.

The empirical assessments indicate a positive and statistically significant relationship between ICT adoption and wages that is supported by productivity growth, but gains are skewed towards higher-skilled workers. Empirical results from the panel analysis show that greater ICT adoption led to higher wages. An additional 1% spent on ICT per year leads to a 0.074% increase in monthly wages. The impact on the services sector is higher at 0.085%, but evidences are mixed in the manufacturing sector, and negligible in the construction sector. Secondly, the impact of ICT utilization on the real productivity growth rate is positive and significant, whereby an additional 1% spent on ICT per year leads to a 0.058% increase in the real productivity growth rate. It is as high as 0.399% in the manufacturing sector, followed by 0.056% in services. Thirdly, cross-sectional analysis of wages by skill levels show that higher skilled workers benefitted more from greater ICT utilization, while it is less evident for low-skilled workers. These findings corroborate literature on the differential impact of technology by skill level of workers.

1. Introduction – Singapore's labor market and technological trends

Singapore's robust wage growth has been witnessed in both manufacturing and services sectors since the 1990s, while the bulk of employment growth is concentrated in services sector. This section provides an overview of Singapore's labour market trends since the 1990s. Figure 1 shows that the average gross wages (including CPF) increased from 1,850 SGD in 1991 to approximately 5,200 SGD by 2017. Wage gains are higher for workers in services industry, even though productivity improvements in manufacturing has outpaced services since the late 1990s (Figure 2). Notably, the relatively slower productivity growth in the services sector has not contributed to a corresponding slower growth in services sector wages. Figures 3 and 4 illustrate the structural changes underpinning the Singaporean economy towards services activities, which tend to be more labor intensive than other sectors. In Figure 3, the number of workers in services occupation increased nearly 3-fold to approximately 2.9 million by 2017 from 1 million in 1991, while its share of the overall workforce increased from 63% to 76% during this period (Figure 4).

Figure 1: Average Monthly Wages by Sector

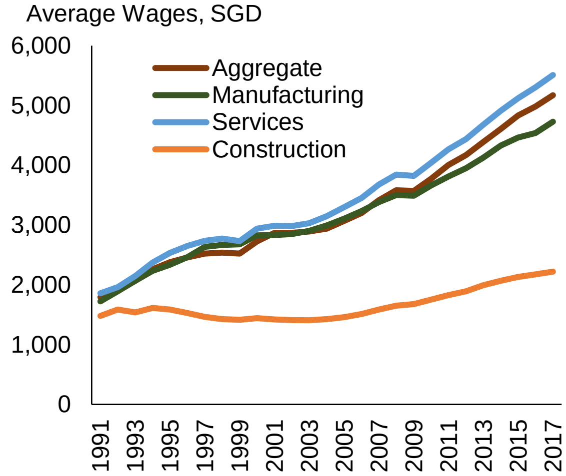


Figure 2: Real VA per worker by Sector, at 2010 Market Prices

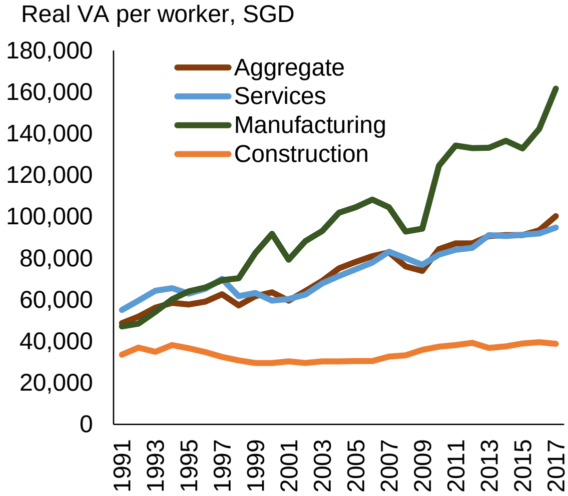


Figure 3: Number of workers by Sector

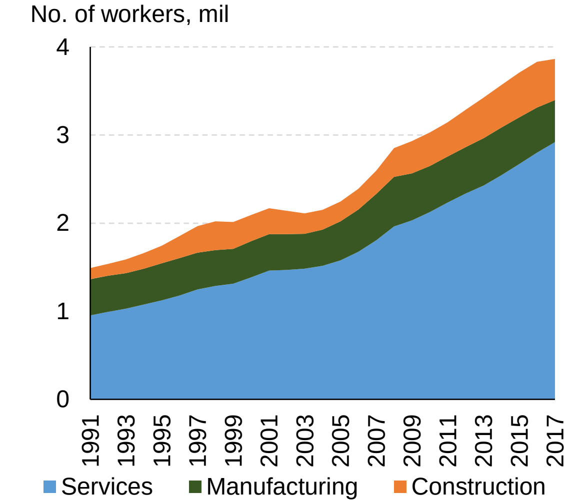
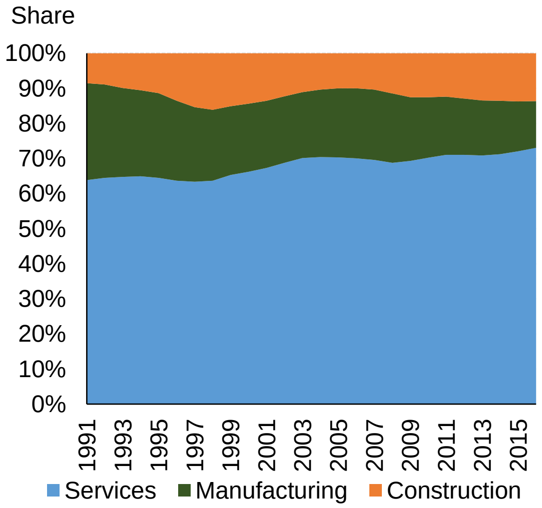


Figure 4: Share of workers by Sector



Sources: Ministry of Manpower, Author's Estimates

From an occupational standpoint, however, wage and employment gains are uneven and skewed towards high-skilled workers. Wage growth of high-skilled workers has outpaced other skill segments, accelerating since the Global Financial Crisis (Figure 5). However, wages in the low-to-medium segments has risen, albeit much more slowly, since the 2010s due to various government support schemes targeted at enhancing productivity and wage growth of workers in these segments (AMRO, 2017). For example, the Workforce Income Scheme introduced in 2007 to top up wages of low-income workers and the Progressive Wage Model in 2012 – mandatory wage increase based on skills-upgrading and productivity improvements. In terms of employment, Figure 6 shows that the number of high-skilled workers also increased significantly from 0.3 million in 1990 to more than 1.2 million by 2017. Even though the number of low-to-medium skilled workers remained largely unchanged, their share of the overall workforce has been on a downward trend in both manufacturing and services over the past several decades (Figure 7). Among the services sub-sectors, ICT, Financial, and Professionals services have the highest share of high-skilled workers, while it is relatively low in Transport, Accommodation, and Other Services (Figure 8).

