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The Heterogeneous Impacts of Digital Transformation and Investment on Indonesia's Labour Market

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Abstract: *In this paper, we provide a nuanced and detailed analysis of the effects on the labour market of digital transformation and investment in Indonesia. This paper is divided into three strands of work, which can be read independently or together. In the first strand, we discuss the impact of digital transformation on rising wage inequality using the approach of skill-biased technological change. Building on the work by Jacoby et al. (2021), we explore channels that may attenuate the skill-biased technological change. The second strand looks at rising wage inequality arising from routine-biased technological change, which theorises that it is those performing routine tasks in their jobs who are left behind as automation emerges, not necessarily the less-educated workers. The third strand looks at the impacts of investment in the digital sectors on the wages and employment of various types of workers. The overall narrative is clear: workers who are more advantaged to begin with, such as high-skilled and better-educated workers, benefit more from digital transformation and digital investment than low- and mid-skilled and lower-educated workers, who are more likely to lose out. There are, however, cases where high-skilled workers may also be adversely affected. This is the case in Indonesia for the period until 2019 (2016 for the study on the effects of digital investment). To address the digital divide potentially arising from skill-biased technological change, routine-biased technological change, and digital investment, we recommend that policies to accelerate Indonesia's digital transformation and liberalise its digital investment are accompanied by policies on education, the labour market, investment, trade (including service trade), and competition. Our policy recommendations shed light on the findings in this report while considering that digital technologies will continuously evolve that may have different impacts on the labour market.*

Keywords: Human capital, labour markets, technological change
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1. Indonesia's Digital Ambition to Leapfrog Development and Avoid the Middle-Income Trap

Labour income is the key contributor to reducing poverty in many developing countries (see, for example, Azevedo et al., 2013). Moreover, a good quality job is a pathway to the middle class, and Indonesia is no exception (Wihardja and Cunningham, 2021). Although Indonesia's poverty rate reached single digits in 2018 for the first time in its history, the large majority of Indonesians live in vulnerability (one in five Indonesians) or aspire to join the middle class but lack the economic security to do so (one in two Indonesians).[1] This means that Indonesia still faces a huge challenge to increase the standard of living and welfare of the majority of Indonesians – a goal that could be achieved through better quality jobs.

In addition, during Indonesia's commodity boom of 2001–2011 and its premature deindustrialisation, inequality rocketed from 30.0 points in 2000 to 37.8 points in 2010. The Gini coefficient continued to rise thereafter, reaching 41.4 points in 2014, the country's highest recorded level. The increase in consumption inequality has been partly driven by earnings inequality.

Wihardja and Cunningham (2021) argued that Indonesia is not creating the middle-class jobs needed to fuel a middle-class country. Indonesia has yet to promote almost half of its citizens from *aspiring* middle-class status – those who have moved out of poverty and vulnerability but still have not reached the middle-income class – to the middle class. To achieve this, Indonesia needs to increase workplace productivity and accelerate structural transformation towards higher-productivity sectors.

As digital technology advances, Indonesia sees an opportunity to 'leapfrog' from upper-middle-income to high-income status by leveraging digital technology. In many of Indonesia's official development planning documents, digital technology and transformation are seen as the solution to challenges of economic development, from low labour productivity to inequality, and to building a more prosperous society (Rohman and Wihardja, 2022).

Indonesia's National Medium-Term Development Plan, 2020–2024 (Rencana Pembangunan Jangka Menengah Nasional), for example, states that:

[1] The poor are defined as those who live below the poverty line. The vulnerable are those who have more than 10% probability of falling into poverty (whose monthly household consumption is 1.0–1.5 times the poverty line). The aspiring middle class are defined as those who have more than 10% probability of falling into poverty and vulnerability (whose monthly household consumption is around 1.5–3.5 times the poverty line). The middle class are those who have less than 10% probability of falling into poverty and vulnerability (whose monthly household consumption is around 3.5–17.0 times the poverty line). The upper class are defined as those whose consumption is more than 17 times the poverty line (World Bank, 2019).

> Digitisation, automation, and the use of artificial intelligence in economic activities will increase productivity and efficiency in modern production, as well as provide convenience and comfort for consumers. Digital technology also helps the development process in various fields, including education, governance, and financial inclusion; and also helps with the development of micro, small, and medium enterprises.

This medium-term development plan identifies the cost of strategic programmes related to the digital economy, including information and communication technology (ICT) infrastructure, Industry 4.0 in five priority manufacturing sectors, and the development of science and technology parks (International Trade Administration, 2022).

Indonesia now has the largest and one of the fastest-growing digital economies in Southeast Asia. Between 2015 and 2020, it grew at an average of 41% per year (Google, Temasek and Bain, 2020) and by 2020 was valued at US$41 billion or 4.2% of gross domestic product (GDP) (Ministry of Trade, 2021). It is expected to grow to US$130 billion by 2025 (Google, Temasek and Bain, 2022) and is targeted to reach US$292 billion or around 18% of GDP in 2030 (Ministry of Trade, 2021). Investment in Indonesia's digital economy thrived during the coronavirus disease (COVID-19) pandemic, accounting for almost 40% of Southeast Asia's total sectoral investment between January 2020 and June 2021. Investment in Indonesia in the first quarter of 2021 alone surpassed the annual investment in the country in the previous 4 years (Coordinating Ministry of Economic Affairs, 2022).

In 2022, Indonesia was home to more than 3,000 start-ups, including 14 unicorns[2] and one decacorn[3] (Ministry of Communications and Information Technology, 2022). The most iconic emergence in the country's digital economy is perhaps the online ride-hailing industry, notably Gojek and Grab, followed by online food delivery, e-commerce, and fintech.

This success is due in part to support from the administration of President Joko Widodo. In 2020, the president issued five directives to speed up digital transformation. These concerned (i) accelerating the expansion and completion of high-speed internet access, (ii) designing a roadmap for digital transformation, (iii) expediting data integration and establishing a national data centre, (iv) training digital talent, and (v) issuing regulations to support the financing of digital transformation (Cabinet Secretariat, 2020). In 2021, the government issued its Digital

[2] Start-ups valued at more than US$1 billion.
[3] Start-ups valued at more than US$10 billion.

Roadmap, 2021–2024 to accelerate digital transformation. This covers digital infrastructure, digital government, the digital economy, and digital citizens, amongst others.

The COVID-19 pandemic also propelled the emergence of healthtech, edtech (education), and agtech (agriculture). By 2030, healthtech and edtech are projected to account for 8.25% and 2.81%, respectively, of Indonesia's digital economy (Ministry of Trade, 2021). There is also significant potential to grow agtech; currently only 2% of Indonesian farmers purchase or sell goods online, but 85%–90% have fast internet access and use WhatsApp regularly (Agarwal et al, 2021).

Restricted physical interactions during the pandemic accelerated the adoption of digital technology amongst households and firms, albeit from a low and unequal base. A survey conducted by the World Bank in the manufacturing, high value-added services, and creative economy and tourism sectors in Java, Bali, North Sumatra, and South Sulawesi provinces showed that, by August 2021, 71% of firms had introduced digital processes and services to adjust to the pandemic. This response was initially stronger amongst large firms, but adoption increased amongst micro, small, and medium-sized enterprises (MSMEs). By August 2021, about 62% of the micro firms[4] and 87% of the small and medium-sized enterprises surveyed had launched digital business practices.

Indonesia's dynamic digital economy also shows great promise for inclusion. Focusing on inclusion is crucial since global evidence shows that creating and fostering a digital divide is a problem of developing and developed countries (see, for example, Herrera Gutierrez, 2022). The World Bank (2021) found stark evidence of Indonesia's digital divide and highlighted the importance of closing the digital divide globally if digital technologies are to benefit everyone everywhere (World Bank, 2016).

In this paper, we provide a nuanced and detailed analysis of the effects on the labour market of digital transformation and investment in Indonesia. This contrasts with the tendency (also seen in the Government of Indonesia) to see technological adoption and digitalisation as a panacea to economic and social challenges without sufficient deliberation.

One of the promises of digital transformation is a productivity increase leading to higher wages, market expansion, and more and better jobs. However, it is not clear which segments of the population and what types of workers are benefitting or lagging in Indonesia's digital transformation. And with the proliferation of artificial intelligence (AI), digital technologies are

[4] Micro firms are defined as enterprises with less than Rp50 million in assets or less than Rp300 million in annual sales (Republic of Indonesia Act No. 20/2008, Article 6, point 1).

increasingly replacing humans, instead of complementing human labour and boosting productivity and prosperity (Acemoglu, 2021).

This paper is divided into three strands of work, which can be read independently or together. In the first strand, we discuss the impact of digital transformation on rising wage inequality using the approach of skill-biased technological change. This argues that digital transformation has increased the productivity of more-educated workers more than that of less-educated workers, increasing the skill premium between more- and less-educated workers. Building on the work by Jacoby et al. (2021), we explore channels that may attenuate the skill-biased technological change.

The second strand looks at rising wage inequality arising from routine-biased technological change, which theorises that it is those performing routine tasks in their jobs who are left behind as automation emerges, not necessarily the less-educated workers. It is the middle-skilled workers who carry out routine tasks and it is they who are most disadvantaged by digital transformation, giving rise to job polarisation or the 'hollow-middle' phenomenon.

The third strand looks at the impacts of investment in the digital sectors[5] on wages and employment of various types of workers. Digital investment has been robust in Indonesia, and we hypothesise that it has heterogeneous impacts on different types of workers. We also look at whether industrial concentration, as indicated by the Herfindahl-Hirschman Index, works in a similar way in the digital sectors as it does in more traditional sectors.

The last section of this paper discusses policy recommendations and concludes.

2. Literature Review

Recent evidence from Indonesia shows that the skill premium increased at the onset of technological advancement. Jacoby et al. (2021) showed that the incremental benefits of internet penetration are greater for more educated workers, further widening the skill premium between less and more educated workers in Indonesia. These effects survive intact after controlling for contemporaneous local trends, such as GDP, urbanisation, a district's average expenditure per capita, and the sectoral composition of jobs. These effects did not predate the arrival of the internet.

The same study, which uses 2005–2015 census data from medium-sized and large manufacturing companies, confirms that there may be skill-biased technological change.[6] Non-

[5] Using the definitions of digital sectors provided by the Organisation for Economic Co-operation and Development (OECD) and the United Nations Statistics Division (UNSD).
[6] No panel data are available after 2015.

production workers (a proxy for more educated workers) earn 35% more than production workers (a proxy for less-educated workers), and a 1% increase in internet penetration increases this marginal return by an additional 0.25 percentage points. This additional wage return of the internet on non-production workers does not predate the introduction of the internet (1990–2004). At this point, however, little is known about how to attenuate the impacts of skill-biased technological change.

Empirical evidence from some developed countries has shown that from the 1990s there was rapid growth for high- and low-skilled jobs but slow growth for middle-skilled jobs (Autor, Katz, and Kearney, 2006; Autor and Dorn, 2013 for the United States (US); Goos and Manning, 2007 for the United Kingdom). As growth in low-skilled workers is faster than in medium-skilled workers, the skill-biased technological change hypothesis becomes invalid in explaining this job polarisation phenomenon.

Routine-biased technological change theory is a refinement of skill-biased technological change and can explain job polarisation. It suggests that it is routine jobs that are replaced by technology, not low-skilled jobs, and these are likely to be middle-skilled jobs. Autor, Levy, and Murnane (2003) found that computer capital substitutes routine tasks, and the lower the price of computers, the lower the demand for routine tasks. They also found that computers are labour-complementing or augmenting for workers to perform non-routine tasks. However, computers cannot take the place of unskilled workers performing mainly non-routine tasks, such as masseuses. The model of Autor, Levy, and Murnane (2003) was developed further by Autor and Dorn (2013), who were able to explain the increase in low-skilled services jobs. In sum, the routine-biased technological change hypothesis explains the recent job polarisation phenomenon better than the skill-biased hypothesis (Buyst, Goos, and Salomons, 2018).

Although the existing empirical studies mainly emphasise the impact of the declining price of technology, Cirillo (2018) added three other factors that may affect job polarisation: consumption spillover, 'offshorability', and labour market institutions. Bárány and Siegel (2018) suggested that structural change affects job polarisation. They observed that around 50% of routine jobs in the US in 1950 were in manufacturing, and the decline in the sector induced the hollowing out of middle-skilled workers performing routine tasks.

The impact of technology on job polarisation in developing countries is still inconclusive (e.g. Maloney and Molina, 2019). Some pieces of evidence in developing countries indicate declining jobs with high routine task intensity or increasing jobs with non-routine and abstract task intensity (e.g. Almeida, Leite Corseuil, and Poole, 2017; Ariza and Raymond Bara, 2020).

The United Nations University World Institute for Development Economics Research initiated a project examining how the changing nature of work affects earnings inequality in 11 developing countries in Africa, Asia, and Latin America through routine-biased technological change. The study finds evidence of job polarisation with respect to routine task intensity that contributes to rising inequality in some countries for some periods of time and geographic locations (e.g. China between 1990 and 2000, urban India post-2004, and Indonesia between 2005 and 2015). Drivers of job polarisation, however, differ across countries depending on changes in their occupational structures and nature of work.

At the individual level, computer or digital skills, which are complementary skills to technology adoption, should have a higher wage premium as technology use increases. Krueger (1993) showed that the wage premium for workers using computers was around 10%–15% during 1984–1989 in the US. However, a study in the United Kingdom showed that computer skills have no significant impact on wages (Borghans and ter Weel, 2004). The ambiguity of the wage premium for computer skills may depend on the computer skill level. Buchmann, Buchs, and Gnehm (2020) separated general computer skills from specialised computer skills and found that only the latter are associated with a higher wage premium.

Performing highly demanding tasks should give a higher wage return. Autor and Handel (2013) showed that the abstract task intensity of jobs had a positive relationship with wages in the US, while the manual and routine task intensity of jobs had a negative relationship. The higher wage premium for the higher abstract task intensity and wage penalty for routine manual tasks is also found in developed countries in East Asia and Europe (De La Rica, Gortazar, and Lewandowski, 2020). A more recent trend shows that social skills are increasingly in demand to perform non-routine interpersonal tasks, resulting in a higher premium for those possessing them (Deming, 2017 for the US; Edin et al., 2022 for Sweden).

In this paper, we also examine the impacts of investment in the digital sectors on wages and employment for various segments of the workforce. Recent production theory tries to explain the capital–labour relationship within a new framework, the skill-content framework. Acemoglu and Restrepo (2019) argued that the relationship could be explained through productivity and reinstatement effects. The productivity effect refers to increased demand for labour in non-automated tasks, while the reinstatement effect induces higher labour demand via reinstating labour to a broader task range – in other words, the creation of new types of jobs – countering the negative displacement effect.

Several studies have attempted to quantify the net impact of investment on the labour market and have documented heterogeneous impacts, but with no conclusive results. A study using Mexican data found that heterogeneity is observed across different industries – e.g. investment in manufacturing has positive impacts on both low- and high-skilled employment, while no employment impact is observed for investment in services (Saucedo, Ozuna, and Zamora, 2020). The same study showed that investment in manufacturing results in a marginal increase in wages for low-skilled workers but no significant change in wages for high-skilled workers. A broader study using data from 41 developing countries found that foreign direct investment (FDI) in services is more likely to be associated with rising wage inequality than FDI in other sectors (Bogliaccini and Egan, 2017).

3. Attenuating Skill-Biased Technological Change: The Role of Certified Training

Building on work by Jacoby et al. (2021), we explore channels that could attenuate skill-biased technological change, closing the gap of internet premiums between highly and less educated workers. We hypothesise that district labour market characteristics such as more supply and demand of educated workers in the districts and workers receiving certified training would have attenuating, equality-enhancing effects.

3.1. Data and Methodology

Using the National Labor Force Survey (Survei Angkatan Kerja Nasional; Sakernas)[7] from 2005 (after the arrival of the internet) to 2019 (before COVID-19), we estimate Mincerian earnings regression (Equations 3.1 and 3.2):

$$lwage_{ijt} = \beta_0 + \beta_1 ED_{ijt} + \beta_2 Int_{jt} + \beta_3 SD_{jt} + \beta_4 X_{ijt} + \beta_5 Int_{jt} * ED_{ijt} + \beta_6 X_{ijt} * ED_{ijt} + \beta_7 Int_{jt} * ED_{ijt} * SD_{jt} + \beta_8 ED_{ijt} * SD_{jt} + \beta_9 Int_{jt} * SD_{jt} + \beta_{10} T + \beta_{11}\theta_t + \beta_{12}\delta_j + \beta_{13}\theta_t * \delta_j + \varepsilon_{ijt} \tag{3.1}$$

$$lwage_{ijt} = \beta_0 + \beta_1 ED_{ijt} + \beta_2 Int_{jt} + \beta_3 CT_{ijt} + \beta_4 X_{ijt} + \beta_5 Int_{jt} * ED_{ijt} + \beta_6 X_{ijt} * ED_{ijt} + \beta_7 Int_{jt} * ED_{ijt} * CT_{ijt} + \beta_8 ED_{ijt} * CT_{ijt} + \beta_9 Int_{jt} * CT_{ijt} + \beta_{10} T + \beta_{11}\theta_t + \beta_{12}\delta_j + \beta_{13}\theta_t * \delta_j + \varepsilon_{ijt} \tag{3.2}$$

[7] Sakernas is an individual-level data set based on an annual, cross-sectional survey conducted biannually (February and August), which is representative up to the district level. The questionnaire comprises the demographic characteristics of the labour force (e.g. age, education, gender, location); employment information for the main job (income, work hours, sector, employment status, occupation level); and brief information on the employment history for each year. The survey records the worker's sector of employment in their main job up to the five-digit Standard Classification of Indonesian Business Fields (KBLI) for 2015.

where:

$lwage_{ijt}$ is the natural logarithm of the real monthly wage of individual i, district j, year t

ED_{ijt}	is a vector of education dummies: primary school (6 years), junior high school (9 years), senior high school (12 years), diploma I/II/III and university (16 years and above)
Int_{jt}	is the percentage of households in district j, year t, with access to the internet, excluding access to the internet at the office and school to control for a potential endogeneity bias
SD_{jt}	is a series of variables proxying the supply and demand of educated workers in district j, year t
CT_{ijt}	is a binary variable indicating whether a worker has completed a certified training
X_{ijt}	are individual-level control variables: age group dummies, job status dummies, sector dummies, employee and casual worker dummies, rural dummy, female dummy
T	are vectors of interaction terms between education and year that absorb secular trends in the returns to education that are common across districts
θ_t, δ_j	are year and district dummies, respectively

The analysis is restricted to workers for whom earnings data are available: wage employees, self-employed workers, and casual workers. It excludes unpaid workers and profit-earning employers.

Coefficient β_1 shows the average wage with respect to workers' level of education – in other words, the return on education. Meanwhile, β_5 presents the marginal return on education conditional on the district's internet penetration, as previously estimated by Jacoby et al. (2021). The phenomenon of skill-biased technological change is marked by higher β_5 for more educated workers, which indicates that more educated workers benefit more from internet penetration, widening the education premium[8] that existed before the emergence of the internet. We are particularly interested in coefficient β_7, which estimates the effect of key district characteristics (such as a higher share of educated workers) on the return on the internet with respect to workers' level of education. We construct an interaction variable between the level

[8] We use 'skill premium' and 'education premium' interchangeably.

of education (*ED)*, district internet penetration (*Int*), and a third variable, SD_{jt} in Equation 3.1 and CT_{ijt} in Equation 3.2.

The variable SD_{jt} refers to the supply of or demand for educated workers at the district level. On the supply side, we use the district's high school net enrolment rate and the share of the district's workers who have at least a high school diploma. In 2018, Indonesia's high school net enrolment rate stood at 80.7% (Statista, 2023), with variations across districts. In the same year, only 41% of Indonesia's workers had a high school diploma or higher (with variations across districts) (World Bank, 2021). The demand for educated workers is proxied by the share of high value-added (finance, transportation, communication) and manufacturing sectors in the district's GDP.

In Equation 3.2, CT_{ijt} refers to whether a worker has participated in and completed certified training from the government or a private training provider; the training may or may not be directly related to the worker's main occupation.[9] The parameter of interest in this analysis is β_7, which highlights the potential attenuating effect of workers' certified training on skill-biased technological change.

3.2. Results

We extend Jacoby et al. (2021) by studying the factors that potentially attenuate skill-biased technological change. We find that increasing the supply of educated workers – as proxied by the district's high school net enrolment rate and the share of workers who completed at least high school education – does not necessarily lead to an attenuation. On the contrary, we find it tends to exacerbate skill-biased technological change, where only workers with the highest level of education (a college degree or higher) enjoy a higher return on the internet as the supply of educated workers in the district becomes higher (Table 3.1). In other words, increasing the supply of educated people in the population does not make the benefits of the internet more equally felt by workers with different educational levels.

Table 3.1 shows that the marginal return of internet penetration for workers with college/university degrees or higher is increased by 0.006 or 0.005 percentage points for every percentage point increase in the district's high school net enrolment rate or in the share of workers who have at least a high school diploma. However, the marginal return of internet

[9] The certified training includes mandatory training required by employers and voluntary training outside the workplace. Certified training refers to training in which workers are given a certificate as a proof of qualification or skills gained. Regression using Equation 3.2 only uses Sakernas from 2012 to 2019, as a question on worker training is only available for that period.

penetration for workers with lower secondary education is *lowered* by 0.003 percentage points, exacerbating skill-biased technological change.

We also conduct a robustness check using the share of workers and the share of the population in the district who have at least a college/university degree as a proxy to the supply of highly educated workers.[10] The result remains consistent: the skill-biased technological change tends to be higher in districts where the educational level is higher.

A similar result is found in the demand-side analysis: workers with higher educational attainment tend to earn higher marginal benefits from the internet as demand in the district for highly educated workers increases, as proxied by the share of high value-added services and manufacturing GDP and employment out of total GDP and employment, respectively (Table 3.1).

Table 3.1 shows that the marginal return of internet penetration for workers with college/university degrees or higher increases by 0.279 or 0.415 percentage points for every percentage point increase in the share of high value-added services and manufacturing in the district's GDP or employment, respectively. The marginal return of internet penetration for workers with higher secondary education is increased by 0.455 or 0.484 percentage points for every percentage point increase in the share of high value-added services and manufacturing in the district's GDP or employment, respectively. However, the marginal return of internet penetration for workers with lower secondary education or below for every percentage point increase in the share of high value-added services and manufacturing in the district's GDP or employment is not significant, exacerbating skill-biased technological change.

[10] This means Diploma 1–4 (D1–D4) and S1–S3 in Indonesia's education system.

Table 3.1: Effect of Increasing the Supply of and Demand for Educated Workers on the Wage Return on the Internet (β_7 in Eq 3.1)

Worker's Educational Level	β_7: the additional return of one percentage point in internet penetration for every percentage point increase in…			
	Supply Side		Demand Dide	
	District's High School Net Enrolment	Share of Educated Workers (those who have completed at least high school) in the District	Share of High Value-added Services and Manufacturing Sector in District GDP	Share of High Value-added Services and Manufacturing Sector in District Employment
Primary school	0.000%	−0.002%**	0.011%	0.020%
Lower secondary school	−0.003%*	−0.003%***	−0.033%	−0.033%
Higher secondary school	0.002%	0.001%	0.455%***	0.484%***
College/university degree or higher	0.006%***	0.005%***	0.279%*	0.415%**

GDP = gross domestic product, Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey); Susenas = Survei Sosial Ekonomi Nasional (National Socioeconomic Survey).
Note: Robust standard errors follow the figures. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.
Sources: Sakernas; Susenas; authors' calculations.

3.3. Heterogeneous Role of Certified Training on Attenuating Skill-biased Technological Change

We find suggestive evidence that training, particularly certified training, could play a role in attenuating the wider wage gap created by digitalisation. Table 3.2 shows that workers with lower educational attainment and a certified training have marginally higher internet premiums compared with those with similar educational attainment but without certified training. However, such effects are muted amongst workers with higher educational attainment. Therefore, it could be argued that certified training could play a role in preparing less-educated workers to take advantage of digitalisation.

Table 3.2 shows that the marginal return of internet penetration for workers with primary or lower secondary school education is increased by 0.29 or 0.24 percentage points, respectively, if workers complete certified training. However, the marginal return of internet penetration for workers with higher secondary school education or a college/university degree who complete certified training is not significant, attenuating skill-biased technological change.

Table 3.2: Effect of Certified Training on the Wage Return on the Internet ($\boldsymbol{\beta_7}$ in Equation 3.2)

Worker's Educational Level	$\boldsymbol{\beta_7}$: the additional return of one percentage point on internet penetration following certified training						
		By Sex		By Age Group			
	All Workers	Male (base)	Female	15–24 Years Old (base)	25–54 Years Old	55–64 Years Old	>64 Years Old
Primary school	**0.29%****	0.316%*	0.088%	2.18%***	−2.1%***	−1.4%*	−0.163%*
Lower secondary school	**0.24%***	0.329%**	0.214%	1.51%*	−1.3%	−1.42%	−1.22%
Higher secondary school	**0.06%**	0.159%	0.306%	1.70%**	−1.73%**	−1.77%**	−1.87%**
College/ university degree or higher	**−0.21%**	0.102%	0.293%	1.56%**	−1.83%**	−1.13%	−1.13%

Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey); Susenas = Survei Sosial Ekonomi Nasional (National Socioeconomic Survey).
Note: Robust standard errors follow the figures. Significance level: *** p<0.01, ** p<0.05, * p<0.10.
Sources: Sakernas; Susenas; authors' calculations.

Due to data limitations, we are unable to uncover whether the training is specific to a worker's main occupation or is training in digital and other related skills. Nevertheless, this analysis could provide a lower-bound estimate of the potential effect of certified training in improving the internet premiums of less-educated workers.

We also examine the heterogeneous effects of certified training in attenuating skill-biased technological change across the gender and age of workers. First, education premiums are higher for female workers with a high school education or more, relative to male workers. Hence, skill-biased technological change is more pervasive for female workers than for male workers. The marginal return on internet penetration for male workers with primary or lower secondary school education increases by 0.316 or 0.329 percentage points, respectively, following certified training, but not for male workers with higher education, reducing skill-biased technological change (Table 3.2). There is no significant difference in the effect of certified training amongst female workers relative to their male counterparts (Table 3.2).

We also find that the marginal return on internet penetration for young workers (15–24 years old) with primary school education or below is increased relative to youth workers with higher education if they complete certified training (Table 3.2). In other words, providing certified training can reduce routine-biased technological change amongst youth workers. However, this effect is weaker for older workers (Table 3.2).

4. Routine-Biased Technological Change: Evidence from Indonesia

Routine-biased technological change theory suggests that low-skilled jobs are not necessarily easily replaced by technology, but routine jobs are. These jobs are likely to be middle-skilled jobs, which in turn may create job polarisation. In this section, we test whether there is evidence of job polarisation and the factors potentially driving it.

4.1. Data and Methodology

We used two data sets: a panel data set at the provincial level to study job polarisation and a pooled cross-sectional data set at the individual level to study the return on task content. Both are sourced from Sakernas. The provincial-level data set is sourced from Sakernas for 2001–2019, and the individual-level data set is sourced from Sakernas for 2001–2010 and 2013–2015, the years when the high-digit level occupational code is consistent. To measure the task content, we use the O*NET database 5.0 (April 2003).[11] We use the list of task items from Acemoglu and Autor (2011) to calculate the scores for five types of task content: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical. We also use the list of task items from Muro et al. (2017) for digital task content scores. The scores are weighted with the Indonesia Population Census 1980.

4.2. Results

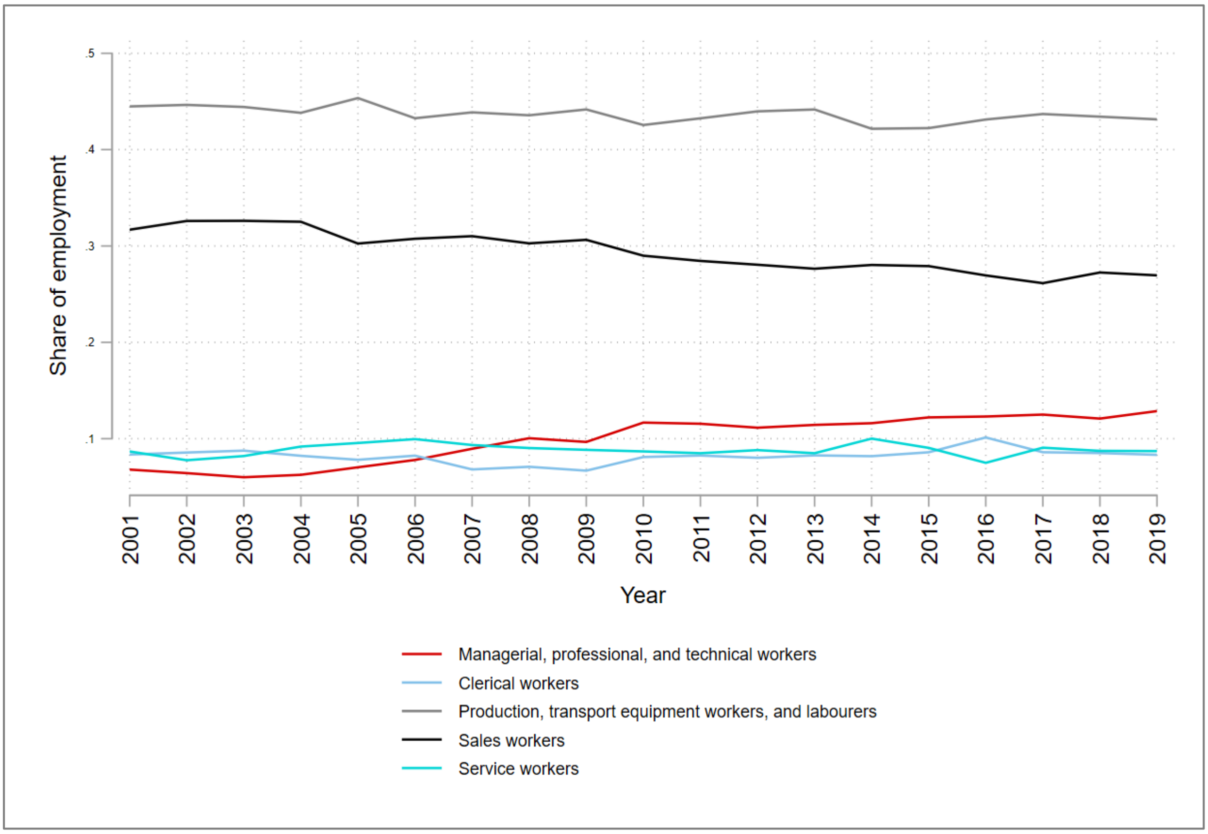
Evidence of job polarisation and factors driving job polarisation in Indonesia

We exclude the agriculture sector since agriculture workers have specific codes and job polarisation will be contaminated by Indonesia's structural transformation from agriculture to manufacturing and services.

We find that at the national level the share of sales workers decreased from 2001 to 2019, while the share of managerial, professional, and technical workers increased (Figure 4.1). These trends are consistent at the provincial level. The shares of clerical workers; production, transport equipment workers, and labourers; and service workers remained relatively stable.

[11] See National Center for O*NET Development, O*NET Resource Center (n.d.).

Figure 4.1: Occupational Shares



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Note: The agriculture sector is excluded from the calculations.
Source: Sakernas, 2001–2019.

We then compare two data points to analyse when Indonesia's occupational structure starts to change. We rank the one-digit level occupational groups by their mean wage in 2001 and then calculate the difference in the share between the two data points to see the change in occupational structure.

We find a notable change in occupational structure from 2006, when there is a decrease in the share of middle-skilled occupations and an increase in the share of high- and low-skilled occupations (Figure 4.2). This coincides with the commodity boom and premature deindustrialisation, which saw a decline in manufacturing and a surge in low-productivity services. Coxhead and Shrestha (2016) argued that using the Dutch disease economic model, the windfall income from the boom would be spent on services. The authors showed that booming commodities, especially coal and palm oil, are correlated with increases in non-tradable sectors and therefore jobs. At the same time, manufacturing's share of GDP and employment decreased (premature deindustrialisation) due to the shift to resource-based sectors and China's increased dominance in global manufacturing, amongst others. Between 2000 and

2014, consumption and wage inequality rose sharply. We hypothesise that job polarisation contributed to the sharp rise in inequality. First, we show evidence of job polarisation (Figure 4.2).