Figure 5: Median Wages (SGD) by Skill Level

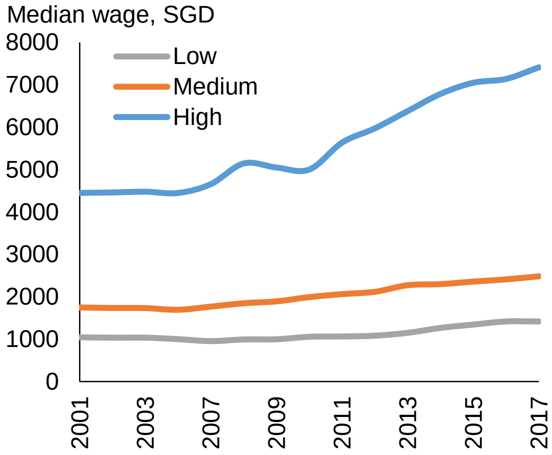


Figure 6: Number of Resident Workers by Skill Level

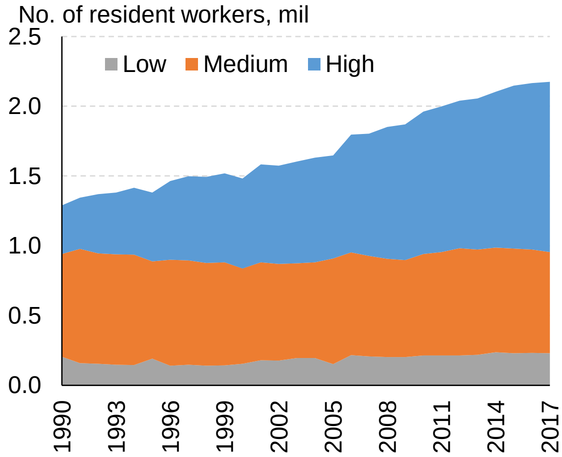


Figure 7: Share of workers' Skill Level in manufacturing and Services

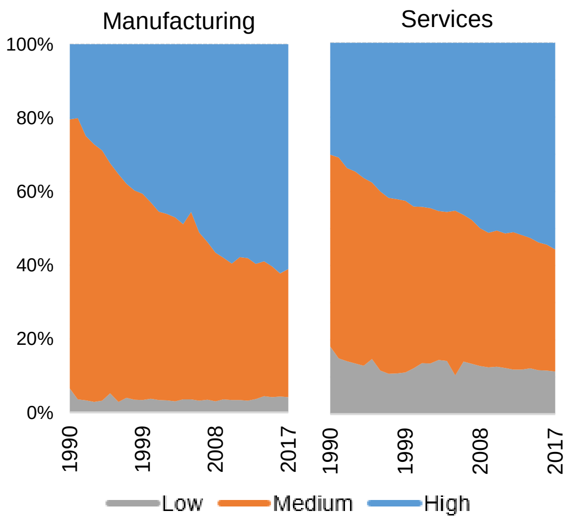
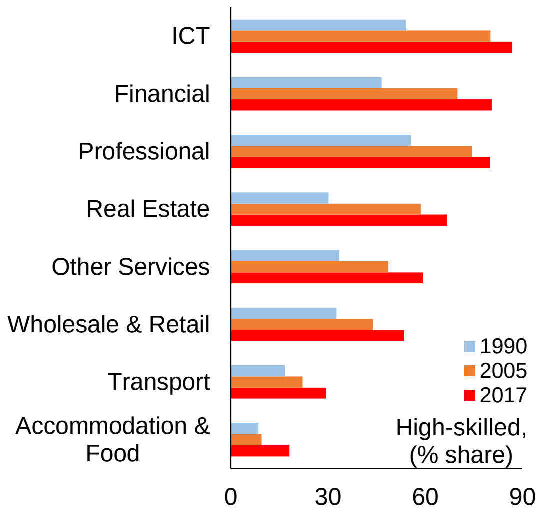
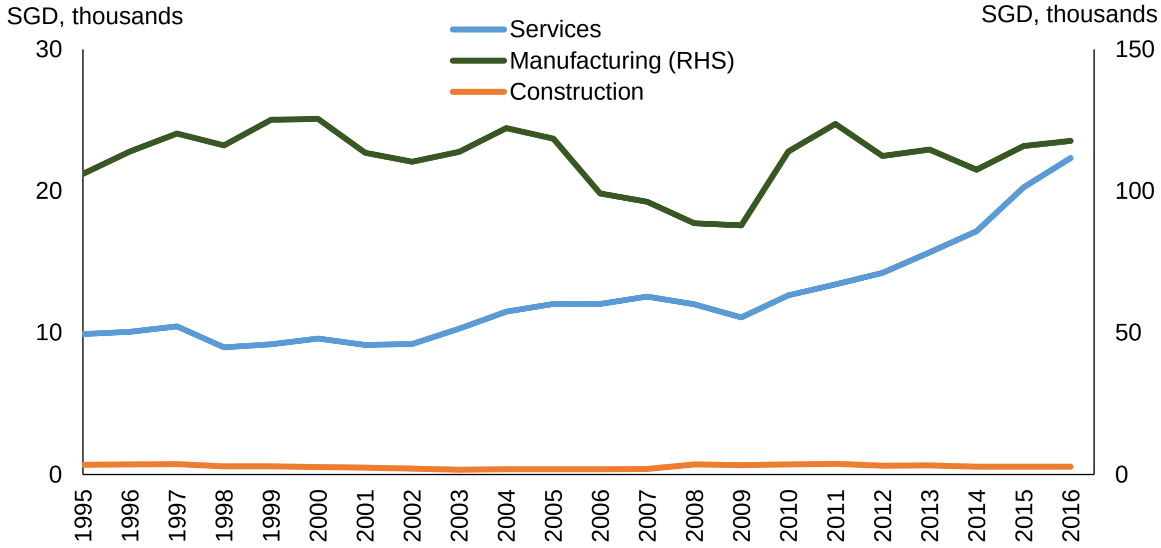


Figure 8: Share of High-Skilled* Workers by Services Sub-Sectors



Sources: Ministry of Manpower, OECD-WTO Trade in Value-Added (TiVA) database, UNCTAD, author's estimates
Note: High-Skilled refers to Mangers, Professionals, Technicians and Associate Professionals; Medium-Skilled – Clerical Support, Services and Sales, and Low-Skilled Agriculture; Low-skilled – elementary occupations

Figure 9: Value of ICT goods utilized per worker by sector



Sources: Ministry of Manpower, Singapore Input-Output Tables (2010, 2012 and 2014), OECD-WTO Trade in Value-Added (TiVA) database, UNCTAD, author's estimates

In the services sector, the use of ICT accelerated since the early 2010s. Concerning technological trends in Singapore, Figure 9 shows that ICT utilized per worker in services has been increasing steadily since the 1990s and accelerating in the more recent years. Moreover, increasing ICT utilization in services occurred in tandem with the increase in services employment, reflecting actual greater utilization of ICT. On the other hand, ICT utilized in manufacturing is relatively unchanged, and exhibit greater fluctuations over time, potentially due to greater sensitivity to fluctuations in the business cycle.

In this paper, I evaluate the impact of technology on monthly wages and productivity in Singapore. Having examined Singapore's labor market and technological trends, this paper seeks to answer two questions: First, do we see wages and productivity increase because of greater technological adoption? Second, is there evidence of a wage dispersion among workers of different skills, amplified by the effects of technology?

To answer these questions, the rest of the paper is organized as follows. Section 2 examines the literature on the link between wages and technology. Section 3 explains the stylized facts while Section 4 describes the methodology and data definitions adopted in this paper. Sections 5 discuss the results, and Section 6 concludes.

2. Literature Review

The technology-led high-skilled employment growth and increasing skill premium is notable not only in Singapore but also in several ASEAN countries, and prevalent in many advanced economies. The upskilling of Singapore's workforce and growing high-skilled premium occurred alongside greater utilized of ICT by workers over time. This shift is also notable in other ASEAN countries, with empirical evidences supporting a technology-induced skill premia in Indonesia (Lee and Wie, 2013) and Malaysia (Justin et al, 2017). However, the impact of ICT on wages of low-to-medium skilled workers and labor intensive sectors such as construction, wholesale and retail, and transport appear to be less significant. The unevenness in Singapore's occupational and wage growth is also apparent in many other advanced economies (Autor and Dorn, 2013).

A survey of literature documents a positive relationship between advances in ICT technology and the high-skill premium, while its impact on lower-skilled workers is less evident. There is a growing number of literature examining the relationship between wages of high-skilled workers and skill-biased technological change (SBTC) (DiMaggio et al., 2004; Mishel et al., 2013; and Autor 2015). Theoretical (Acemoglu and Autor, 2011) and empirical evidences (Autor and Dorn, 2013; Autor, Kaz and Kearney, 2008) show that the emergence of new technologies has substantially altered labour market dynamics across many countries. In particular, technology had led to greater demand for high-skilled workers, with stronger wage growth in tandem. However, the benefits of technology to lower-skilled workers are less evident. Wage and employment growth in this segment are slower and mostly reflect aggregate demand effects stemming from higher productivity of higher-skilled workers (Baumol, 1993). Using firm-level data, Loh and Chin (2016) also showed that low-skilled workers in Singapore have not benefitted from greater ICT investments.

The technology-induced skill premium stems from its productivity enhancing attributes which are skewed towards high-skilled workers involved in non-routine and cognitively-intensive tasks. The key hypothesis for this trend is the manner in which ICT is considered to complement high-skilled jobs, but substitute routine and repetitive tasks which are more common in lower-skilled occupations (Autor, Kaz and Kearney, 2008). For example, jobs in the latter group include bookkeeping, clerical or data entry tasks that were significantly automated due to advances in computerisation. This in turn lowers overall demand and wages for these occupations. Conversely, ICT complements high-skilled and highly-educated workers that are involved in data analysis, problem-solving, coordinating and creative-thinking tasks, who experience greater productivity and wage gains (Autor and Dorn, 2013). Card and DiNardo (2002) argued that the increase in the high-skill premium occurred mostly during the 1990s, where technological innovation occurred at a much more rapid pace. Moreover, the spread of technology favored industries with greater usage of internet and robots, operated by high-skilled workers which inadvertently replace low-skilled and labor-intensive tasks (Moore and Ranjan, 2005; Hutter and Weber, 2017). Additionally, Lindley and Machin (2014) and Beaudry, Green, and Sand (2016) emphasized the importance of developing cognitive and problem solving skills via tertiary education, which partly explained the factors of skill premium that is distinct from the effects of technology.

The resulting technology-led productivity improvements are evident in firm-level empirical studies. Firm-level evidences also showed that improvements in productivity are more evident where there are greater investments in computer networks and telecommunications (Atrostic and Nguyen, 2005), particularly when combined with internal efforts to upskill the workforce via piecemeal courses and staff training (Bresnahan et al, 2002). A comprehensive literature review of 150 studies by Cardona et al (2013) showed that a 1% increase in ICT investments led to higher productivity growth of 0.05% to 0.06% in the US and Europe between the 1980s and 2000s.