Figure 4.2: Changes in Occupational Share and Illustration of Job Polarisation

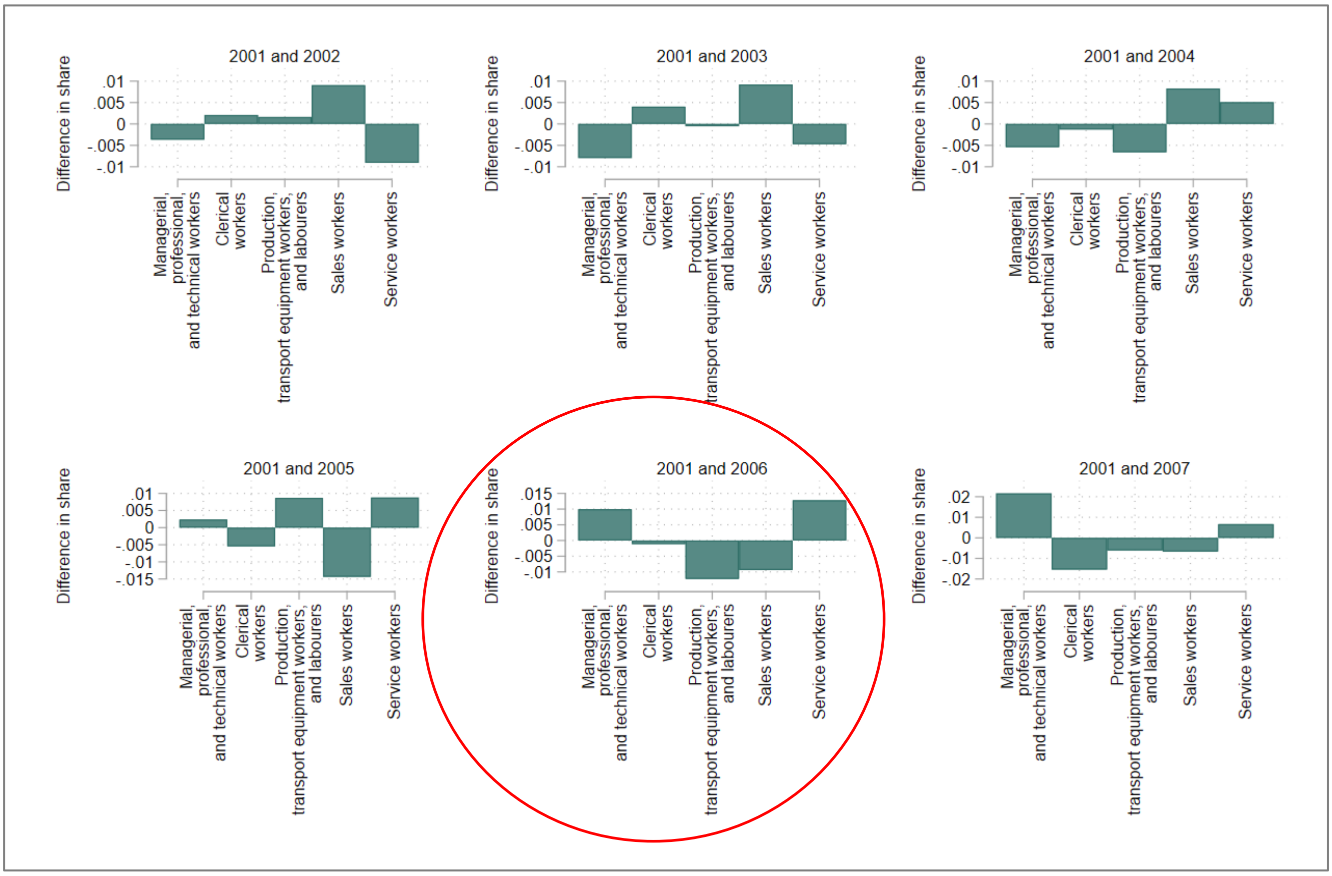
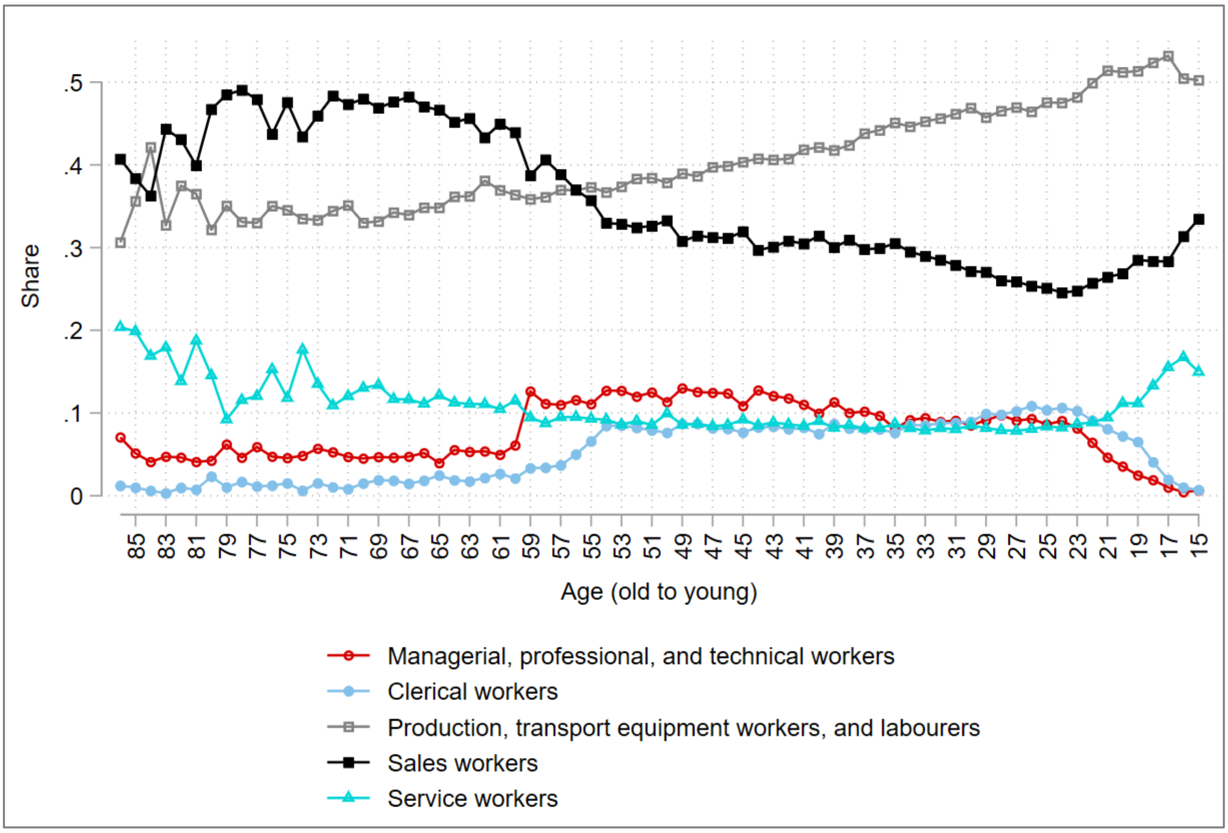


Figure 4.2: ***Continued***

Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Note: Agriculture is excluded from the calculations.
Source: Sakernas, 2001–2019.

We then analyse the share of one-digit level occupations by age to see the lifetime occupational trajectory. Those aged 23 (the age of fresh university graduates) to 59 (around retirement age) hold the highest share of high-skilled occupations, meaning managerial, professional, and technical roles (Figure 4.3). The shares of production, transport equipment workers, and labourers, whose jobs require physical strength, decrease with age. Retirees, aged 63–79, hold the highest share of sales roles – with the trend increasing with age – except for youth (15–23). Clerical occupations are filled by middle-aged workers (24–62), while service occupations are filled by school-age children and older workers.

Figure 4.3: Occupational Share by Age



Sakernas = Survei Angkatan Kerja Nasional (National Labour Force Survey).
Note: Agriculture is excluded from the calculations.
Source: Pooled Sakernas, 2001–2019.

4.2. Sources of Job Polarisation

We study factors that may drive job polarisation. Middle-skilled occupations that are more likely to have more intense routine tasks, such as cashiers, could be more easily substituted by computers, and hence computers could drive job polarisation, for example. Autor, Levy, and Murnane (2003) built a model to predict the effect of changes in computer prices. They predicted that a decline in computer prices that resulted in higher investment in computer capital would increase the demand for non-routine labour but decrease the demand for routine labour.

On the one hand, demand for managerial, professional, and service workers who have intense non-routine tasks would increase. High-skilled occupations usually require tertiary education as these occupations involve non-routine tasks and computer skills. On the other hand, the rise in demand for low-skilled occupations is in line with Indonesia's rising income, where richer households spend more on personal, low-skilled services, e.g. domestic helpers. Besides the cost of technology, which we proxy using the cost of memory computers, we also hypothesise that the demand and supply of educated workers may affect changes in the occupational structure.

We examine our hypothesis using the model in Equation 4.1:

$$\begin{aligned} y_{pt} = \beta_0 + \beta_1 \log\,(cost\ per\ MB)_{pt-1} + \sum_{k=2}^{4} \beta_k \boldsymbol{E_{pt-1}} + \sum_{k=5}^{8} \beta_k \boldsymbol{S_{pt-1}} \\ + \beta_9 urban\ share_{pt-1} + \beta_{10} \log\,(mean\ real\ expenditure\ per\ capita)_{pt-1} \\ + \beta_{11}\theta_t + \beta_{12}\delta_p + \varepsilon_{pt}, \end{aligned} \tag{4.1}$$

where:

y_{pt} is the share of occupation in the non-agriculture sector in province p at year *t*

$\log\,(cost\ per\ MB)_{t-1}$

is the price of memory computers (hard disc drive) as a proxy for computer prices in province p at time *t-1*

$\boldsymbol{E_{pt-1}}$ is a vector of the share of the population aged 15 and over by educational level (primary, secondary, and tertiary) as a proxy for the supply of workers by educational level in province p in year *t-1*

$\boldsymbol{S_{pt-1}}$ is a vector of the share of workers by economic sector (manufacture, low value-added services, high value-added services, and other industries) as a proxy for demand for workers by educational level in province p in year *t-1*

$urban\ share_{pt-1}$

is the share of the urban population in province p in year *t-1*

$\log(mean\ real\ expenditure\ per\ capita)_{pt-1}$

is the mean of total consumption per capita in natural logarithm in province p in year *t-1*

θ_t, δ_j are year and province dummies, respectively

We use the August round of Sakernas for 2001–2019 with unit analysis at the provincial level. Data for total consumption per capita are from the July/March rounds of the National Socioeconomic Survey (Survei Sosial Ekonomi Nasional; Susenas) of 2001–2019. The total consumption variable is deflated using the Jakarta poverty line in 2001. Another treatment is crosswalking the provinces with 1995 codes, where the total number of unique provinces was only 26. The data for cost per megabyte are from McCallum (2002) and are updated in McCallum (2022). The original data are US dollars per megabyte, which we convert to Indonesian rupiah per megabyte. We assume that the base province for the cost is the capital, Jakarta. To account for provincial price differentiation, we multiply the cost in Jakarta by the ratio of Consumer Price Index (CPI) in the two places (Jakarta's CPI divided by the CPI for a provincial capital).

We provide the descriptive statistics of the variables used in the regression in Table 4.1. We find that the cost of memory decreased exponentially from 2001 to 2019, when technology became increasingly accessible and affordable. The share of the population completing secondary and tertiary education increased from 2001 to 2019. As expected, the contribution of agricultural employment decreased significantly from 52% between 2001 and 2005 to 36% between 2016 and 2019, while the share of services and other industries increased. The contribution of manufacturing decreased during the commodity boom but increased from 2015 onwards. The share of the urban population increased, indicating the trend towards urbanisation, while the mean of real expenditure per capita increased, representing economic welfare improvement.

Table 4.1: Descriptive Statistics

Control Variable	2001–2005	2006–2010	2011–2015	2016–2019	Total
Share of managerial, professional, and technical	0.0901	0.127	0.151	0.151	0.128
Workers	(0.0278)	(0.0365)	(0.0354)	(0.0318)	(0.0415)
Share of clerical workers	0.103	0.0865	0.0970	0.106	0.0971
	(0.0361)	(0.0251)	(0.0271)	(0.0322)	(0.0310)
Share of production workers, transport equipment	0.404	0.403	0.386	0.399	0.398
workers, and labourers	(0.0617)	(0.0532)	(0.0537)	(0.0448)	(0.0548)
Share of sales workers	0.323	0.296	0.283	0.267	0.295
	(0.0430)	(0.0396)	(0.0344)	(0.0311)	(0.0427)
Share of service workers	0.0803	0.0875	0.0826	0.0771	0.0824
	(0.0360)	(0.0290)	(0.0289)	(0.0226)	(0.0303)
Log(cost per megabyte)	2.534	0.313	-0.756	-0.986	0.398
	(0.616)	(0.615)	(0.188)	(0.0633)	(1.469)
Share of those with no schooling	0.190	0.201	0.194	0.169	0.190
	(0.0793)	(0.0700)	(0.0635)	(0.0548)	(0.0693)
Share of those having completed primary education	0.332	0.289	0.248	0.227	0.278
	(0.0620)	(0.0656)	(0.0502)	(0.0460)	(0.0693)
Share of those having completed secondary education	0.437	0.452	0.479	0.499	0.463
	(0.0897)	(0.0724)	(0.0692)	(0.0581)	(0.0777)
Share of those having completed tertiary education	0.0415	0.0589	0.0799	0.105	0.0679
	(0.0185)	(0.0224)	(0.0252)	(0.0287)	(0.0322)
Share of agricultural employment	0.518	0.478	0.420	0.362	0.453
	(0.164)	(0.152)	(0.145)	(0.130)	(0.159)
Share of manufacturing employment	0.0860	0.0806	0.0814	0.0940	0.0846

Control Variable	2001–2005	2006–2010	2011–2015	2016–2019	Total
	(0.0526)	(0.0467)	(0.0515)	(0.0459)	(0.0497)
Share of low value-added services employment	0.284	0.310	0.354	0.388	0.328
	(0.0890)	(0.0886)	(0.0819)	(0.0731)	(0.0922)
Share of high value-added services employment	0.0591	0.0660	0.0659	0.0727	0.0652
	(0.0282)	(0.0271)	(0.0295)	(0.0358)	(0.0299)
Share of other industries' employment	0.0532	0.0647	0.0789	0.0832	0.0687
	(0.0213)	(0.0204)	(0.0248)	(0.0213)	(0.0249)
Share of urban population	0.387	0.381	0.430	0.466	0.410
	(0.168)	(0.164)	(0.175)	(0.173)	(0.172)
Log(mean real expenditure per capita)	12.11	12.18	12.43	12.48	12.28
	(0.167)	(0.155)	(0.173)	(0.170)	(0.227)

Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey); Susenas = Survei Sosial Ekonomi Nasional (National Socioeconomic Survey).
Note: Standard deviations in parentheses.
Sources: Sakernas, 2001–2019; Susenas, 2001–2019; McCallum (2002; 2022); authors' calculations.

In summary, we find that more affordable technology may benefit high-skilled occupations but may substitute middle-skilled occupations, especially clerical and sales occupations (Table 4.2). Moreover, better access to tertiary education leads to a higher share of high-skilled jobs. Further, the changes in economic structural transformation during the commodity boom and premature deindustrialisation may contribute to job polarisation.

Table 4.2: Regression Results Showing Factors Driving Job Polarisation

Control Variable	(1) Share of Managerial, Professional, and Technical Workers	(2)	(3) Share of Clerical Workers	(4)	(5) Share of Production, Transport Equipment Workers, and Labourers	(6)	(7) Share of Sales Workers	(8)	(9) Share of Service Workers	(10)
log(cost per MB) t-1	-0.016***	-0.016***	0.007***	0.012***	0.000	-0.001	0.011***	0.006***	-0.003*	-0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
share who completed primary education t-1	-0.025	-0.023	-0.180***	-0.200***	0.153**	0.157**	-0.072	-0.054	0.124***	0.120***
	(0.041)	(0.042)	(0.041)	(0.043)	(0.071)	(0.072)	(0.050)	(0.051)	(0.036)	(0.038)
share who completed secondary education t-1	-0.106***	-0.102***	-0.012	-0.056	0.072	0.081	0.012	0.052	0.034	0.025
	(0.032)	(0.035)	(0.040)	(0.047)	(0.066)	(0.072)	(0.050)	(0.054)	(0.036)	(0.043)
share who completed tertiary education t-1	0.191**	0.213*	0.099	-0.153	0.160	0.214	-0.336**	-0.108	-0.115	-0.166
	(0.086)	(0.111)	(0.076)	(0.128)	(0.138)	(0.188)	(0.135)	(0.172)	(0.100)	(0.136)
share of workers in manufacturing t-1	-0.035	-0.034	-0.147**	-0.166***	0.279***	0.282***	-0.311***	-0.294***	0.215***	0.211***
	(0.057)	(0.058)	(0.060)	(0.061)	(0.099)	(0.100)	(0.089)	(0.087)	(0.058)	(0.059)
share of workers in low VA services t-1	0.013	0.013	0.013	0.013	-0.080	-0.080	0.107*	0.107*	-0.054	-0.054
	(0.042)	(0.042)	(0.049)	(0.048)	(0.069)	(0.069)	(0.064)	(0.064)	(0.048)	(0.048)
share of workers in high VA services t-1	-0.065	-0.066	-0.219***	-0.209***	0.334**	0.332**	-0.147	-0.156	0.097	0.099
	(0.086)	(0.086)	(0.081)	(0.079)	(0.165)	(0.165)	(0.145)	(0.144)	(0.125)	(0.125)
share of workers in other industries t-1	0.180***	0.181***	-0.189**	-0.198***	0.127	0.129	-0.296***	-0.287***	0.178**	0.176**
	(0.057)	(0.058)	(0.076)	(0.076)	(0.119)	(0.118)	(0.093)	(0.093)	(0.070)	(0.071)

Control Variable	(1) Share of Managerial, Professional, and Technical Workers	(2)	(3) Share of Clerical Workers	(4)	(5) Share of Production, Transport Equipment Workers, and Labourers	(6)	(7) Share of Sales Workers	(8)	(9) Share of Service Workers	(10)
share of urban population t-1	-0.077**	-0.075**	0.093***	0.072**	0.032	0.036	-0.011	0.008	-0.038	-0.042
	(0.035)	(0.035)	(0.035)	(0.031)	(0.053)	(0.052)	(0.041)	(0.040)	(0.044)	(0.043)
log(mean real expenditure per capita) t-1	-0.009	-0.009	0.014	0.006	-0.026*	-0.025*	0.005	0.012	0.017	0.015
	(0.008)	(0.008)	(0.009)	(0.009)	(0.015)	(0.015)	(0.014)	(0.015)	(0.012)	(0.012)
Observations	464	464	464	464	464	464	464	464	464	464
Adjusted R-square	0.874	0.874	0.769	0.776	0.779	0.778	0.741	0.744	0.685	0.685
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey); Susenas = Survei Sosial Ekonomi Nasional (National Socioeconomic Survey).
Notes: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.
Sources: Sakernas, 2001–2019; Susenas, 2001–2019; McCallum (2002; 2022); authors' calculations.

In Table 4.2, columns 1 and 2, we find that the lower the cost of technology, the higher the share of high-skilled occupations (managerial, professional, and technical workers). A higher supply of educated workers, as proxied by the share of people with tertiary education in the population, is associated with an increase in high-skilled occupations. Mining and quarrying, construction, and utilities ('other industries') are significant drivers for high-skilled occupations. The rise of this sector coincides with the commodity boom era. The sector is a highly capital-intensive sector that may need high-skilled workers to operate sophisticated machinery, for example.