3. Analysis of data and stylized facts

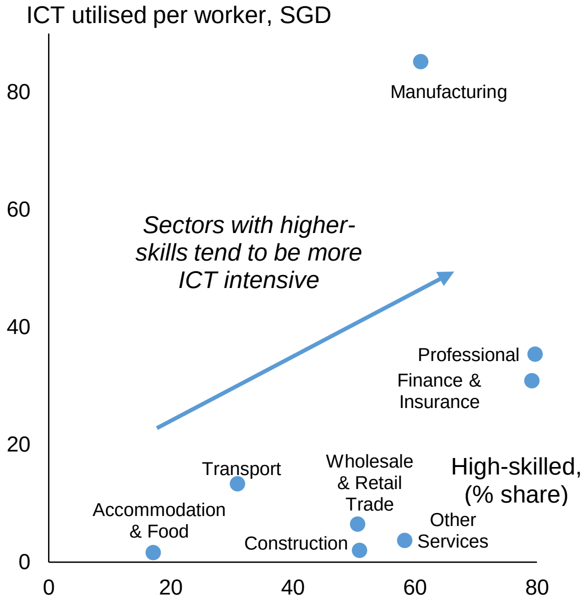
3.1. The difference between the role of skills and years of formal education

A first-pass analysis of Singapore's PISA (Programme for International Student Assessment) survey and the workforce-based PIAAC (Survey of Adult Skills) assessment show a clear distinction between the role of skills and years of formal education in human capital formation. As discussed by Justin et al (2017), productivity and wage gains stemming from skills is distinct from years of education for several reasons. Firstly, skills upgrading reflect important productivity enhancing attributes that are attained beyond years of formal education, such as the quality of education, on-the-job training, and operating environment of firms (Hanushek, 2013). Such differences are evident when contrasting survey findings from the school-based PISA (Programme for International Student Assessment) survey and the workforce-based PIAAC (Survey of Adult Skills) assessment, which is conducted among adults age 16 to 65. Among the 72 countries participating in the 2015 PISA survey, Singapore's 15-year's old students were ranked first for all science, reading and math subjects (OECD, 2016a). On the other hand, the findings from the PIAAC survey in Table 1 show that Singapore's average computer-based numeracy and literacy score is only slightly above the OECD average, while the non-ICT based assessment score is even lower. The sharp divergence between Singapore's educational- and skill-based competencies is partly attributed to the lower educational attainment among its older cohorts (OECD, 2016b). A similar divergence in Korea's PISA and PIAAC results was also documented by Lee and Wie (2017).

Table 1: Results of the 2015 PIAAC survey for ICT and non-ICT based assessment

Country	ICT Score	Country	Non-ICT Score
Lithuania	319	Japan	265
Estonia	318	Estonia	262
Israel	315	Czech Republic	260
Netherlands	314	Poland	259
Norway	313	Finland	256
Finland	313	Denmark	255
Japan	312	Korea	255
Australia	312	Israel	253
Denmark	312	Slovak Republic	253
Slovenia	311	Australia	253
Canada	310	Norway	253
UK	310	Netherlands	252
New Zealand	310	Lithuania	252
Singapore	**309**	UK	250
OECD average	**308**	**OECD average**	**250**
Slovak Republic	308	Slovenia	249
United States	307	Canada	248
Czech Republic	306	Germany	248
Poland	306	New Zealand	247
Korea	305	**Singapore**	**246**
Ireland	302	Greece	242
Germany	301	Ireland	241
Greece	300	United States	235
Chile	279	Chile	205

Figure 10: Scatterplot of ICT utilized per worker and high-skilled share by sector



Sources: OECD 2015 Survey of Adult Skills (PIAAC), author's estimates

The PIACC survey findings show that the utilisation of computers and other automation technologies in the workplace further enhances productivity of higher-skilled workers. In addition to assessing written-based literacy and numeracy competencies, the PIAAC survey also assesses problem solving abilities using ICT tools. Participants are tested based on their proficiency in navigating, communicating, analysing and transforming data across multiple software and applications such as e-mail, web, and Microsoft office tools. In Table 1, the difference between ICT- and non-ICT based PIAAC results for all countries shows that technologically-savvy adults had outperformed their non-ICT counterparts, including Singapore. The effects of aging and lower educational attainment of older workers also matter for the observed survey findings. Consistent with literature, Figure 10 also shows that sectors in Singapore which have greater share of high-skilled workers tend to be more ICT intensive.

For instance, nearly 80% of workers in the ICT, Professional, and Finance and Insurance sub-sectors are high-skilled workers, where the corresponding ICT intensity varies from SGD15,000 to SGD30,000 per worker. Conversely, sectors with relatively lower shares of high-skilled workers, i.e.: Construction, Accommodation and Food, and Wholesale and Retail tend are less ICT intensive.

3.2. An overview of Singapore's wages and its determinants

The relationship between wages and years of education as well as the share of high-skilled workers are shown to be positive and strongly correlated. In this section, I undertake a *prima facie* analysis between wages and its determinants. Firstly, I examine the effects of human capital on wages along two dimensions – years and education and workers' skill level. Figures 11 and 12 plot average wages against the years of schooling and share of high-skilled workers. Both determinants reflect significant improvements in the quality of Singapore's workforce and are strongly correlated with wages. Figure 11 shows that the average years of schooling for Singaporeans ages 25 and above rose from 6.9 in 1991 to 10.9 by 2016, which is among the highest globally (Barro and Lee, 2013). Formal education increases wages by various means of productivity-enhancing measures, be it through intrinsically augmenting capacity and skillset of workers (Mincer, 1973), or via signalling and "credential" channels (Spence, 1973). In Figure 12, the share of high-skilled workers which comprises managers, professionals and technicians, also rose significantly from 27% in 1991 to 56% in 2016.

Figure 11: Average Monthly Wages and Schooling Years

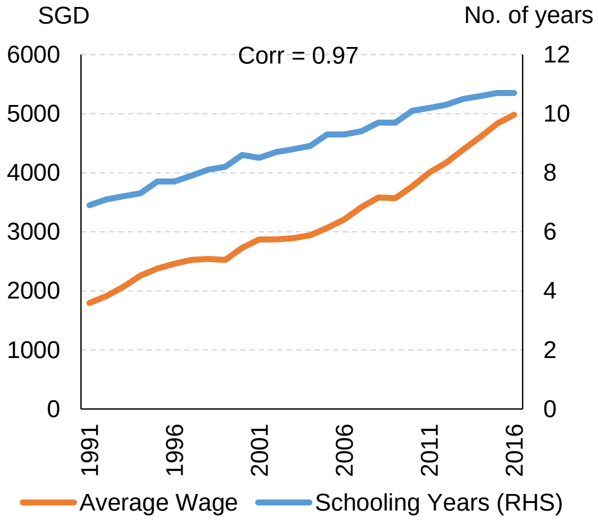
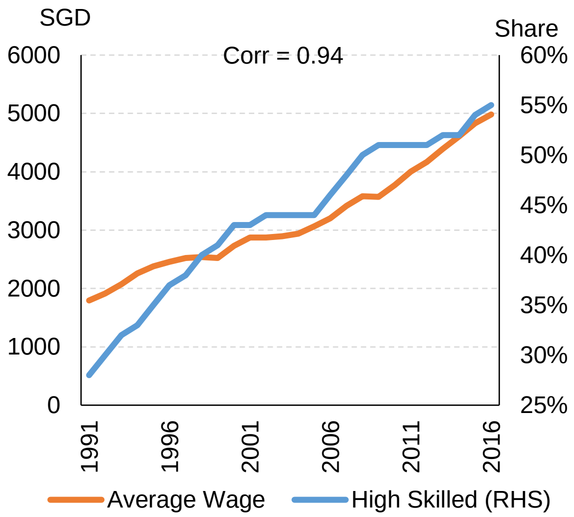


Figure 12: Average Monthly Wages and Share of High Skilled Workers



Sources: Ministry of Manpower, Singapore Department of Statistics, author's estimates

The relationship between trade openness and wages was initially positive and strongly correlated but weakened considerably post-GFC, while financial openness and wages remains positively correlated. In addition to the human capital variables, I also examine another two wage determinants from a macroeconomic standpoint. The impact of trade and financial flows on wages have been extensively examined and debated in both theoretical and empirical literature, but the evidence so far is mixed. Wages between countries are expected to converge as a result of trade, but also has the potential to worsen wage inequality (Goldberg and Pavcnik, 2007). Increased financial openness led to significant reduction in cost of financing and capital deepening in recipient economies, allowing firms to operate more efficiently and gain better access to foreign capital that has better technology, thereby increasing the productivity and wages of workers (Chari et al, 2012). Figures 13 and 14 plot wages against measures of trade and financial openness, which are the sum of exports and imports and net foreign assets and liabilities scaled by GDP respectively. In Figure 13, the degree of trade openness rose from nearly 3 times of Singapore's GDP in 1991 to its peak of 4 times in 2009. However, the measure of trade openness has steadily declined thereafter, with wages and Singapore's financial openness decoupling from this declining trend (Figure 14).