Moreover, we find in Table 4.2, columns 3 and 4, that the lower the cost of technology, the lower the share of clerical workers, indicating that technology substitutes clerical occupations. For example, digital data management has become affordable. The lower the share of primary educated people in the population, the higher the share of clerical workers. The higher the share of the manufacturing sector, high value-added services, and other industries, the lower the share of clerical workers. The higher the share of the urban population, the higher the share of clerical workers.

From columns 5 and 6 of Table 4.2, we find that the higher the share of manufacturing, the higher the share of production, transport equipment workers, and labourers. Manufacturing absorbs production workers to support the production process. The higher the share of high value-added services (including transportation and communications), the higher the share of production workers, transport equipment workers, and labourers. The higher the share of primary educated people in the population, the higher the share of production workers, transport equipment workers, and labourers.

From columns 7 and 8 of Table 4.2, we find that the more affordable the technology, the lower the share of sales workers. Occupations such as sales demonstrators and news vendors may fade due to the ease of finding information on the internet. The higher the share of manufacturing and other industries, the lower the share of sales workers, meaning that there are not many sales workers in the manufacturing sector and other industries.

In Table 4.2, columns 9 and 10, we find that the higher the share of primary educated people in the population, the higher the share of service workers, since the less-educated labour force is more likely to be absorbed in these occupations. The higher the share of other industries, the higher the share of low-skilled occupations. This may be evidence of the Dutch disease economy, as explained by Coxhead and Shrestha (2016), where demand for personal services increases due to windfall income in a commodity boom. The higher the share of manufacturing, the higher the share of service workers. This is expected since the manufacturing sector is high in services content (Duggan, Rahardja, and Varela, 2013). Interestingly, a higher share of low value-added services does not lead to a higher share of service workers. This may indicate that indirect demand for service workers from the high-service-content manufacturing sector and other industries is stronger than the direct demand from the low value-added services sector.

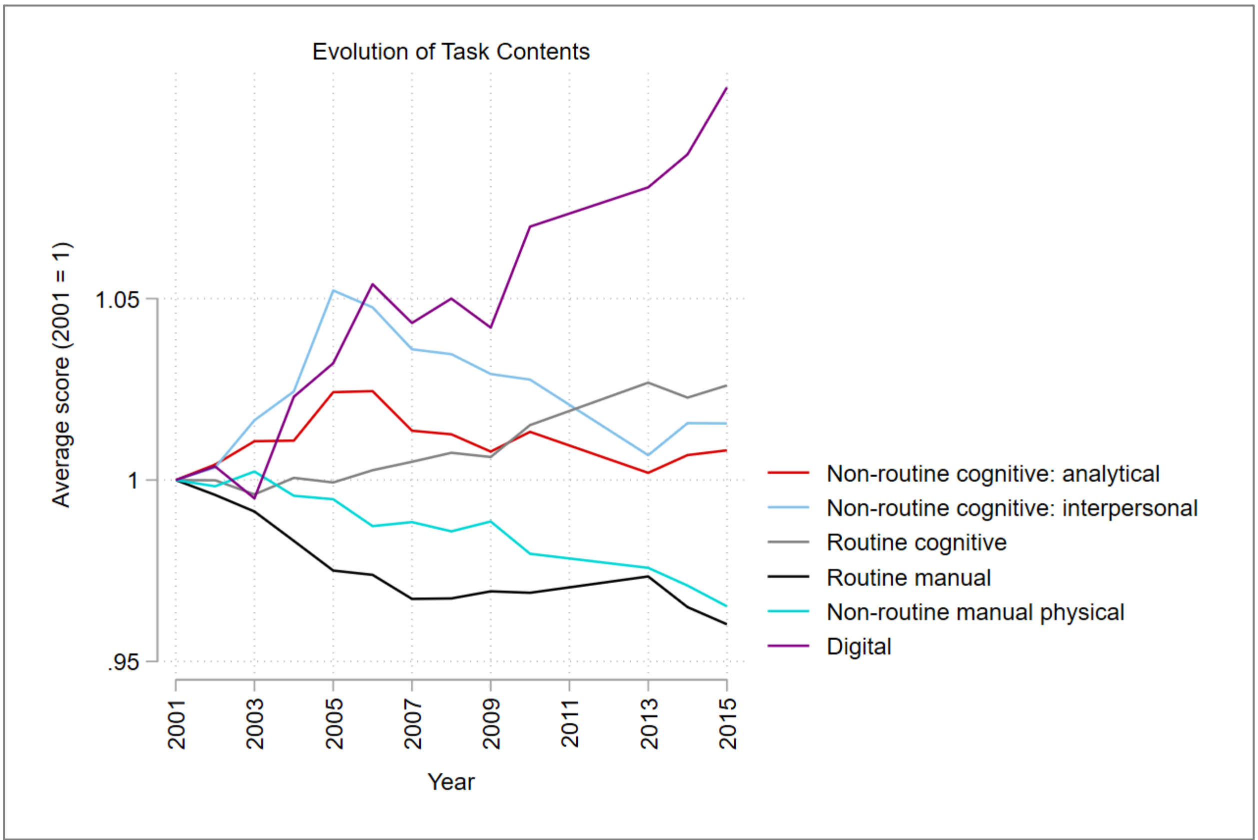
4.3. Evolution of Task Content of Jobs and Their Wage Returns

We use the August round of Sakernas for 2001–2010 and 2013–2015 to analyse the task content of jobs and their wage returns. Task content scores are from the O*NET database 5.0 (April 2003).[13] We crosswalk the O*NET-SOC 2010 occupational codes to the International Standard Classification of Occupations (ISCO) 1968, then link them to the Klasifikasi Jabatan Indonesia (KJI-82). We adopt the list of task items from Acemoglu and Autor (2011) to calculate the scores for non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical tasks. In addition, we use the list of task items from Muro et al. (2017) for the digital task content score. The scores are weighted with the 1980 Indonesia Population Census.

Occupations in Indonesia are still dominated by manual task content. However, manual task content decreased over 2001–2015. Digital task content increased significantly between 2001 and 2015 (Figure 4.4).

[13] See National Center for O*NET Development, O*NET Resource Center (n.d.).

Figure 4.4: Task Content Scores



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Sources: O*NET 5.0; Sakernas, 2001–2010, 2013–15; authors' calculations.

4.4. Complementarity and Substitutability of Digital Task Content

Using a cross-correlation matrix, we study the complementarity and substitutability of the digital task content of jobs with other task content. We find that digital task content is complementary to non-routine cognitive analytical, non-routine cognitive interpersonal, and routine cognitive task content, but is a substitute for routine manual and non-routine manual physical task content (Table 4.3). This supports our hypothesis that digital technology may replace jobs with high routine contents.

Table 4.3: Cross-Correlation by Task Content Scores

Task content	Non-routine cognitive: analytical	Non-routine cognitive: interpersonal	Routine cognitive	Routine manual	Non-routine manual physical	Digital
Non-routine cognitive: analytical	1					
Non-routine cognitive: interpersonal	0.8751*	1				
Routine cognitive	−0.0842*	−0.3314*	1			
Routine manual	−0.6790*	−0.6523*	0.2683*	1		
Non-routine manual physical	−0.6065*	−0.4730*	−0.1385*	0.6484*	1	
Digital	0.5614*	0.3596*	0.4516*	−0.5444*	−0.7403*	1

Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Sources: O*NET 5.0; Sakernas 2001–2010, 2013–2015; authors' calculations.

4.5. Heterogeneous Returns to Digital Task Content of Jobs

We estimate the wage returns of various task content of jobs using the regression specification:

$$\log\,(real\ wage)_{idt} = \beta_0 + \boldsymbol{\theta task_{idt}} + \boldsymbol{\beta X_{idt}} + \gamma_d + \delta_t + \varepsilon_{idt} \tag{4.2}$$

where:

$task_{idt}$ is the score of task content for individual i in district d in year t

$\boldsymbol{X}$ is the vector of each individual's characteristics, including years of education, age and its square term, gender, marital status, urban/rural (place of residence), job status, and economic sector. The variables γ_d and δ_t indicate district fixed effects and year fixed effects, respectively.

Our dependent variable is the real monthly wage in natural logarithm. Non-routine cognitive analytical, routine cognitive, non-routine manual physical, and digital task content have a positive return (Table 4.4). Only routine manual task content has a negative return, while non-routine cognitive interpersonal tasks do not have any significant return once we control for year and district fixed effects. Digital task content has the highest return compared with other task content.

Regressions by economic sector show that digital task content has a consistent positive return across all economic sectors and is highest in the agriculture sector, which may be due to the base effect (workers in the agriculture sector have the lowest average wage with relatively low digital task content).

By interacting task content with year dummies, we find that the return on digital task content has a positive trend, which indicates an increasing return over the years.

Table 4.4: Returns on Task Content

Control variable	(1)	(2)	(3)
	Log(real monthly wage)		
Non-routine cognitive analytical	0.024***	0.002	0.012***
	(0.007)	(0.004)	(0.003)
Non-routine cognitive interpersonal	-0.061***	0.005	0.005
	(0.007)	(0.004)	(0.004)
Routine cognitive	0.102***	0.007	0.019***
	(0.008)	(0.005)	(0.004)
Routine manual	-0.065***	-0.010***	-0.008***
	(0.006)	(0.003)	(0.003)
Non-routine manual physical	0.029***	0.015***	0.010***
	(0.005)	(0.003)	(0.002)
Digital	0.133***	0.084***	0.068***
	(0.005)	(0.004)	(0.003)
Observations	2,012,349	2,012,349	2,012,349
F-statistics	539.773	955.097	1558.895
Adjusted R-square	0.129	0.337	0.401
Year fixed effects	Yes	Yes	Yes
Control variables	No	Yes	Yes
District fixed effects	No	No	Yes

Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Notes: * p<0.10, ** p<0.05, *** p<0.01. Clustered standard errors at the district level in parentheses.
Sources: O*NET 5.0; Sakernas, 2001–2010, 2013–2015; authors' calculations.

We then study the heterogeneous wage returns of task content across different segments of the population, including gender, rural/urban (place of residence), age, and years of education, using the regression specifications:

I. Gender

$$\log\,(real\ wage)_{idt} = \beta_0 + \theta * male_{idt} * \boldsymbol{task_{idt}} + \boldsymbol{\beta X_{idt}} + \gamma_d + \delta_t + \varepsilon_{idt}$$

II. Location

$$\log\,(real\ wage)_{idt} = \beta_0 + \theta * urban_{idt} * \boldsymbol{task_{idt}} + \boldsymbol{\beta X_{idt}} + \gamma_d + \delta_t + \varepsilon_{idt}$$

III. Age

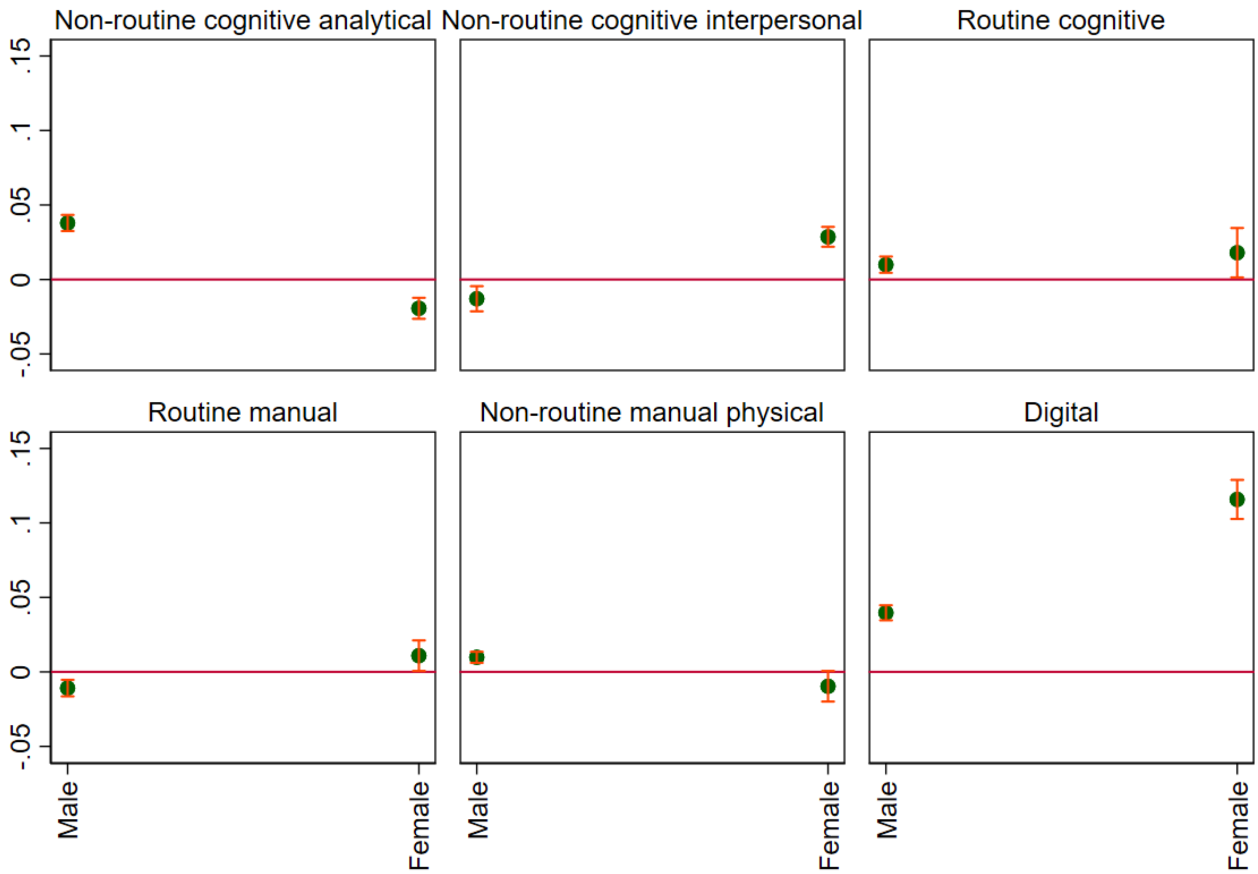
$$\log\,(real\ wage)_{idt} = \beta_0 + \theta_1 * age_{idt} * \boldsymbol{task_{idt}} + \theta_1 * age_{idt}^2 * \boldsymbol{task_{idt}} + \boldsymbol{\beta X_{idt}} + \gamma_d + \delta_t + \varepsilon_{idt}$$

IV. Education

$$\log\,(real\ wage)_{idt} = \beta_0 + \theta * years\ of\ education_{idt} * \boldsymbol{task_{idt}} + \boldsymbol{\beta X_{idt}} + \gamma_d + \delta_t + \varepsilon_{idt}$$

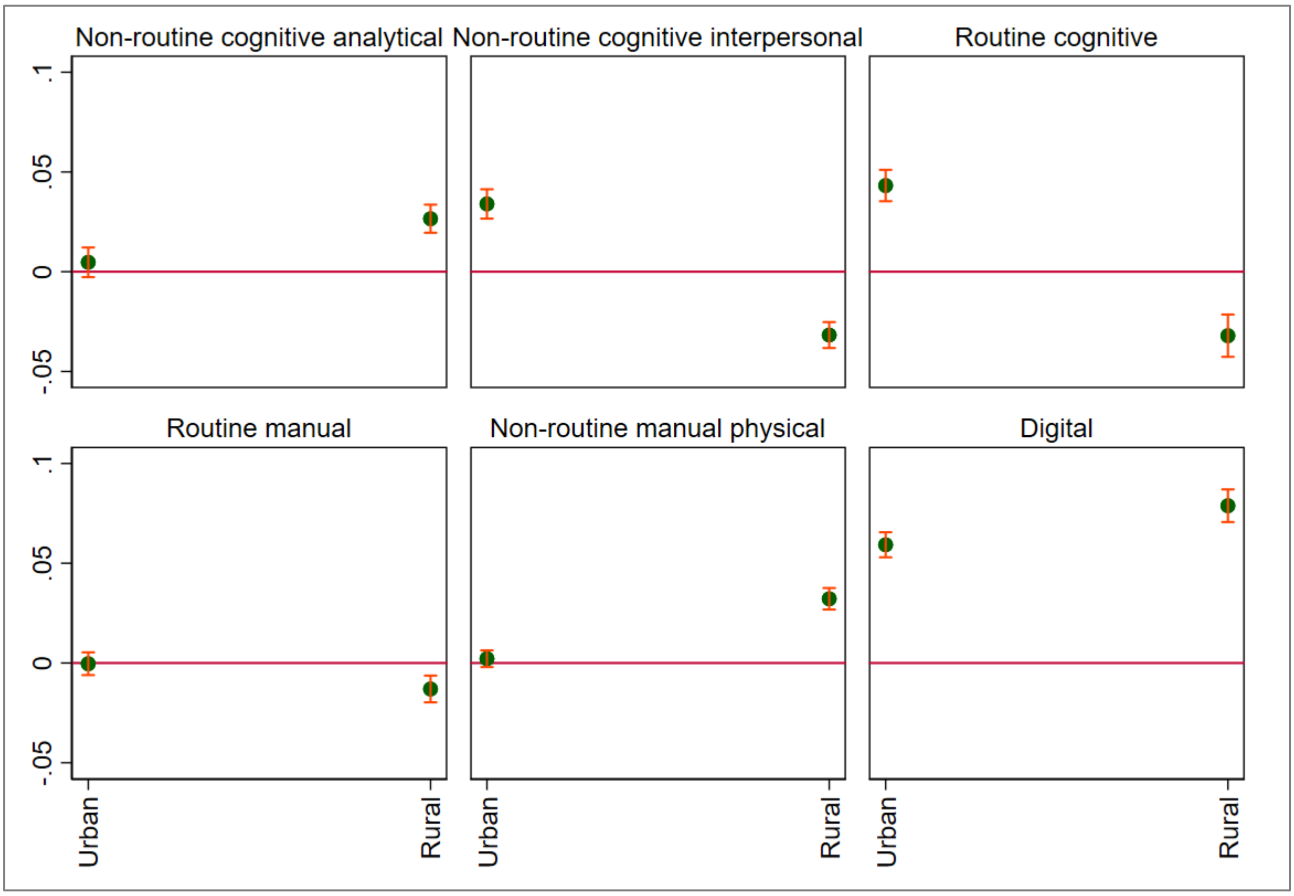
We find that, first, females have a higher return on digital and non-routine cognitive interpersonal task content than males (Figure 4.5). Second, rural workers have a higher return on digital, non-routine cognitive analytical, and non-routine manual physical task content than urban workers (Figure 4.6). Returns on non-routine cognitive interpersonal and routine cognitive task content are higher for urban workers. Third, returns on digital task content increase as workers age (Figure 4.7). This may be influenced by work experience or the base effect, whereby older workers hold jobs with lower digital task content. Finally, the return on digital task content declines with years of education (Figure 4.8). This again may be due to the base effect, as lower-educated workers may have lower digital task content.