Figure 13: Average Monthly Wages and Trade Openness

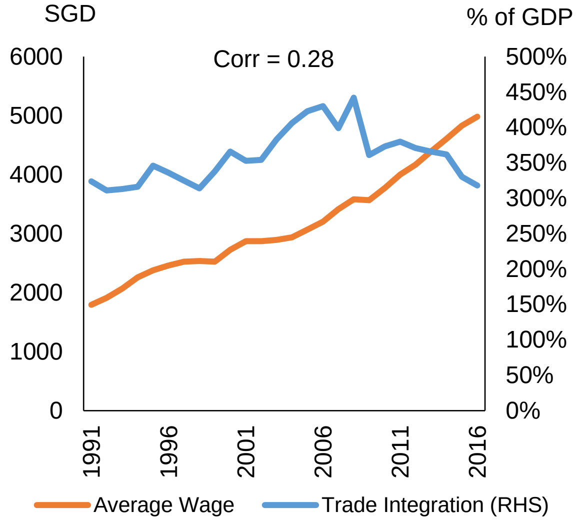
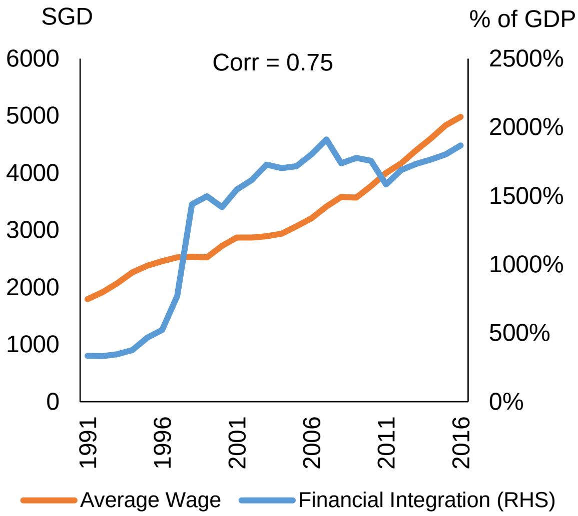


Figure 14: Average Monthly Wages and Financial Openness



Sources: Ministry of Manpower, Singapore Department of Statistics, World Bank's Development Indicators, author's estimates

There is positive correlation between wages and ICT utilization per worker. Figures 15 and 16 plot ICT utilisation per worker and average wages for the aggregate and sectoral levels (in logs), respectively. From 1995 to 2016, overall correlation between the two is about 0.52 in Figure 15, and appears stronger after the 2010s. At the sectoral level (Figure 16), a positive association between logged wages and logged ICT utilized per worker is also shown.

Figure 15: Average Monthly Wages and ICT Utilized per Worker

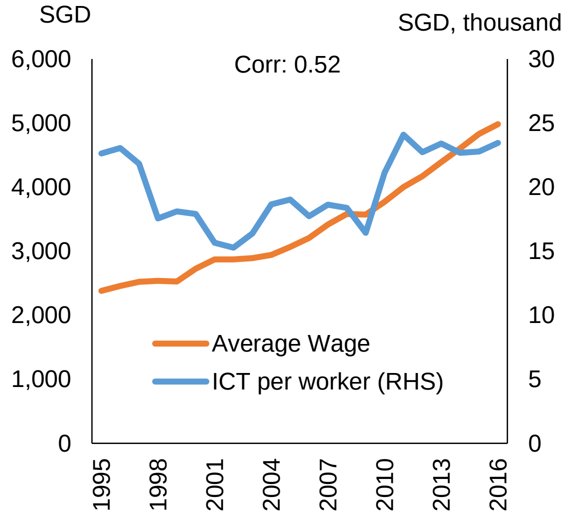
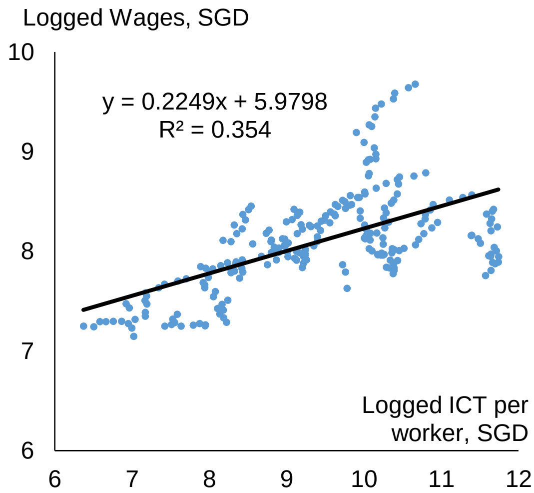


Figure 16: Logged Average Wages and Logged ICT Utilized per Worker, '95-'16



Sources: Ministry of Manpower, Singapore Department of Statistics, OECD-WTO Trade in Value-Added (TiVA) database, UNCTAD, World Bank's Development Indicators, author's estimates

4. Data Definition and Empirical Methodology

In this section, I define the variables used for the empirical analysis, and further examine the stylized facts presented in the earlier section.

4.1. Data Definitions

The panel data consists of 9 major economic subsectors based on the Singapore Standard Industrial Classification 2015, ranging from 1995 to 2016. The broad 9 categories are, Construction, Manufacturing, Accommodation & Food, Finance & Insurance, Information & Communications, Professional, Transport, Wholesale & Retail Trade and Other Services Industries. The dependent variables are average wages (SGD) and labour productivity (SGD) per worker, expressed in natural logarithmic terms. The key variables used in the model are: i) share of high-skilled worker, ii) logged value of ICT utilized per worker expressed in Singapore Dollars, iii) Average years of schooling, (iv) trade and (v) financial openness.

Table 2: List of Variables and Definitions

Variable	Definition	Source
Wages	Average, 25th, 50th and 75th percentile monthly gross wages before deductions of CPF contributions and income tax, and includes overtime pay and other allowances, SGD	Ministry of Manpower, Singapore, 2016 Occupational Wage Survey data, author's estimate
Hours worked	Totals weekly hours worked per employee is the sum of paid weekly hours worked and overtime weekly hours worked	Ministry of Manpower, Singapore, author's estimate
Labour Productivity	Real value-added per worker at current market prices by industry (SSIC 2015), SGD (Real GDP divided by total employment)	Singapore Department of Statistics
Share of High-Skill workers	The number of workers in Manager, Professional, Technicians and Associate Professionals occupations as a percentage share of total employment (Table 3)	Ministry of Manpower, Singapore, author's estimate
ICT per worker	Total value of software, computer, electronic equipment, programming, information and telecommunication services, converted into Singapore Dollars (1995 to 2011) obtained from OECD Input-Output Tables. Data between 2012 and 2014 are based on Singapore's 2010, 2012 and 2014 Input-Output Tables. 2015 and 2016 estimates are derived from a 3-year moving-average ICT utilization growth rate, SGD	2016 OECD Input-Output Tables, 2010, 2012 and 2014 Singapore Input-Output Tables, author's estimate
Exchange rate	Average annual SGD/USD exchange rate	Singapore Department of Statistics, author's estimate

Years of Schooling	The average years of schooling for adults ages 25 years and above	Singapore Department of Statistics, author's estimate
Trade and Financial Openness	Sum of exports and imports, and sum of net foreign assets and liabilities scaled by GDP	World Bank's Development Indicators, author's estimate
Capital-output ratio	Gross fixed capital formation divided by GDP	Singapore Department of Statistics

The classification of skills is based on 3 levels. In determining the skill level of workers, I reclassify the 9 major occupational groups which correspond to the one-digit occupational code based on the Singapore Standard Occupational Classification 2015 into either Low, Middle or High skilled workers in Table 3.

Table 3: Skill level of workers

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

4.2. Methodology

The impact of technology on wages is jointly examined with other determinants via a human capital model framework à la Mincer (1973) using the Generalised Least Squared (GLS) estimator. I estimate a panel model of wages based on the life-cycle earnings human capital model first popularized by Mincer (1974), whereby wages are determined as an exponential function of years of schooling and working experience at the individual or household level. Its aggregated panel form was introduced by Card (2001) and extended by Cohen and Soto (2007). The model is estimated under the Feasible Generalized Least Squared (GLS) estimator to account for within-panel autocorrelation that follows an autoregressive process of order 1. It is estimated in levels due to measurement and specification issues if the model is characterized in first-differences (Cohen and Soto, 2007). The standard errors are robust to cross-sectional correlation and heteroscedasticity. The baseline macro-Mincer wage model takes the following form:

$$Ln\, W_{it} = \alpha Z_{it} + \beta lnI_{it} \,.\, \boldsymbol{\rho_i} + \gamma S_t + \delta T_t + \nu F_t + \eta k_t + \boldsymbol{\rho_i} + \varepsilon_{it} \quad (1)$$

Where $Ln\, W_{it}$ is the logged average monthly wages (SGD) of worker in sector i at year t, Z_{it} is the share of high-skilled workers in sector i, lnI_{it} is the logged value of ICT utilized per worker (SGD) interacted with $\boldsymbol{\rho_i}$, which is a vector of sector dummies, S_t is the average years of schooling for adults ages 25 years and above, and T_t and F_t are measures of trade and financial openness, and $\boldsymbol{k_t}$ denotes the capital-to-GDP ratio at year t. Due to data constraints, the model also assumes common years of schooling, trade and financial openness, and capital-to-output ratio in all sectors.