Figure 4.5: Returns on Task Content by Gender



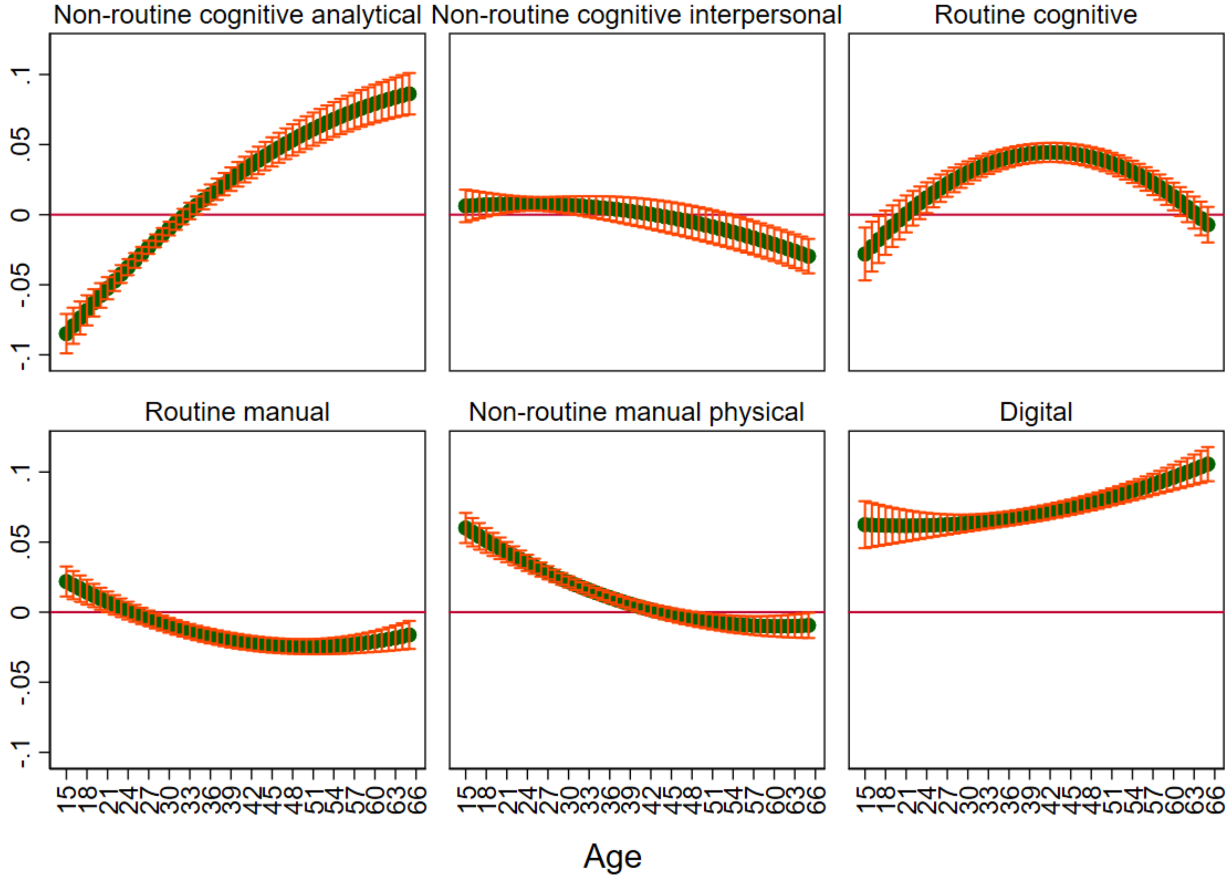
Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Source: O*NET 5.0; Sakernas, 2001–2010, 2013–2015; authors' calculations.

Figure 4.6: Returns on Task Content by Location



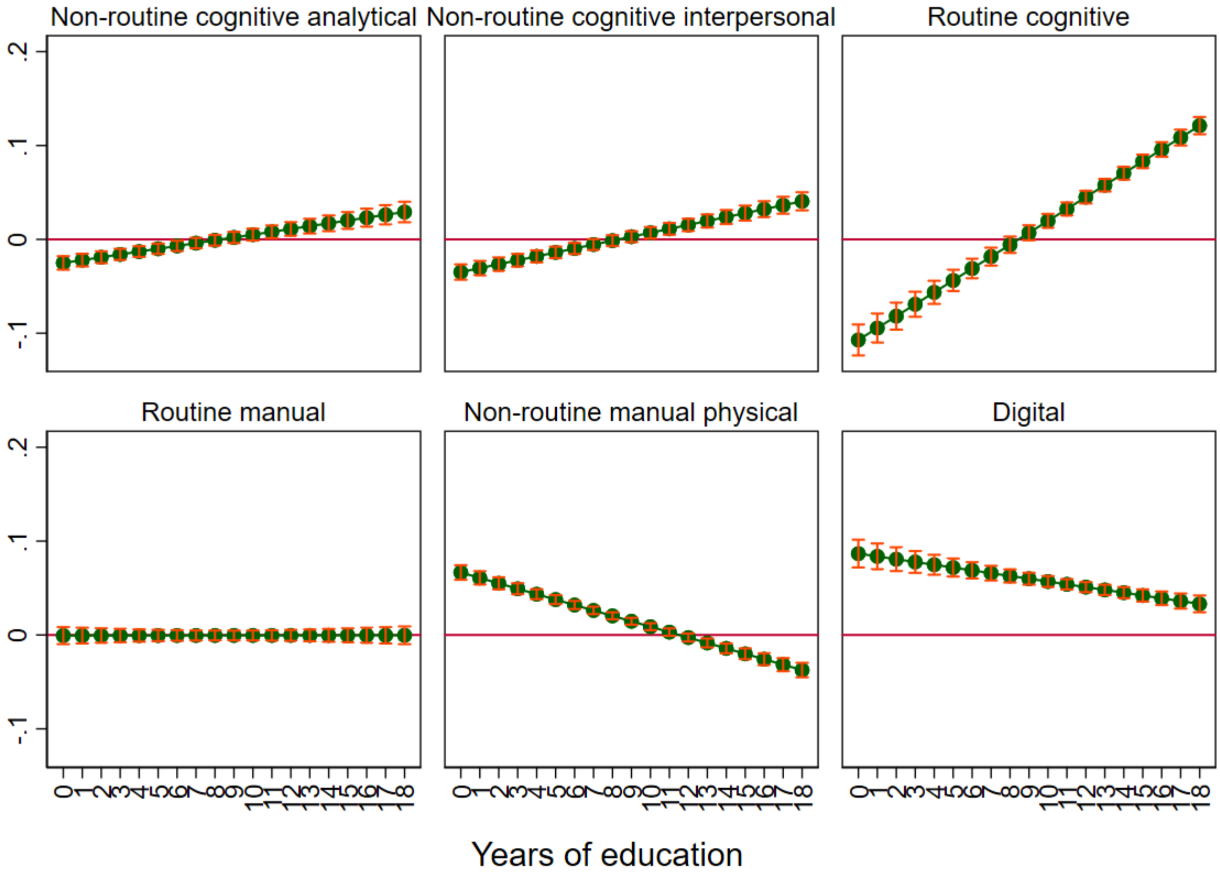
Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Sources: O*NET 5.0; Sakernas, 2001–2010, 2013–2015; authors' calculations.

Figure 4.7: Returns on Task Content by Age



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Sources: O*NET 5.0; Sakernas 2001–2010, 2013–2015; authors' calculations.

Figure 4.8: Returns on Task Content by Education



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Sources: O*NET 5.0; Sakernas 2001–2010, 2013–2015; authors' calculations.

4.6. Who are More Likely to Hold Jobs with Certain Task Content?

We find that education is positively correlated with the likelihood of having higher non-routine cognitive, routine cognitive, and digital task content, while it is negatively correlated with the likelihood of having higher routine and non-routine manual task content.

The correlation between age and the likelihood of having higher non-routine cognitive and digital task content resembles an inverted U, while the correlation between age and the likelihood of higher manual task content resembles a U.

Males are more likely to work in manual occupations, while females are more likely to work in occupations with high cognitive and digital task content.

Workers in rural areas are more likely to work in jobs with high non-routine cognitive task content, while urban workers are more likely to work in jobs with routine task content. The prior may be affected by the agriculture sector, which has a high average score in non-routine cognitive task content while the latter may be affected by the trade and manufacturing sector.

5. Effects of Digital Investment on Wages and Employment[14]

We examine the effects of investment in the digital sectors on wages and employment for various types of workers. We hypothesise that digital investment has heterogeneous impacts on different types of workers. We also assess whether industrial concentration, as indicated by the Herfindahl-Hirschman Index (HHI), works in a similar way in the digital sectors as it does in more traditional sectors.

5.1. Data

We used two data sources. Investment data for 2010–2016 were obtained from Indonesia's Ministry of Investment. The data set reports investment at the four-digit Standard Classification of Indonesian Business Fields (KBLI) 2015 industry code:[15] the number of projects and monetary value of investment for both planned and realised investments across domestic and foreign funding. In total, the data set covers 514 sectors (unique at the four-digit KBLI). Labour market statistics are derived from Sakernas for 2010–2016. We restrict the sample used in the regressions to workers for whom wage information is available – wage employees, the self-employed, and casual workers.[16] The wage level is deflated to real terms using 2010 as the base year.

The next step is the identification of the digital sector. According to the United Nations Statistical Division (UNSD, 2008: 278), the ICT sector is defined as:

> The production (goods and services) of a candidate industry [that] must primarily be intended to fulfil or enable the function of information processing and communication by electronic means, including transmission and display.

[14] This section is co-authored by Aufa Doarest.

[15] The KBLI is a Statistics Indonesia (BPS) standard for industry codes, which corresponds directly to the United Nations Statistical Division (UNSD) International Standard Industrial Classification of All Economic Activities (ISIC) Rev. 4, 2008. Whereas the ISIC is only available up to four digits, the KBLI provides an additional fifth digit, which denotes further categories for each sector based on the Indonesian context.

[16] Sakernas only asks for income information for four out of six employment statuses: self-employed, employee, casual workers in agriculture, and casual workers in non-agriculture. Sakernas does not hold income information for profit-seeking employers (with and without permanent workers) and unpaid family workers. See Wihardja and Cunningham (2021).

Meanwhile, the Organisation for Economic Co-operation and Development (OECD, 2020: 5) core measure of the digital economy is 'economic activity from producers of Digital content, ICT goods and digital services'. Both definitions contain a specific industry code (either four or two digits), and there are some intersections between the two. Here, we define the digital sectors as the union of industry codes from both the UNSD and OECD definitions (Annex 1). This definition based on industry codes can be grouped into three digital sectors: manufacturing, trade, and services (Annex 1).

Examples of industries in the digital manufacturing sector are consumer electronics, electronic components, and computers. Examples of industries in the digital trade sector are wholesale and retail sales of consumer electronics, electronic components, and computers, including those via mail order or internet order. Examples of industries in the digital service sector are computer programming and data processing activities.

Besides investment, we are also interested in studying competition policy. So, in addition to data on investment and labour, we combine other industry-level information such as market concentration measured by the HHI. The index is obtained from the decadal Economic Census 2006.

The HHI can be used to analyse the level of market concentration and hence competition in specific digital sectors. For example, if the HHI for a particular digital sector is high, it may suggest that a small number of companies have significant market power; this could affect investment decisions and outcomes due to high barriers to entry. It could also affect wages and employment depending on the level of monopsonist power. We are interested to see the extent to which market concentration mediates the effect of new investment on wages and employment. Table 5.1 provides examples of specific digital sectors by market competition level.

Table 5.1: Examples of Digital Sectors by Market Competition Level

Herfindahl-Hirschman Index	Digital Manufacturing	Digital Trade	Digital Services
Highly concentrated (high Herfindahl-Hirschman Index, >1,500)	Manufacture of computers and peripheral equipment Manufacture of communications equipment Manufacture of consumer electronics	Wholesale of electronic and telecommunication equipment and parts	Satellite telecommunication activities Internet service providers Computer consultancy, computer facilities management activities
Competitive (low/medium Herfindahl-Hirschman Index, <=1,500)	Manufacture of electronic components and boards	Retail sale of computers, peripheral units, software, and telecommunication equipment in specialised stores Retail sale via mail order or via internet	Software publishing Other information service activities (e.g. resale of internet services) Repair of computers and communications equipment

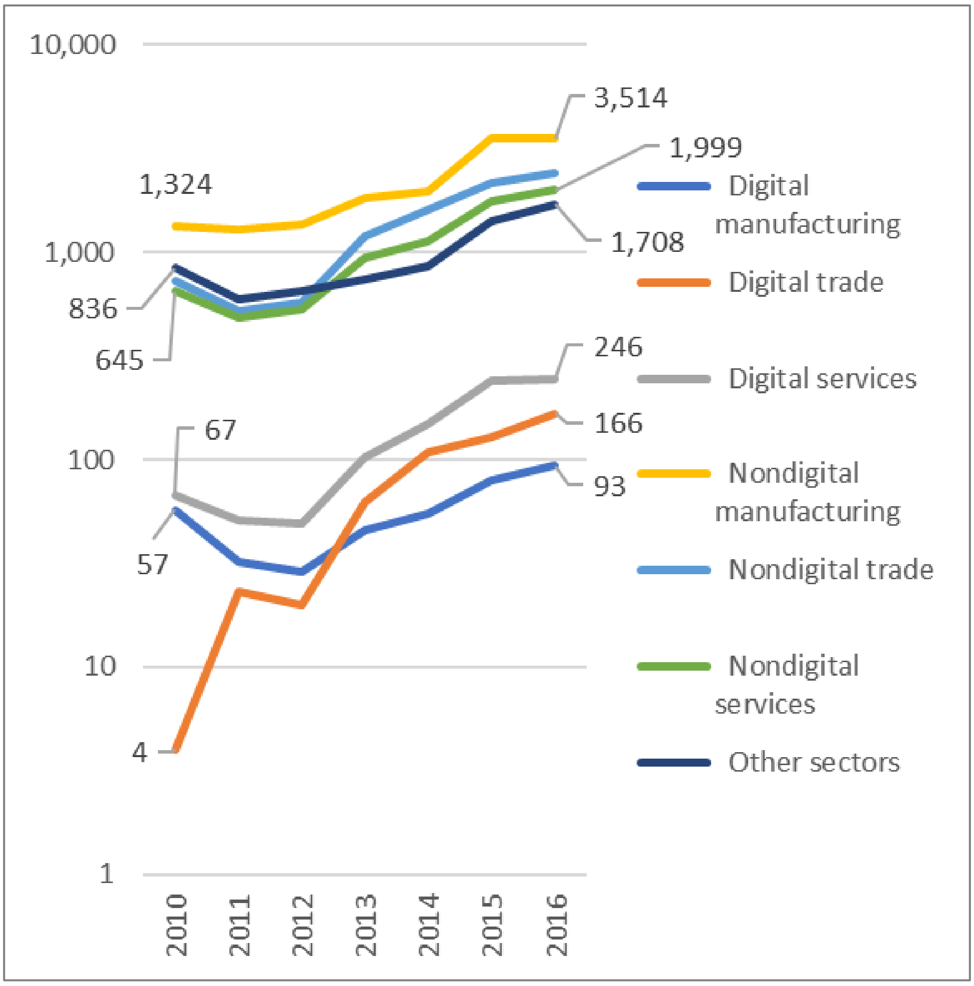
Sources: OECD (2020); UNSD (2008); Economic Census 2006; authors' calculations.