The impact of technology on labour productivity per worker is also estimated in a similar manner as above, but in first-differences. To estimate the role of ICT in affecting productivity, the macro-Mincer wage model in Equation (1) is augmented based on the empirical framework adopted by Belorgey et al (2006). The years of schooling variable is replaced by the total number of weekly hours worked. Following Belorgey et al (2006), the model in first-differences takes the following form:

$$\Delta Ln\, Y_{it} = \alpha \Delta Ln\, Y_{it-1} + \mu \Delta Z_{it} + \beta \Delta lnI_{it}.\boldsymbol{\rho_i} + \gamma \Delta H_{it} + \delta \Delta T_t + \nu \Delta F_t + \eta k_t + \boldsymbol{\rho_i} + \varepsilon_t \quad (2)$$

Where $\Delta Ln\, Y_{it}$ and $\alpha \Delta Ln\, Y_{it-1}$ are the logged first-differenced value-added per worker (SGD) at year t and $t-1$, and ΔH_{it} is the first-differenced number of hours worked in sector i at year t respectively.

The differential impact of technology on wages according to the skill level of workers is assessed via Ordinary Least Squares (OLS) using data from the 2016 Occupational Wage Survey. I examine the impact of ICT on wages at the 25th, 50th and 75th quantiles by each workers' skill level separately. The cross-sectional analysis is based on the granular data obtained from the 2016 Occupational Wage Survey. It is estimated via OLS with robust standard errors as shown in equation (3) below:

$$Ln\, W_j = \beta\, lnI_i + \gamma\, Z_i + \boldsymbol{\rho_i} + \varepsilon_t \quad (3)$$

Where $Ln\, W_j$, I_i and Z_i are the logged average monthly wages (SGD), ICT utilized per worker (SGD) and share of high-skilled workers of sector i respectively, and $\boldsymbol{\rho_i}$, which is a vector of sector dummies.

5. Empirical findings

Empirical results from the panel-based wage regressions show that there is a positive and statistically significant relationship between ICT adoption and wages. Controlling for other factors, a 1% increase in the value of ICT utilized per worker leads to a 0.074% increase in monthly wages. Table 4 presents estimates based on Equation (1). Column (1) first reports the empirical findings based on the basic macro-Mincer equation as proposed by Cohen and Soto (2007). The coefficient for schooling years is positive and statistically significant, indicating that an additional year of schooling increases monthly wages by approximately 19.4%. In Column (2), the share of high-skilled workers is included as an additional explanatory variable. It is also positive and significant, which implies that a 1ppt increase in the share of high-skilled workers increases monthly wage by 0.866%. In the meantime, the returns to schooling decreases from to 14.0%, which is broadly in line with empirical evidences (Cohen and Soto, 2007), once the skill level of the workforce is accounted for. These dynamics are consistent with earlier discussions on the wage implications from workforce upskilling, which is distinct from education. Next, Column (3) further incorporates the effects of trade and financial openness, but both coefficients are mostly small and insignificant. Given that Singapore liberalized at a much earlier stage, the marginal benefits from subsequent liberalization since the 1990s may be more moderate compared to the past. Next, Column (4) considers the effects of ICT utilization per worker on wages jointly with the other determinants. The results show that a 1% increase in the value of ICT utilized per worker leads to a 0.074% increase in monthly wages. Lastly, Column (5) includes the sector dummies interacted with ICT, to show the differential impact of ICT on each sector. The impact is most evident for services workers, which is higher at 0.085%. Manufacturing workers also benefitted to a certain extent, but evidences are mixed based on alternative definitions of wages (real wages, hourly wages and real hourly wages) in columns (6), (7) and (8). Lastly, all the results show that the impact on the Construction sector is insignificant. Additional regressions for the purposes of robustness checks are shown in Table A1, A2 and A3 in the Appendix. The stability of the estimated coefficients of Column (4) are also shown in the Appendix.

Table 4: Determinants of Wages, 1995-2016

Dependent Variable (logged)	Wages					Real wages	Hourly wages	Real Hourly wages
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Schooling Years	0.194***	0.140***	0.149***	0.149***	0.148***	0.041***	0.156***	0.049***
	(0.016)	(0.017)	(0.019)	(0.014)	(0.014)	(0.012)	(0.013)	(0.013)
High Skill Share		0.866***	0.869***	0.911***	0.873***	0.852***	0.814***	0.784***
		(0.052)	(0.053)	(0.066)	(0.071)	(0.069)	(0.084)	(0.086)
Trade Openness			-0.022	-0.021	-0.023*	-0.020*	-0.042***	-0.038***
			(0.016)	(0.014)	(0.014)	(0.012)	(0.013)	(0.012)
Financial openness			-0.003	-0.001	-0.001	0.000	-0.000	0.001
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Logged ICT per worker				0.074***				
				(0.010)				
x Manufacturing					0.055*	0.069**	-0.036	-0.023
					(0.029)	(0.029)	(0.043)	(0.039)
x Services					0.085***	0.080***	0.094***	0.082***
					(0.011)	(0.010)	(0.011)	(0.011)
x Construction					0.034	0.026	0.016	0.010
					(0.035)	(0.035)	(0.026)	(0.025)
Capital Ratio	0.449**	0.328*	0.265	0.417**	0.437***	-0.138	0.221	-0.252*
	(0.222)	(0.187)	(0.189)	(0.171)	(0.163)	(0.141)	(0.163)	(0.145)
Constant	5.522***	5.819***	5.862***	5.055***	5.409***	1.780***	0.195	1.133***
	(0.187)	(0.194)	(0.195)	(0.176)	(0.319)	(0.299)	(0.221)	(0.218)
Observations	198	198	198	198	198	198	198	198
Number of Sectors	9	9	9	9	9	9	9	9
Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses
*** Indicates that the coefficients are statistically significant at 1%, ** indicates that the coefficients are statistically significant at 5%, * indicates that the coefficients are statistically significant at 10%

Estimates from the cross-sectional analyses show that wages of higher-skilled workers rose because of greater ICT adoption, while the impact is negligible for low-skilled workers. This result is consistent with literature on the differential impact of technology according to the skill level of workers. Results based on Equation 3 for wages corresponding to the 25th, 50th, and 75th percentiles are shown in Table 5. The regressions control for the workforce compositional effect in each sector (share of high-skilled) and include sector dummies. In Table 5, the ICT utilization coefficients in Columns (9) to (11) refer to the sensitivity of wages of low-skilled workers to ICT utilization for each quantile respectively. The results show that the impact of ICT utilization on wages of low-skilled workers are small and insignificant. Moreover, wages appear to be negatively correlated with the share of high-skilled workers. This seems to suggest that low-income workers are potentially adversely affected by, in part, the growing share higher skilled workers which have relatively better bargaining powers (Wolcott, 2018). The small sample size for low-skilled workers, however, warrants a cautious interpretation of this finding. Secondly, the impact is greater for medium-skilled workers, whereby a 1% increase in ICT utilization led to a 0.067% to 0.08% for each quantile in Columns (12) to (14) respectively. Similarly, Columns (15) to (17) show that high-skilled workers at each quantile have benefitted from ICT, ranging from 0.065% to 0.093% respectively.

Table 5: Sensitivity of Wages to ICT utilization by skill and quantile, 2016

Dependent Variable (logged)	Low			Medium			High		
	25th	50th	75th	25th	50th	75th	25th	50th	75th
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Logged ICT per worker	0.012	-0.004	0.013	0.080**	0.074***	0.067***	0.065***	0.083***	0.093***
	(0.008)	(0.013)	(0.022)	(0.024)	(0.018)	(0.012)	(0.013)	(0.014)	(0.017)
High Skill Share	-0.166**	-0.192**	-0.337**	0.041	0.036	0.083	0.097	0.090	0.109
	(0.045)	(0.075)	(0.118)	(0.151)	(0.115)	(0.091)	(0.136)	(0.144)	(0.154)
Constant	6.898***	7.051***	7.206***	6.763***	7.100***	7.384***	7.574***	7.661***	7.804***
	(0.059)	(0.091)	(0.137)	(0.190)	(0.143)	(0.114)	(0.147)	(0.170)	(0.204)
Observations	46	46	46	208	208	208	490	490	490
Number of sectors	7	7	7	9	9	9	9	9	9
Number of occupations	26	26	26	86	86	86	166	166	166
Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.038	0.057	0.114	0.050	0.040	0.044	0.041	0.044	0.042

Note: Robust standard errors in parentheses
*** Indicates that the coefficients are statistically significant at 1%, ** indicates that the coefficients are statistically significant at 5%, * indicates that the coefficients are statistically significant at 10%

Findings from the panel-based productivity regressions show that there is also a positive and statistically significant relationship between ICT adoption and the real labour productivity growth rate. A 1% increase in the growth rate of ICT utilized per worker increases the real productivity growth rate by 0.058%. Table 6 shows the labor productivity growth determinants based on Equation (2). Columns (18) to (22) show that a 1% change in total hours worked results in an approximately 20% to 30% change in the real productivity growth rate, which are broadly in line with the estimates by Belorgey et al (2006); an increase in hours worked naturally increases real output per worker. In Column (20), trade and financial openness are insignificant, corroborating results in Table 4. Finally, Columns (21) and (22) show that a 1% increase in ICT utilization rate increases the average real productivity growth rate by 0.058%. It is as high as 0.399% in the manufacturing sector, followed by 0.056% in services, but insignificant in the construction sector. These findings remain robust to an alternative productivity measure adjusted for total hours worked. The impact of ICT on real hourly productivity growth per worker is marginally higher, as shown in Columns (23) and (24). Overall, the findings in Table 6 concur with the notion that wage gains were supported by productivity improvements attributed to greater ICT utilisation in the workplace.

Table 6: Determinants of Real Productivity Growth per Worker, 1995-2016

Dependent Variable (logged)	Real Productivity Growth per Worker					Real Productivity Growth per worker per hour	
	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Lagged Productivity Growth per worker	0.043	0.038	0.064	0.105	0.053		
	(0.067)	(0.067)	(0.07)	(0.068)	(0.068)		
Lagged Productivity Growth per worker per Hour						0.168**	0.127*
						(0.068)	(0.068)
Change in Logged Hours Worked	0.322***	0.302***	0.259***	0.196*	0.205**		
	(0.092)	(0.094)	(0.089)	(0.116)	(0.102)		
Change in High Skill Share		-0.103	-0.066	-0.137	-0.049	-0.043	0.056
		(0.173)	(0.185)	(0.201)	(0.192)	(0.213)	(0.210)
Change in Trade Openness			-0.000	0.003	0.006	-0.008	-0.008
			(0.012)	(0.012)	(0.011)	(0.015)	(0.014)
Change in Financial Openness			-0.003	-0.003	-0.003	-0.003	-0.004
			(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Change in Logged ICT per worker				0.058***		0.066***	
				(0.014)		(0.018)	
x Manufacturing					0.399***		0.403***
					(0.110)		(0.095)
x Services					0.056***		0.067***
					(0.014)		(0.018)
x Construction					-0.064		-0.082
					(0.047)		(0.050)
Capital Ratio	-0.136**	-0.119*	-0.085	-0.061	-0.068	-0.067	-0.076
	(0.065)	(0.064)	(0.084)	(0.082)	(0.077)	(0.098)	(0.090)
Constant	0.049**	0.045**	0.038	0.030	0.031	0.031	0.033
	(0.020)	(0.020)	(0.025)	(0.025)	(0.023)	(0.029)	(0.027)
Observations	198	198	198	198	198	198	198
Number of Sectors	9	9	9	9	9	9	9
Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses
*** Indicates that the coefficients are statistically significant at 1%, ** indicates that the coefficients are statistically significant at 5%, * indicates that the coefficients are statistically significant at 10%

6. Concluding Remarks

To conclude, this paper evaluates the role of technology in affecting wages and productivity in Singapore, which shows a positive and statistically significant relationship between ICT adoption and wages, supported by real productivity growth. However, gains are skewed towards higher-skilled workers. The effects of technology on wages and productivity are summarized in three key findings. Firstly, greater ICT adoption led to higher wages. An additional 1% spent on ICT per year leads to a 0.074% increase in monthly wages. The impact on the services sector is higher at 0.085%, but evidences are mixed in the manufacturing sector, and negligible in the construction sector. Secondly, the impact of ICT utilization on productivity is positive and significant, whereby an additional 1% spent on ICT per year leads to a 0.058% increase in the real productivity growth rate. Thirdly, cross-sectional analysis of wages by skill levels show that higher skilled workers benefitted more from greater ICT utilization, while it is less evident for low-skilled workers. These findings corroborate literature on the differential impact of technology according to the skill level of workers.

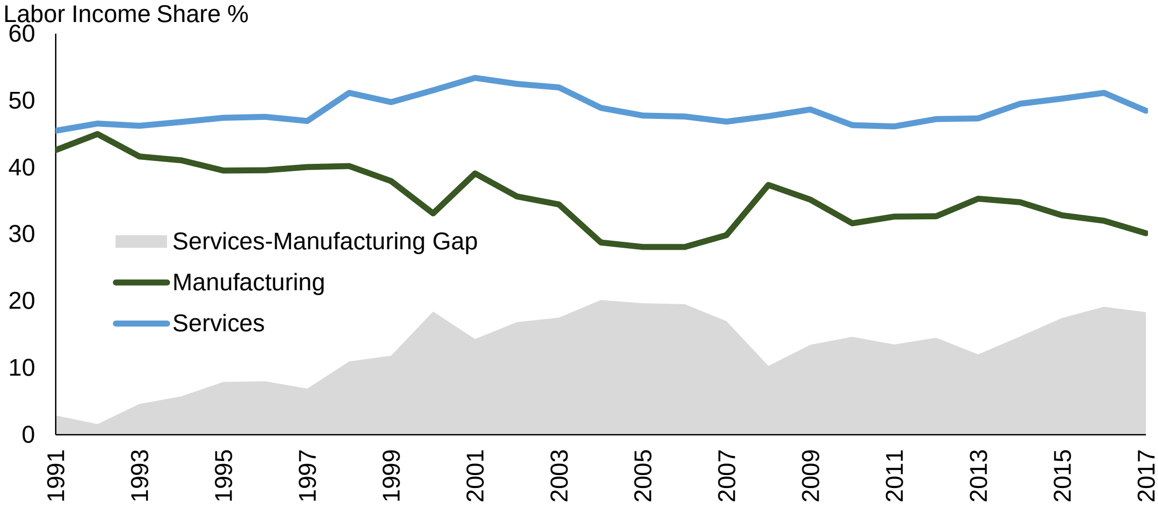
Additional studies based on firm-level ICT utilization data and employee characteristics may yield additional insights into the differential impacts of technology on wages and productivity. Further research using granular firm-level ICT investments data that is matched with employee characteristics such as occupational type, age, and education background can yield further insights into the role of technology. Moreover, the study can be extended to examine the impact of different types of ICT goods separately, for instance, distinguishing between the effects of physical (computers and data storage devices) and intangible (software) ICT capital.

Going forward, the emergence of new digital technologies will likely enhance prospects of higher-skilled workers in Singapore, particularly in services sectors. The advent of new digital technologies such as big data analytics, Internet of Things (IOT), artificial intelligence (AI) and cloud computing bode well for productivity and wage growth prospects of high-skilled workers, particularly in services sectors such as Finance and Insurance, and Professional and Business services. Meanwhile, the impact of ICT is less evident in others, for instance, the Construction sector. In general, this sector is labor-intensive and potentially has less scope for automation, and thus greater ICT utilization may not be feasible from a cost-benefit standpoint. Hence, industry-specific approaches to promote greater ICT adoption may be more appropriate, as opposed to broad-based policy measures.

Continued investments in skills training and upgrading are essential to ensure that the benefits of these technologies can be fully reaped. The findings in this paper show that the extent of ICT adoption is greater in sectors that have higher shares of skilled workers. Recognizing the importance of lifelong learning in the digital economy, efforts to transform Singapore's economy via the 23 Industry Transformation Maps (ITMs) which emphasize, amongst others, greater investment and adoption of new digital technologies, are complemented by a wide range of active labor market policies aimed at training skilled workers for this purpose. These measures provide funding support to improve job mobility (Adapt and Grow), acquire new skills (SkillsFuture) and facilitate skills transfer from foreign expertise (Capability Transfer Programme). In this regard, employers should actively encourage and incentivize workers to participate in these programs while investing in new digital technologies in the workplace, thereby boosting productivity and wages.

Structural and institutional factors also matter in translating productivity gains stemming from technology into wage increases. Evidences in this study show that wage increases of services workers are due to, in part, the productivity-enhancing attributes of ICT. However, despite recording higher ICT-driven productivity improvements in the manufacturing sector, the benefits to workers are at best mixed and inconclusive. The divergence between wages and productivity in the manufacturing sector is also reflected in its declining labour income share since the 1990s, while it is relatively unchanged for services (Figure 17). Several interrelated factors may contribute to the changing labor market dynamics in the manufacturing sector, for instance, increased globalization and the rise of global value chains, shifting market structure and consumer preferences, and greater exposure to global business cycle fluctuations (Dao et al, 2017). More importantly, advances in ICT could have resulted in greater substitutability between labour and capital over time, for instance, newer labor-substituting technologies – adoption of more sophisticated robots in the assembling lines. This is turn raises productivity, but not necessarily for employment and wages. More broadly, this suggests that strategies that focus solely on productivity growth to spur wage gains may not sufficient. Relatedly, the tripartite committee on labor market issues comprising the government, workers and employers will continue to be a key mechanism through which these issues are raised and mediated.