5.2. Digital Investment in Indonesia: Descriptive Statistics

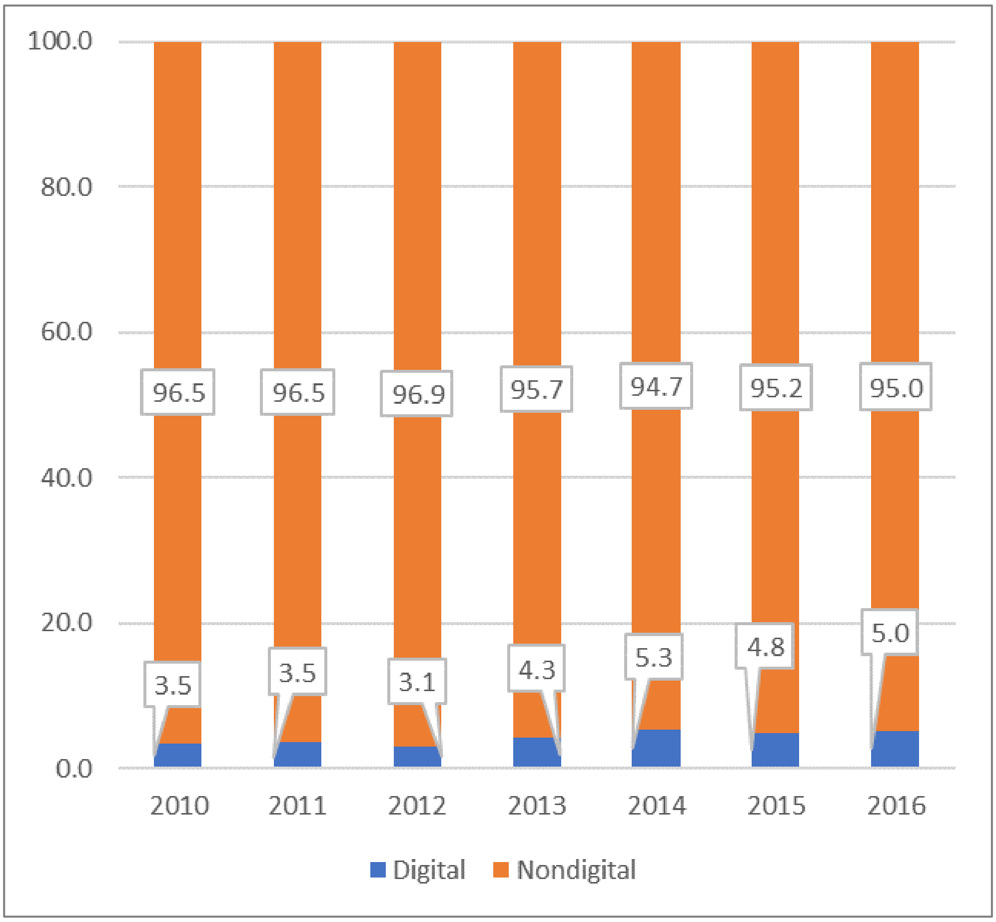
Digital investment in Indonesia is growing rapidly (Figure 5.1a), though it still accounts for a relatively small share of all investment. The share of new investment projects in the digital sectors relative to the nondigital sectors significantly increased in 2013 and has hovered at around 5% of total new investment projects since then (Figure 5.1b). The digital services sector dominates new digital investment projects, accounting for 50% between 2010 and 2016. In the same period, the number of new investment projects in digital manufacturing grew more slowly than in digital trade and digital services. While the number of new digital manufacturing investment projects almost doubled (from 57 to 93) between 2010 and 2016, the number of digital services investment projects increased fourfold (67 to 246) and in digital trade, 40-fold (from 4 to 166).

Figure 5.1: New Realised Investment Projects

a. Total Number of New Investment Projects

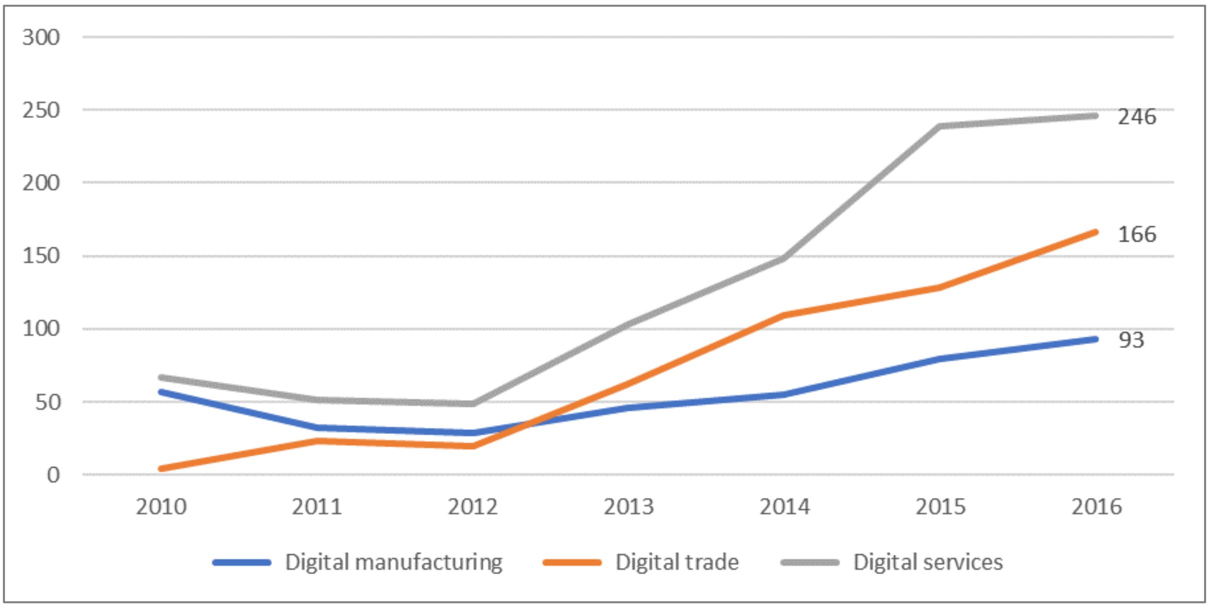


b. Share of Digital New Investment Projects
(%)



Source: Authors' calculations based on investment data from the Ministry of Investment (retrieved in 2020).

Figure 5.2: Total Number of New Investment Projects in the Digital Sector

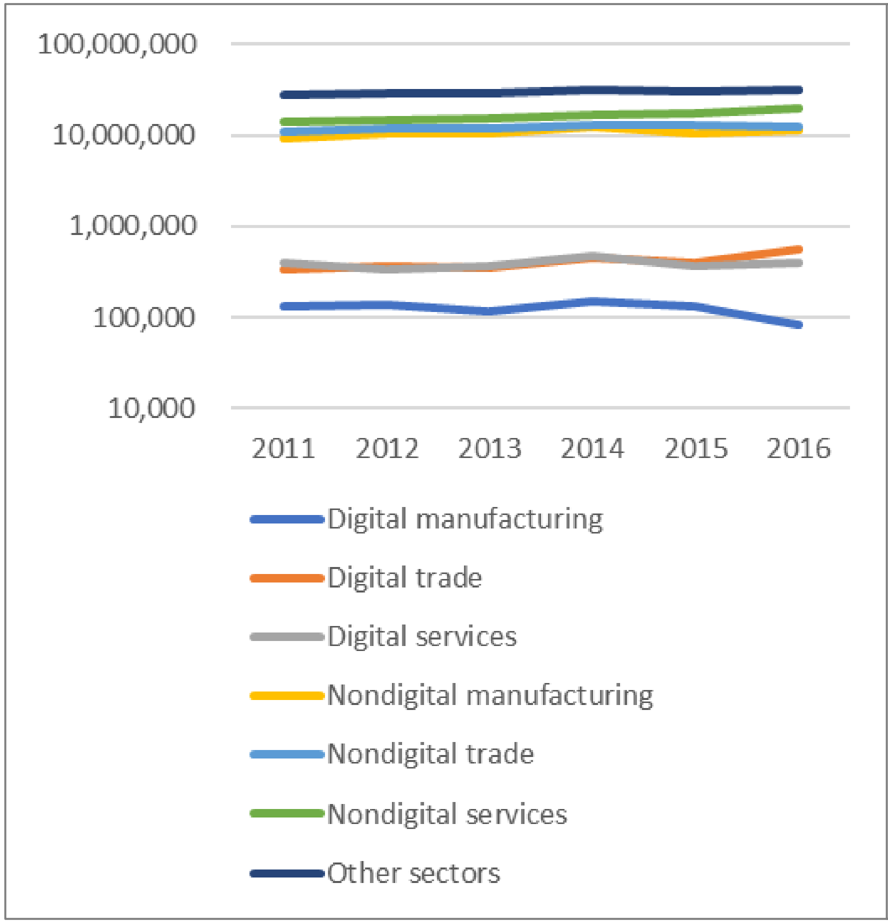


Sources: Authors' calculations based on investment data from the Ministry of Investment (retrieved in 2020).

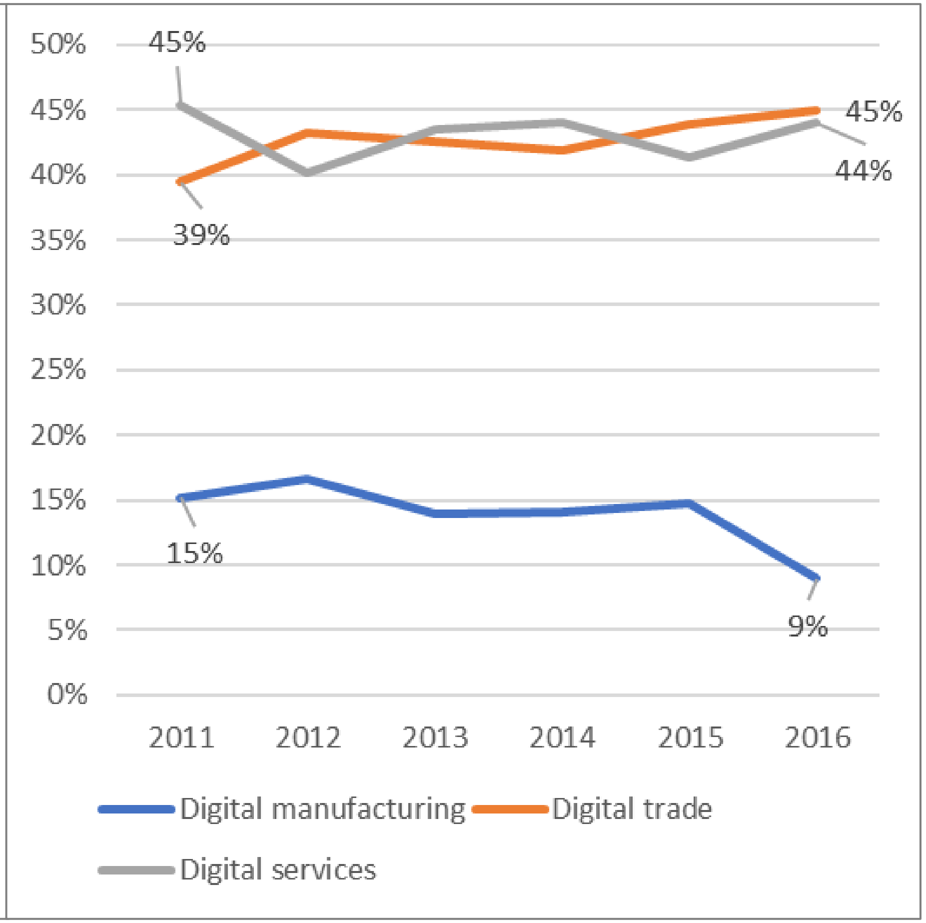
This upward trend in digital investment is, however, not reflected in the employment share. Between 2011 and 2016, the share of employment in the digital sectors out of all employment hardly changed, hovering around 1.2%. Within the digital sectors, the employment share of digital services remained stable at 45% and the employment share of digital manufacturing declined from 15% in 2011 to 9% in 2016 while the digital trade sector increased its contribution to digital employment, rising from 39% in 2011 to 45% in 2016 (Figure 5.3b). In absolute terms, employment in digital manufacturing fell by 38.5% between 2011 and 2016 (Figure 5.3a).

Figure 5.3: Employment

a. Total Employment



b. Share of Employment (%)



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Note: Employment refers to the self-employed, employees, and casual workers.
Source: Authors' calculations based on Sakernas 2011–2016.

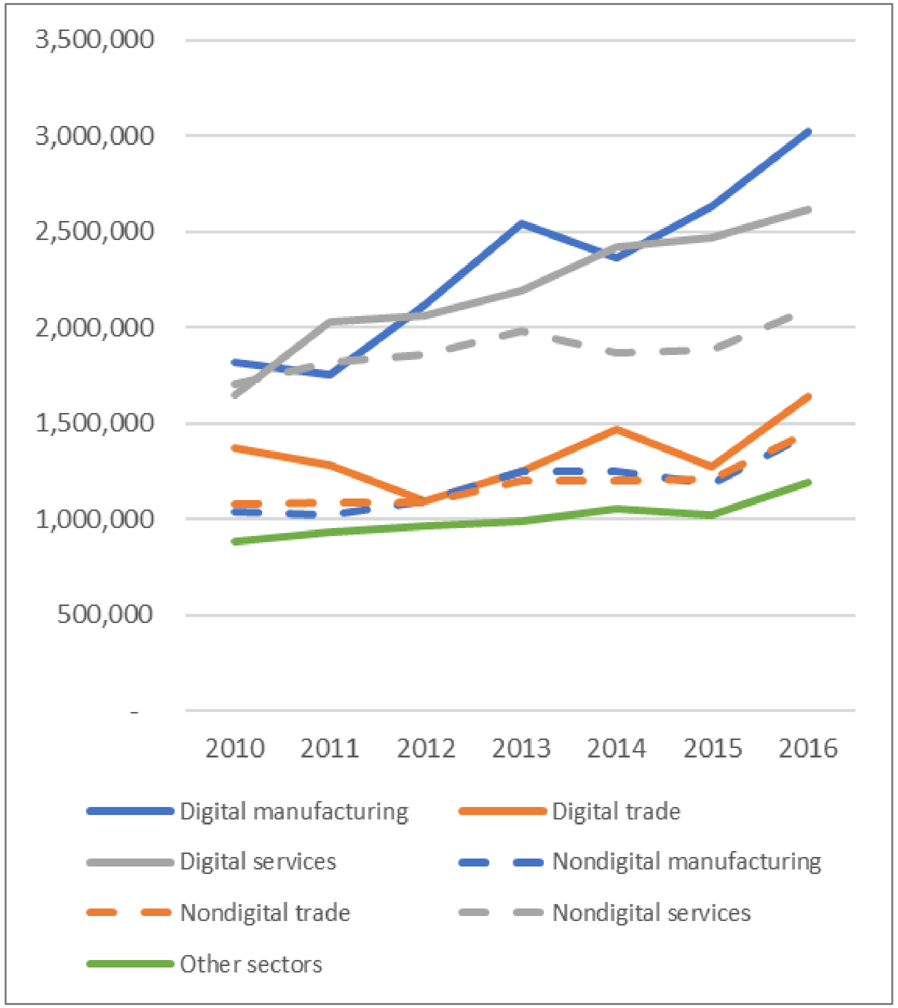
The fact that the employment share of the digital sectors as a whole does not increase despite increasing digital investment raises questions as to how new investment affects the wages and employment of workers in the sectors. Increased investment that is not followed by a proportionate increase in employment might initially suggest that the new investment is capital-intensive or that the enterprises are self-employed businesses. As the capital per labour ratio becomes higher, one could expect the marginal productivity of labour to increase, leading to higher wages.

Looking at the Sakernas data, workers in the digital sectors generally enjoy higher wages than their nondigital counterparts. Workers in the digital and nondigital sectors enjoy a similar rate of growth in real wages, but some heterogeneity persists across the three digital sectors. Workers in digital manufacturing earn the highest mean wage, followed by digital services, and last, digital trade.

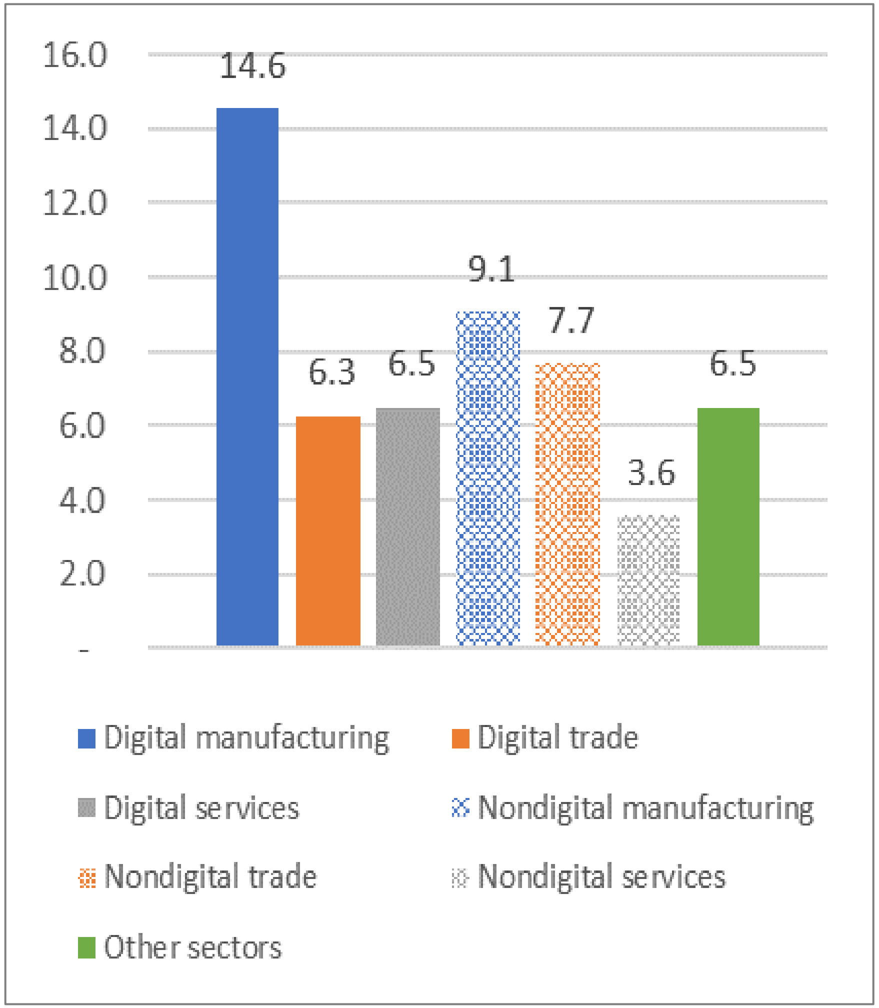
The decrease in employment in digital manufacturing is followed, however, by a positive trend in real wages. The digital services sector has the second-highest real wage for most of the years of observation (Figure 5.4a). Meanwhile, wages in digital trade for the period are comparable to the nondigital sector. Digital manufacturing had the highest wage growth, followed by digital services and digital trade (Figure 5.4b).