Figure 17: Labor Income Share* by Sector



Sources: Singapore Department of Statistics author's estimates
Note: Labour Income Share is computed as the ratio between compensation of employees and value-added by sector at current market price

Policies that improve productivity and wages of lower-skilled workers should continue to be prioritized, and potentially encompass broader social wellbeing considerations. Unlike high-skilled workers, the benefits of technology to lower-skilled workers have been less apparent, as evidenced in this paper. More importantly, there is a consensus view that technology has significantly altered the demand for different types of workers, namely greater demand for skilled relative to unskilled workers. Unattended, these workers may face diminished employment and wage growth prospects over the longer-term, in light of accelerating technological adoption in the economy. The various policies introduced focusing on these workers can partly facilitate the possible rapid adjustments in the labor market. This includes the Progressive Wage Model (PWM), which encompasses workers in the cleaning, security and landscaping industries, and the Workforce Income Supplement scheme, targeted at low-income workers. Given the effectiveness of the PWM, policymakers should consider broadening its coverage to other similar occupations, i.e., waiters, waste disposal workers, kitchen, food stall assistants, and retail workers. More importantly, a holistic approach encompassing broader social wellbeing considerations is welcomed.

7. References

Acemoglu, D., and Autor D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. in Handbook of Labor Economics edited by Orley Ashenfelter and David Card, Vol. 4B, Ch. 12, 1043-1171.

AMRO (2017). AMRO Annual Consultation Report – Singapore, Selected Issues.

Atrostic B. K., and Nguyen S. V. (2005). ICT and Productivity in U.S. Manufacturing: Do Computer Networks Matter? Economic Inquiry, Western Economic Association International, vol. 43(3), pages 493-506, July.

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives, 29 (3): 3-30.

Autor, D. H., and Dorn D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. The American Economic Review, 103(5), 1553–97.

Autor, D. H., Katz L. F., and Kearney M. S. (2008). Trends in US Wage Inequality: Revising the Revisionists. Review of Economics and Statistics 90 (2): 300–323.

Barro, R., and Lee J. W. (2013). A New Data Set of Educational Attainment in the World, 1950-2010. Journal of Development Economics, vol 104, pp.184-198.

Baumol, W. (1993). Health Care, Education and the Cost Disease: A Looming Crisis for Public Choice. Public Choice, vol. 77, no. 1, pp. 17–28.

Beaudry P., Green D. A., and Sand B. M. (2016). The Great Reversal in the Demand for Skill and Cognitive Tasks. Journal of Labor Economics. S199-S247

Belorgey N., Lecat R. and Maury T. (2006). Determinants of productivity per employee: An empirical estimation using panel data. Economics Letters, Volume 91, Issue 2, Pages 153-157

Bresnahan T. F., Brynjolfsson E. and Hitt L. M. (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. The Quarterly Journal of Economics, Volume 117, Pages 339–376

Card D. (2001). Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems, Econometrica, Vol. 69, No. 5., pp. 1127-1160.

Cardona M., Kretschmer T., Strobel T. (2013). ICT and productivity: conclusions from the empirical literature. Information Economics and Policy, Volume 25, Issue 3, Pages 109-125.

Chari A., Peter B. H. and Diego S. (2012). Capital Market Integration and Wages. American Economic. Journal: Macroeconomics, 4 (2): 102-32.

Cohen D., and Soto M. (2007). Growth and human capital: good data, good results. Journal of Economic Growth. Volume 12, Issue 1, pp 51–76

Constantinescu, C., Mattoo A. and Ruta M. (2015). The Global Trade Slowdown: Cyclical or Structural? IMF Working Paper No. 15/6, Washington, DC.

DiMaggio P., Hargittai E., Celeste C., and Shafer S. (2004). From unequal access to differentiated use: A literature review and agenda for research on digital inequality. Social inequality, 355-400.

Goldberg P. K., and Pavcnik N. (2007). Distributional Effects of Globalization in Developing Countries. Journal of Economic Literature, American Economic Association, vol. 45(1), pages 39-82, March.

Hanushek, E. A., and Schwerdt, G., and Wiederhold, S. and Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. European Economic Review, Elsevier, vol. 73(C), pages 103-130.

Hutter, C., & Weber, E. (2017). Labour market effects of wage inequality and skill-biased technical change in Germany (No. 5/2017). IAB-Discussion Paper.

Justin L.M.H., Kevin W.T.F., Rosaida M. R., Sonia K. S. (2017), Wage premiums in the digital economy: Evidence from Malaysia. Bank Negara Malaysia 5th Economics Research Workshop Conference Proceedings.

Lee J. W., and Wie D. (2013). Technological Change, Skill Demand, and Wage Inequality in Indonesia. ADB Economics Working Paper Series.

Lee J. W., and Wie D. (2017). Returns to Education and Skills in the Labor Market: Evidence from Japan and Korea. Asian Economic Policy Review, 12: 139-160.

Lindley J., and Machin S. (2014). Spatial changes in labour market inequality. Journal of Urban Economics, Volume 79, Pages 121-138.

Loh Y. A. C., and Chib A. (2016). Increased Wage Inequality via ICTs: Making a Case for Human Capital Investment. In Proceedings of the Eighth International Conference on Information and Communication Technologies and Development (ICTD '16). ACM, New York, NY, USA, Article 32, 5 pages.

Mai C. D., Mitali D., Zsoka K., Weicheng L. (2017). Why Is Labor Receiving a Smaller Share of Global Income? Theory and Empirical Evidence. IMF Working Paper

Mincer J. (1974). Schooling, experience, and earnings. New York: Columbia University Press.

Mishel, L., Schmitt, J., and Shierholz, H. (2013). Assessing the job polarization explanation of growing wage inequality. Economic Policy Institute. Working Paper.

Moore, M. P., and Ranjan, P. (2005). Globalisation vs Skill-Biased Technological Change: Implications for Unemployment and Wage Inequality. The Economic Journal, 115(503), 391-422.

Ministry of Trade and Industry (2017). The Digital Economy in Singapore, MTI Economic Survey in Singapore 3Q 2017.

OECD (2016a), PISA 2015 Results (Volume I): Excellence and Equity in Education, PISA. OECD Publishing, Paris.

OECD (2016b), Skills Matter: Further Results from the Survey of Adult Skills, OECD Skills Studies, Singapore Country Note. OECD Publishing, Paris.

Spence, M. (1973). Job Market Signaling. The Quarterly Journal of Economics, 87(3), 355-374.

Wolcott L., E. (2018). Employment Inequality: Why Do the Low-Skilled Work Less Now? Middlebury College Working Paper.

8. Appendices: Robustness of Results

Table A1: Determinants of Real Wages (Deflated by CPI), 1995-2016

Dependent Variable Logged Real Wages	(1)	(2)	(3)	(4)	(5)
Schooling Years	0.089***	0.048***	0.056***	0.044***	0.041***
	(0.013)	(0.016)	(0.016)	(0.012)	(0.012)
High Skill Share		0.805***	0.792***	0.874***	0.852***
		(0.053)	(0.054)	(0.064)	(0.069)
Trade Openness			-0.021	-0.020	-0.020*
			(0.014)	(0.012)	(0.012)
Financial openness			-0.001	0.000	0.000
			(0.002)	(0.002)	(0.002)
Logged ICT per worker				0.066***	
				(0.009)	
x Manufacturing					0.069**
					(0.029)
x Services					0.080***
					(0.010)
x Construction					0.026
					(0.035)
Capital Ratio	-0.086	-0.231	-0.274*	-0.182	-0.138
	(0.172)	(0.166)	(0.163)	(0.142)	(0.141)
Constant	1.821***	2.020***	2.061***	1.448***	1.780***
	(0.154)	(0.174)	(0.172)	(0.155)	(0.299)
Observations	198	198	198	198	198
Number of Sectors	9	9	9	9	9
Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses
*** Indicates that the coefficients are statistically significant at 1%, ** indicates that the coefficients are statistically significant at 5%, * indicates that the coefficients are statistically significant at 10%

Table A2: Determinants of Hourly Wages, 1995-2016

Dependent Variable Logged Hourly Wages	(1)	(2)	(3)	(4)	(5)
Schooling Years	0.195***	0.146***	0.159***	0.159***	0.156***
	(0.018)	(0.019)	(0.019)	(0.013)	(0.013)
High Skill Share		0.830***	0.862***	0.825***	0.814***
		(0.086)	(0.084)	(0.076)	(0.084)
Trade Openness			-0.040**	-0.046***	-0.042***
			(0.017)	(0.014)	(0.013)
Financial openness			-0.002	0.001	-0.000
			(0.002)	(0.002)	(0.002)
Logged ICT per worker				0.094***	
				(0.010)	
x Manufacturing					-0.036
					(0.043)
x Services					0.094***
					(0.011)
x Construction					0.016
					(0.026)
Capital Ratio	0.425**	0.215	0.121	0.227	0.221
	(0.211)	(0.205)	(0.194)	(0.166)	(0.163)
Constant	0.073	0.341	0.411**	-0.461***	0.195
	(0.195)	(0.209)	(0.196)	(0.161)	(0.221)
Observations	198	198	198	198	198
Number of Sectors	9	9	9	9	9
Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses
*** Indicates that the coefficients are statistically significant at 1%, ** indicates that the coefficients are statistically significant at 5%, * indicates that the coefficients are statistically significant at 10%

Table A3: Determinants of Real Hourly Wages (Deflated by CPI), 1995-2016

Dependent Variable Logged Real Hourly Wages	(1)	(2)	(3)	(4)	(5)
Schooling Years	0.091***	0.055***	0.064***	0.052***	0.049***
	(0.018)	(0.017)	(0.017)	(0.012)	(0.013)
High Skill Share		0.802***	0.769***	0.795***	0.784***
		(0.087)	(0.086)	(0.076)	(0.086)
Trade Openness			-0.040***	-0.040***	-0.038***
			(0.015)	(0.012)	(0.012)
Financial openness			-0.000	0.002	0.001
			(0.002)	(0.002)	(0.002)
Logged ICT per worker				0.083***	
				(0.010)	
x Manufacturing					-0.023
					(0.039)
x Services					0.082***
					(0.011)
x Construction					0.010
					(0.025)
Capital Ratio	-0.135	-0.229	-0.299*	-0.220	-0.252*
	(0.204)	(0.187)	(0.169)	(0.139)	(0.145)
Constant	0.966***	1.111***	1.209***	0.526***	1.133***
	(0.194)	(0.192)	(0.174)	(0.147)	(0.218)
Observations	198	198	198	198	198
Number of Sectors	9	9	9	9	9
Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses
*** Indicates that the coefficients are statistically significant at 1%, ** indicates that the coefficients are statistically significant at 5%, * indicates that the coefficients are statistically significant at 10%

Figure A1: Stability of Wage Determinants

Figure 1a: Elasticity of Wages to ICT Utilisation per Worker

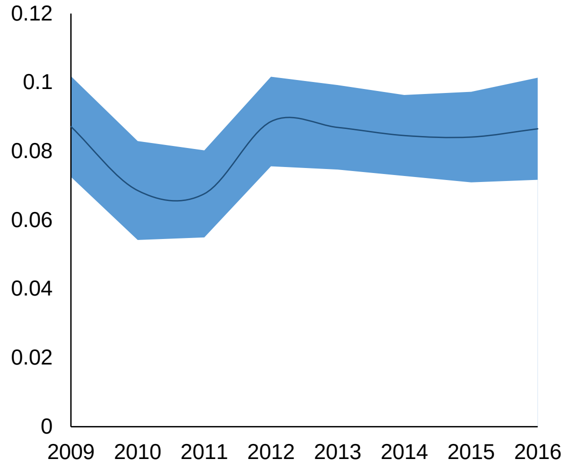


Figure 1b: Sensitivity of % wage change to ppt change in high-skilled share

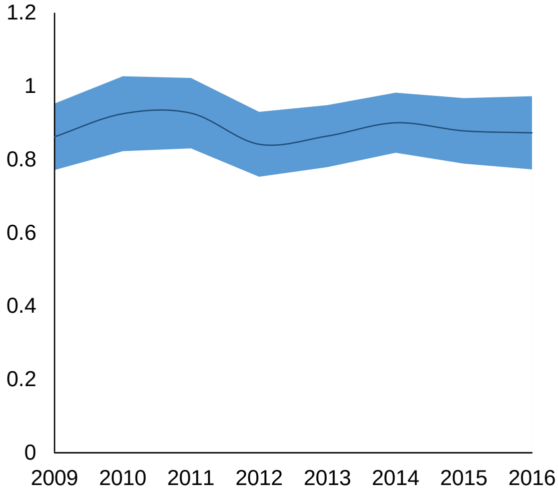


Figure 1c: Sensitivity of a % wage change to change in schooling years

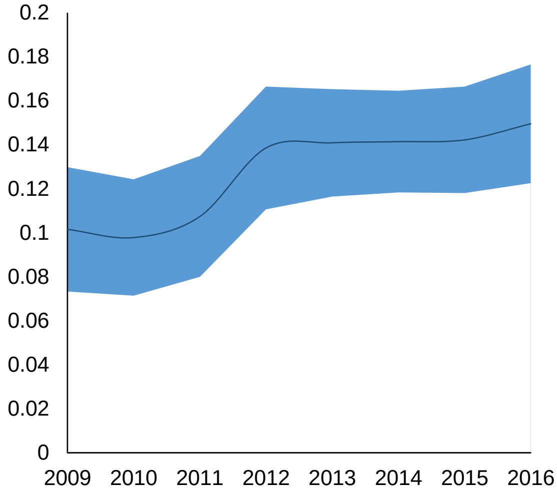


Figure 1d: Sensitivity of ppt change in trade integration to % wage change

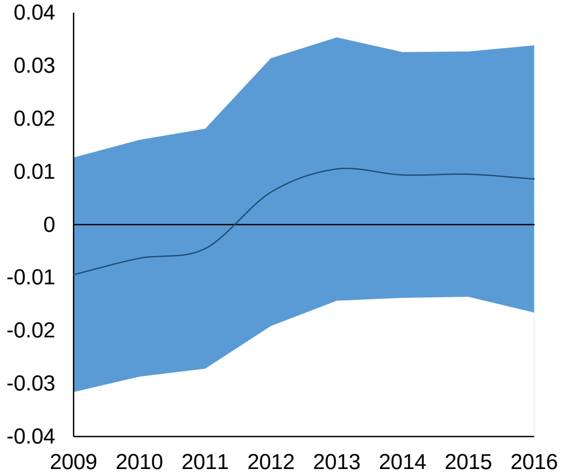
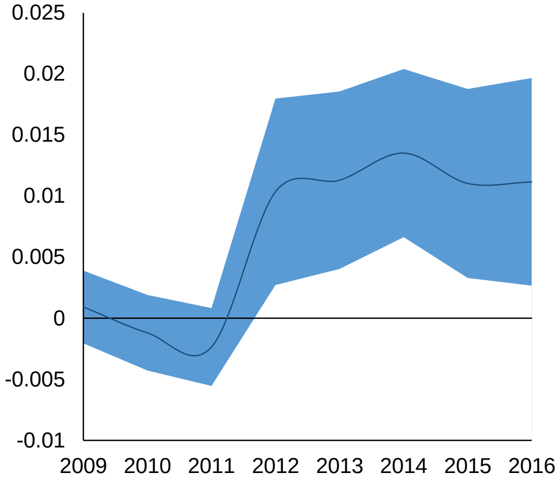


Figure 1e: Sensitivity of ppt change in financial integration to % wage change



Note: The shaded area shows the 90 percent confidence bands. Time variation of the coefficients are estimated over a rolling 15-year window sample.
Sources: Author's estimates

Table A4: Determinants of Real Hourly Productivity Growth Per Worker, '95-'16

Dependent Variable Change in Logged Real Productivity per worker per hour	(1)	(2)	(3)	(4)	(5)
Lagged Change in Real Productivity growth per worker per hour	0.138**	0.142**	0.166**	0.168**	0.127*
	(0.068)	(0.069)	(0.071)	(0.068)	(0.068)
Change in High Skill Share		-0.027	0.000	-0.043	0.056
		(0.193)	(0.204)	(0.213)	(0.210)
Change in Trade Openness			-0.010	-0.008	-0.008
			(0.014)	(0.015)	(0.014)
Change in Financial Openness			-0.003	-0.003	-0.004
			(0.003)	(0.003)	(0.003)
Change in Logged ICT per worker				0.066***	
				(0.018)	
x Manufacturing					0.403***
					(0.095)
x Services					0.067***
					(0.018)
x Construction					-0.082
					(0.050)
Capital Ratio	-0.125*	-0.108	-0.077	-0.067	-0.076
	(0.072)	(0.072)	(0.093)	(0.098)	(0.090)
Constant	0.046**	0.042*	0.035	0.031	0.033
	(0.022)	(0.022)	(0.027)	(0.029)	(0.027)
Observations	198	198	198	198	198
Number of Sectors	9	9	9	9	9
Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses
*** Indicates that the coefficients are statistically significant at 1%, ** indicates that the coefficients are statistically significant at 5%, * indicates that the coefficients are statistically significant at 10%