Figure 5.4: Real Wages

a. Real Wage Across Sectors
(Rupiah, 2010)



b. Average Annual Change in Real Wage, 2011–2016
(%)



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Source: Authors' calculations based on Sakernas 2011–2016.

The descriptive statistics indicate that the trends in digital investment and real wages in the digital sectors were more dynamic than the trend in (the share of) digital employment.

5.3. Methodology

To further test the relationship between digital investment, wages, and employment, we conducted an econometric analysis. In this study, we use empirical strategies to estimate digital investment effects on wages and employment. The wage analysis is conducted at the mean level and the employment analysis is conducted as the sum of total employment. Moreover, we use the number of realised new investment projects in our analyses. Such data are arguably more accurate than investment values, while planned investment might not be realised. This section describes these two approaches.

a. Wage estimation

We estimate the impact of investment on wages using individual-level data sets available from Sakernas. Our empirical model adheres to Equation 5.1:

$$\begin{aligned}\ln(Wage)_{i,j,t} = {} & \beta_0 Dig_j + \beta_1 Inv_{j,t} \\ & + \beta_2 Dig_j * Inv_{j,t} + \beta_3 HHI_j + \beta_4 Dig_j * HHI_j + \beta_5 Dig_j * Inv_{j,t} * HHI_j \\ & + \boldsymbol{\beta X_{i,j,t}} + \theta_t + \epsilon\end{aligned} \quad (5.1)$$

where:

$\ln(Wage)_{i,j}$	is the monthly wage (in terms of 2010 Indonesian rupiah)
Dig_j	is the dummy if sector j classifies as a digital manufacturing, trade, or service sector
$Inv_{j,t}$	is the total investment (using the number of new realised investment projects) in sector j in year t
$HHI_{j,t}$	is the industry concentration dummy, =1 if HHI > 1,500 (highly concentrated)
$\boldsymbol{X_{i,j,t}}$	is the vector of individual characteristics (age, years of education, gender, urban, employment status, formality of job, high skill dummy)
θ_t	is the year-specific effect
ϵ	is the error term

One could estimate Equation 5.1 using ordinary least squares (OLS) regression to obtain the effect of the coefficient of interest (β_2) on the mean wage. However, as we are interested in examining the heterogeneity of the effects of new investment projects, we study how the effects are distributed across the income distribution and on wage inequality. To estimate the distributional statistics apart from the mean, we use the recentred influence function (RIF) regression approach (Firpo, Fortin, and Lemieux, 2009; Rios-Avila, 2020), which allows us to model how changes in the independent variables affect the values of some distributional statistics of our dependent variables (Annex 2). We then estimate Equation 5.1 with the mean of the monthly wage as the left-hand side variable, but also its first to ninth decile, in addition to the Gini coefficient of the wage distribution. We cluster the standard errors at the industry level.

b. Employment estimation

In estimating the effects of new, realised investment on employment, we aggregate the individual-level data set at the four-digit industry code level. The estimated number of workers employed in each sector can be constructed by adding frequency weights of samples that belong within each industry code. We conduct further disaggregation of workers, including by gender, educational level, age group, and skill level.[17]

We use Equation 5.2 to estimate the effects on employment:

$$\begin{aligned} \ln(Nempl)_{j,t} &= \beta_0 Inv_{j,t} \\ &+ \beta_1 Dig_j * Inv_{j,t} + \beta_2 Inv_{j,t} * HHI_j + \beta_3 Dig_j * Inv_{j,t} \\ &* HHI_j + \beta_4 Formal_{j,t} + \theta_t + \omega_j + \epsilon \end{aligned} \tag{5.2}$$

where:

$\ln(Nempl)_{j,t}$ is the log of the total number of employments in sector *j* at time *t*

$Dig_j Inv_{j,t}$ is the total investment (using the number of new realised investment projects) in sector *j* in year *t*

Dig_j is the dummy if sector *j* classifies as a digital manufacturing, trade, or service sector

$HHI_{j,t}$ is the industry concentration dummy, =1 if HHI > 1,500

$Formal_{j,t}$ is the share of formal workers in sector *j* in year *t*

θ_t is the year-specific effect

ω_j is the industry-specific fixed effect

ϵ is the error term

[17] Skill level is constructed based on one-digit ISCO-88 codes for each worker. See Eurofound (2010).

Since the Sakernas data are collapsed into four-digit industry codes, we treat our data set as panel data. We then estimate Equation 5.2 using panel data OLS and adding industry-specific fixed effects.

5.4. Results

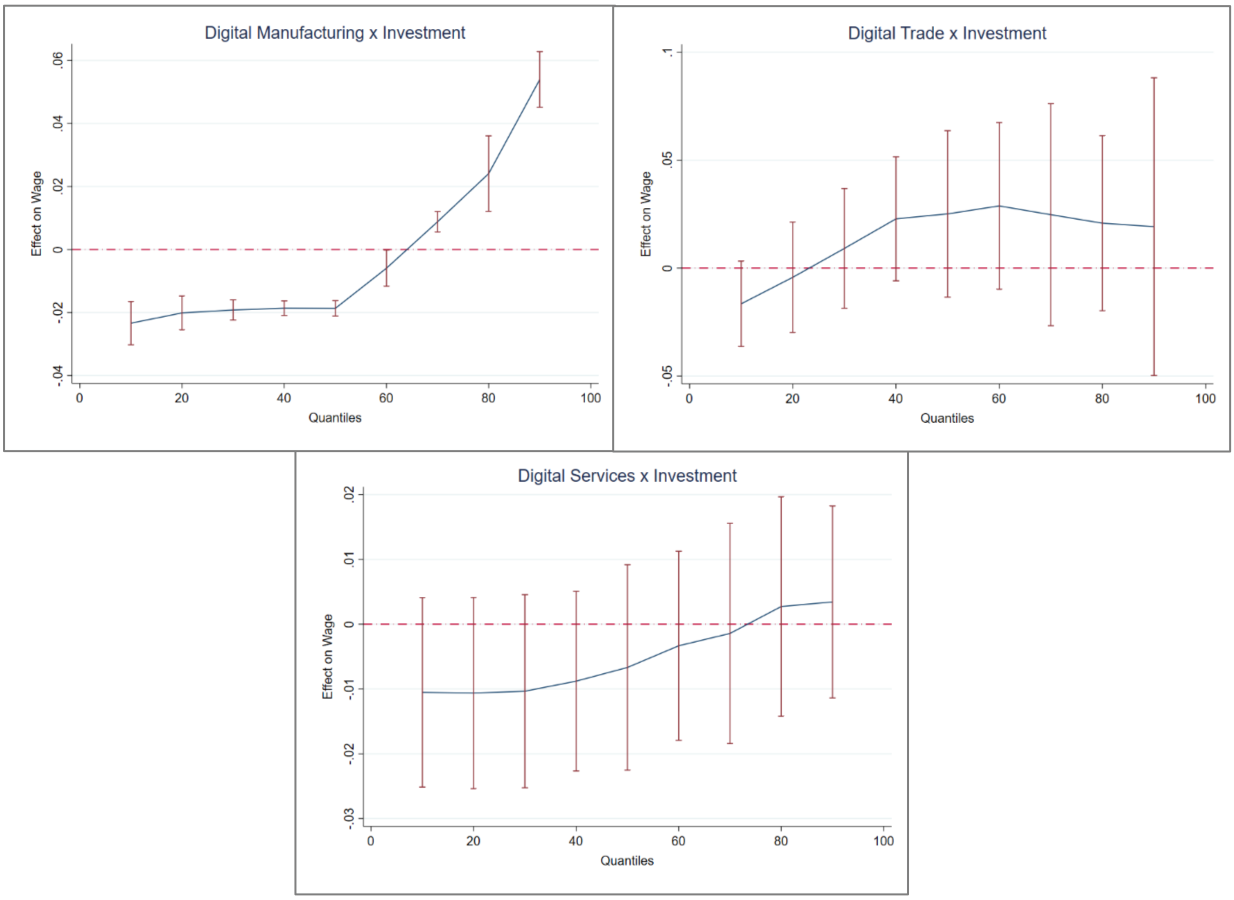
Wage estimation

The estimated regression coefficients reveal a heterogeneous effect of digital investment on the wages of workers across different quantiles of the income distribution (Annex, Table A5.1). On average, a new investment project significantly increases the mean wage by 0.2%. The mean wage in the digital manufacturing sector is about 56% higher than in the nondigital sector, while the mean wages in the digital trade and service sectors are not significantly different from the nondigital sectors after controlling for other variables. A new investment project in any of the three digital sectors does not increase or decrease the mean wage for workers in the respective sectors. However, a new investment project in digital manufacturing significantly impacts the wages of workers across quantiles of income distribution differently.

The quantile regressions show that investment in digital manufacturing disproportionately benefits (disadvantages) workers at the top (bottom) of the income distribution (Figure 5.5). A new investment project in digital manufacturing offers significantly lower wages for workers in the lower quantiles (bottom 60 percentiles) while increasing wages for those in the upper quantiles (upper 40 percentiles). In other words, new digital manufacturing investment tends to favour high-income workers, who are more likely to be highly skilled workers, while disfavouring low- and middle-income workers, who are more likely to be low- and middle-skilled workers. This presumably occurs through automation and other high-skilled-biased technological change.

Since lower wages are often positively associated with lower educational level of workers, this result is consistent with the findings on skill-biased technological change regarding internet penetration. This result may also be related to the fact that new investment in digital manufacturing is capital-intensive and more likely to benefit highly skilled and specialised workers whose skills complement emerging technologies and who can operate advanced machinery. Low- and middle-skilled production workers may be more easily replaced by machines or automated processes. Hence, this result is also consistent with the findings on routine-biased technological change in Section IV.

Figure 5.5: Marginal Impact of New Investment Projects on Wages



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Note: Bars show a 95% confidence interval.
Sources: Sakernas; investment data from Ministry of Investment (2020); authors' calculations.

In contrast, new investment projects in digital trade and digital services have no significant impact on wages across the income distribution.

The heterogeneous impact of digital manufacturing investment on wages of workers across quantiles is reflected in the Gini measures of wage distribution. Although, on average, a new investment project is found to not significantly affect income inequality as measured by the Gini coefficient, a new investment project in digital manufacturing appears to significantly increase income inequality – albeit only by 0.1 percentage points. A new investment project in digital trade and digital services also increases income inequality in the mean regression, albeit by only a small magnitude, and it is not evident in the quantile regressions. This result echoes the study by Lee and Wie (2015), who found that technological progress has contributed to the widening income inequality in Indonesia, with both the between- and within-industry shifts of labour demand favouring skilled workers, who are generally concentrated at the top of the income distribution.

We further study how market concentration changes mean wages and income inequality and whether it changes how a new investment project impacts wages and income inequality. First, the results show that, on average, a more concentrated industry does not significantly result in higher or lower average wages, though it does exhibit a higher level of wage inequality – by 1.4 percentage points. However, in digital trade and services, mean wages in a more concentrated industry tend to be significantly higher on average – by 29% and 35%, respectively. This result does not hold for digital manufacturing.

One reason for this could be the network effect that comes with a highly concentrated digital trade and services sector, where the value of a product, service, or platform is dependent on and/or exponentially increases with the number of users. This is the case for social media platforms like Facebook. Furthermore, the network effect creates barriers to entry for new competitors, giving established companies more capacity to create value on their network (Norbäck, Persson, and Tåg, 2014). The benefits accrued from this network effect may exacerbate existing income inequality (Ioannides and Loury, 2004).

Furthermore, highly concentrated industries in digital trade and services, including satellite communications, wholesalers of ICT products, and internet service providers, often consist of large businesses (Table 5.1). These platforms, technology companies, and businesses tend to be formal and large, and offer higher wages. This is in contrast to more crowded and competitive industries such as e-commerce retailers and other gig economy enterprises, many of which are informal and comprise the self-employed.

Interestingly, market concentration does not change how a new investment project impacts the mean wage and wages across different quantiles.

Employment estimation

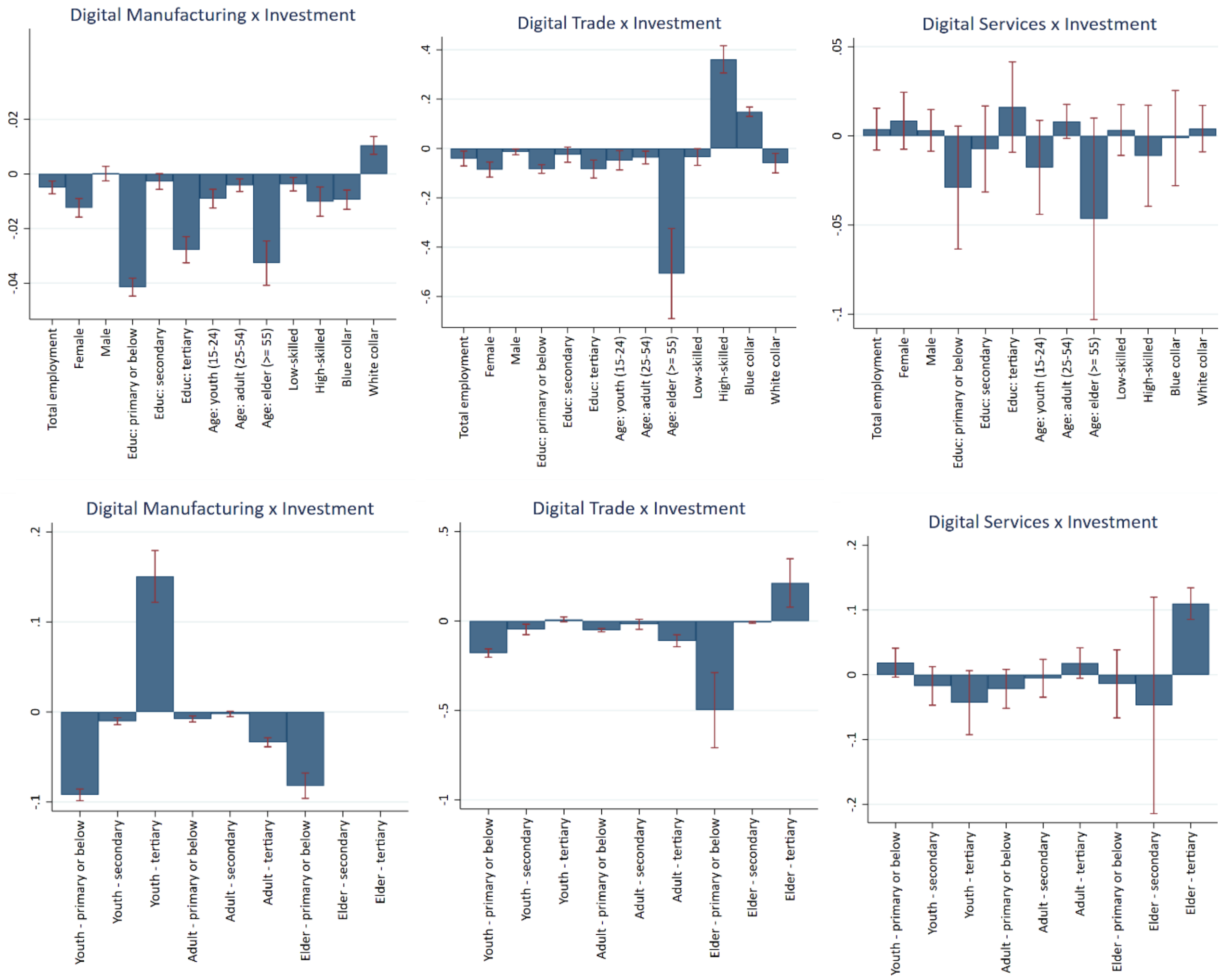
Using sector-level regression, we estimate the effects of a new investment project on total employment and the employment of specific groups of workers (by age, gender, education, and skill level). Our coefficients of interest are the interaction term between a new investment project and dummies for each digital sector. We are also interested to see how market concentration affects employment and whether it changes how a new investment project affects employment.

On average, a new investment project, whether digital or nondigital, has a significantly positive effect on employment (Annex, Table A5.2). A new investment project increases total employment by 0.2%. However, a new investment project in digital manufacturing and digital trade reduces employment by 0.5% and 4.1%, respectively.

The negative impact on employment of a new investment project in digital manufacturing is most pronounced amongst female workers; less-educated youth and older workers; and blue-collar (both low- and high-skilled) workers (Figure 5.6). Blue-collar, low-skilled workers include plant and machine operators and assemblers, while blue-collar, high-skilled workers include electrical installers and repairers. Meanwhile, highly educated youth and white-collar workers benefit most from a new digital manufacturing investment project.

The negative impact on employment of a new investment project in digital trade is most pronounced amongst female workers; less-educated older workers; and white-collar, low-skilled workers (often associated with clerical and sales workers) (Figure 5.6). Meanwhile, highly educated older workers and high-skilled, blue-collar workers (such as electrical and electronics trade workers) benefit the most from such a project.

Figure 5.6: Marginal Impact of New Investment Projects on Employment, by Worker Group



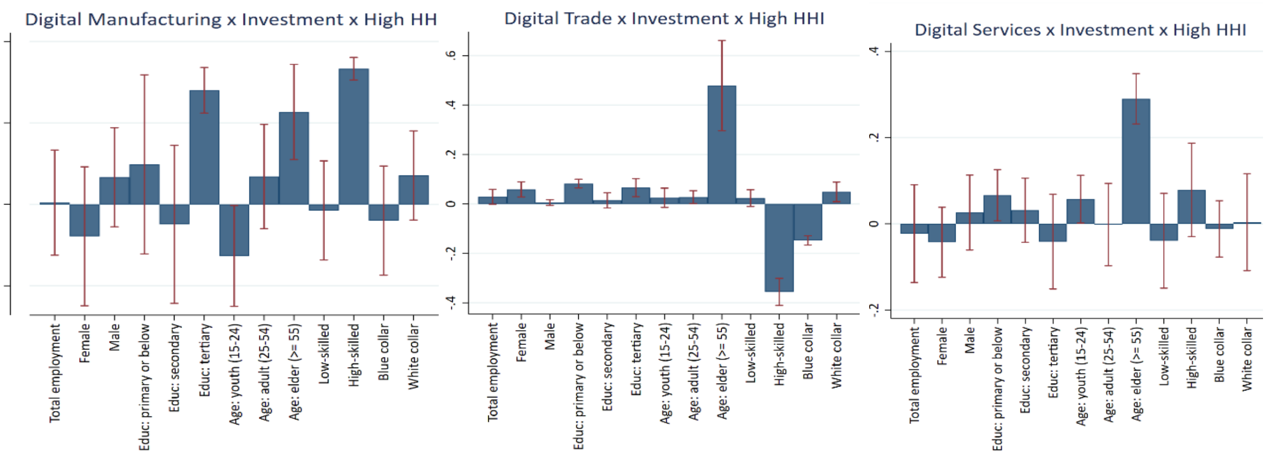
Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Note: Bars show a 95% confidence interval.
Sources: Sakernas; authors' calculations.

The finding of section 3 and 4 corroborates the finding of this section that less-educated workers and workers with high routine task content – whether in blue- or white-collar jobs – are more easily replaced at the onset of digital technological change. There are, however, cases where high-skilled jobs could also be adversely affected.

It is also worth noting that a new investment project in digital services has no effect on total employment but has a positive effect on the employment of highly educated older workers.

Looking at the interaction terms of the industrial concentration dummy, results indicate that a new investment project in a more concentrated industry significantly reduces overall employment by 0.2%. However, a new investment project in a more concentrated industry in digital trade offsets this overall effect. It marginally increases employment by 2.9%. Again, this could be due to the network effect. Older workers benefit the most in terms of employment from a new investment project in a more concentrated industry in digital trade.

Figure 5.7: Marginal Impact of Market Concentration on the Marginal Return on A New Investment Project on Employment, by Worker Group



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Source: Authors' calculations based on Sakernas.

In conclusion, the effects of a new investment project in the digital sectors on wages and employment are more complex and nuanced than the dichotomous narrative of absolute good or bad. Investment in the digital sectors has varying effects on different types of workers in different digital sectors. However, the overall narrative still holds: workers who are more advantaged to begin with, such as high-skilled and better-educated workers, benefit more from a new investment project, while low- and mid-skilled and lower-educated workers are more likely to lose out, although there are cases where high-skilled workers could also be adversely affected.

We show that digital investment has increased income inequality, albeit trivially, where workers in the upper income distribution benefit more from a new project. The interplay between displacement and reinstatement effects may take place amongst some types of workers and reinforce or reduce income inequality. In some cases, such as in digital trade and manufacturing, a new investment project has reduced overall employment, especially for workers whose jobs involve largely routine tasks, such as production, clerical, and sales workers. However, a new investment project in the digital sectors could provide better opportunities for other groups of workers to participate in the formal economy. A new investment project in digital manufacturing provides better employment opportunities for highly educated youth, while a new investment project in digital trade provides better employment opportunities for blue-collar, high-skilled workers. Market concentration has also worked differently in the digital sectors than in the traditional nondigital sector, which may call for different competition policies.

By taking a comprehensive and proactive approach to digital investment, policymakers can help ensure that the benefits of technology are harnessed and felt by all. Given the distinct and differentiated impacts, policymakers could tailor and target their policies accordingly. The narrative that digital investment has an absolute positive or negative impact on employment needs to go deeper, looking beyond the aggregates and examining each group of workers. The evidence from this study could inform policymakers on how to put in place (pre-emptive) policies that compensate (potential) losers, including policies that help workers retrain and enter jobs and sectors that potentially benefit more from digital investment.

Box 1: The Effect of COVID-19 on Digital Gig Workers in Indonesia

The mobility restrictions imposed by governments to cope with the coronavirus disease (COVID-19) had a severe impact on location-based businesses. They also led businesses, workers, and customers to adopt digital technology. The use of digital technology, including for e-commerce and remote work, had already become increasingly important, and it is expected that workers who were already familiar with the digital economy and were already using the internet in their work will have been less affected by the pandemic.

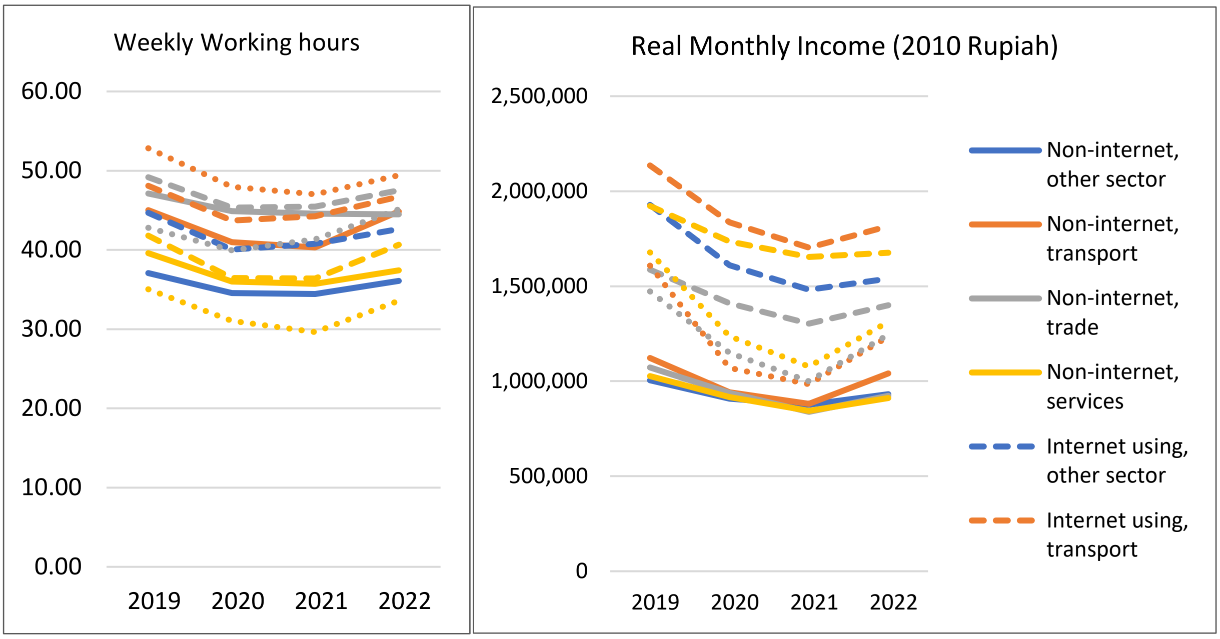
We explore the impact of the pandemic on one type of digital role – the gig worker. The gig economy has become a popular employment option, and the pandemic highlighted the importance of this type of work. Gig workers rely on digital platforms to find work such as ride-hailing and food delivery. This type of work provides flexibility and independence for workers, allowing them to work when and where they want. However, it also brings challenges, including income instability and lack of protection (e.g. from long working hours, accidents, and death). The pandemic exposed these challenges, as many gig workers faced greater economic uncertainty due to reduced demand for their services, mostly due to COVID-19 mobility restrictions.

Gig workers are relatively young, with a higher level of education than the general labour force (World Bank, 2021). Men are more likely to work in gig jobs than women (Annex, Table A5.3).

This may be because some gig jobs, such as ride-sharing or delivery services, are seen as more appropriate for males. Gig workers tend to reside in urban areas, where there is high demand for services such as ride-sharing, food delivery, and short-term rentals, for example, of cars.

We found that workers who used the internet before the pandemic, including gig workers, already enjoyed a wage premium compared with workers who did not. However, during the first year of the pandemic, internet-using workers experienced a drop in income. Gig workers in the transport sector experienced the sharpest decline, with a 33.5% drop in income, followed by those in services (down 26.3%) and trade (down 21.9%). Meanwhile, internet-using non-gig workers on average only experienced an income drop of 11.9%, comparable to the 11% decline for non-internet-using workers. Even into 2022, on average none of these groups had restored their monthly income to pre-pandemic levels. This indicates the significant impact of the pandemic on the digital economy and the vulnerability of gig workers, most of whom are informal and uncovered (i.e. not covered by the labour law), to economic shocks. It also highlights the need for policymakers to support gig workers and other internet-using workers who have been affected by the pandemic.

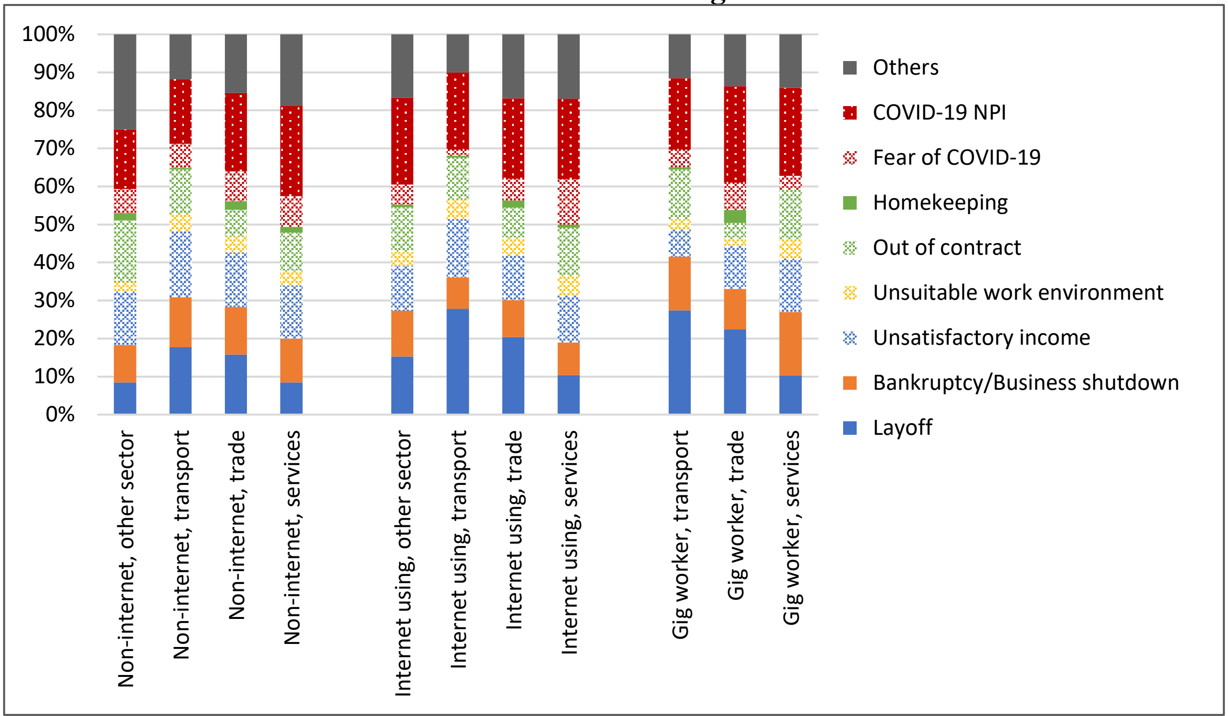
Figure B1.1: Weekly Working Hours and Monthly Income, Before and After the Pandemic



Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Source: Authors' calculations based on the August rounds of Sakernas, 2019–2022.

This downshift in wages may not entirely be due to the nature of internet and gig work or mobility restrictions, but may reflect the shift of workers towards gig jobs, which has driven down tariffs. During the first year of the pandemic, many workers lost their jobs due to mobility restrictions and the general economic downturn. At the same time, gig jobs managed to absorb some of these, with around 310,000 people turning to gig work between March and August 2020. Most of these workers (around 58%) joined the trade sector as gig workers, followed by transportation at 27%, and services at 14.9%. While this number is much smaller than the number of jobs absorbed by non-internet-using workers, it shows that gig jobs provide an alternative source of income for many people who have lost their jobs. It is interesting to note that a larger share of new gig workers, compared with other types of workers, reported that they were once jobless for reasons related to the economic downturn accompanying the COVID-19 pandemic, such as being laid off or their workplace shutting down, indicating that gig jobs are a valuable alternative for those who are struggling to find work elsewhere.

Figure B1.2: Reason for Unemployment Amongst Those Becoming Jobless between March and August 2020



COVID-19 = coronavirus disease, NPI = non-pharmaceutical intervention, Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Source: Authors' calculations based on August rounds of Sakernas, 2019–2022.

In conclusion, the gig economy became increasingly crucial during the pandemic, serving as an alternative income source offering some level of income for workers and acting as a bridge between low-paying, low-skilled jobs and high-paying, high-skilled internet jobs. However, this experience also highlights the fact that digitalisation alone does not guarantee higher wages or economic security. Upskilling must accompany digitalisation to maximise the benefits for workers.

6. Policy Recommendations

To address the digital divide potentially arising from skill-biased technological change, routine-biased technological change, and digital investment, we recommend that policies to accelerate Indonesia's digital transformation and liberalise its digital investment are accompanied by policies on education, the labour market, investment, trade (including service trade), and competition (Table 6.1).

Table 6.1: Complementary Policies to Ensure an Inclusive Digital Transformation in Indonesia

Policy	Actions
Education, including technical and vocational education and training	Improve educational outcomes (enrolment and quality) and facilitate (lifelong) learning.
Active labour market	Constantly review and adjust labour market policies to fit with the changing nature of jobs and business models.
Trade and investment	Reduce restrictions/barriers to importing equipment and key personnel and on FDI in the digital sectors or sectors supporting the digital sectors.
Competition (especially for a networked industry)	Use existing economic cooperation (the Regional Comprehensive Economic Partnership, ASEAN Digital Economy Framework Agreement) and other existing frameworks (e.g. the EU's Digital Markets Act) to discuss best practices in competition policy for the digital sector.
Internet infrastructure	Improve access to and quality of internet connections and reduce internet prices to facilitate digital learning.

ASEAN = Association of Southeast Asian Nations, FDI = foreign direct investment, EU = European Union.
Source: Authors' analysis.

Improving educational outcomes: Indonesia could improve educational outcomes (enrolment and quality) and facilitate learning, especially for adult workers with low levels of education. It is evident that less-educated workers are most likely to lose (but also most likely to gain) from the rapid digital transformation, as they are usually least equipped with digital and nondigital skills. We list four key policy recommendations to improve educational outcomes and facilitate learning as proposed in Wihardja and Cunningham (2021).

- Indonesia could support students at risk of dropping out of school to ensure they complete high school. Currently, only around 40% of the Indonesian workforce has completed high school. Such policies may include developing a systematic protocol for mapping youth who are at risk of dropping out and the reasons for this, as well as fine-tuning interventions.
- Indonesia could support the development of and access to certified online distance learning, including technical and vocational education and training courses for adult workers. Indonesia could continuously assess the quality of web-based training courses, provide public financing for adult workers, incentivise employers to provide more on-the-job training, and support the development of a database of accredited online training.
- Indonesia could revise its curriculum and pedagogical methods to teach non-routine interpersonal, analytical, and digital skills to students and adult learners. This could be achieved by fine-tuning a strategy for developing analytical, routine cognitive, interpersonal, and digital skills from early childhood through adulthood; developing pedagogical methods and learning materials to implement the expanded curricula; training teachers to adopt the materials; and tracking progress.
- Indonesia could improve its training system by prioritising the development of quality-assurance mechanisms and more effectively engaging the enterprise sector.

Japan's reskilling and education reform may provide lessons for Indonesia. Japan reformed its labour law in 2019 to address outdated workplace rules, but also introduced reskilling and education reforms (Schaede and Shimizu, 2022). Japan is also revising its high school curriculum to prepare the next generation of digitally savvy workers (Schaede and Shimizu, 2022).

Active labour market: Indonesia could allow flexibilities in labour market policies to accommodate rapid changes in jobs as digital technologies evolve. The recent phenomenon of generative AI is one example of how fast-changing digital technology leaves policymakers and other stakeholders with no choice but to adapt and adopt more agile policies.

Gig jobs are a relatively new phenomenon. More workers are no longer tied to one company for a 9-to-5 job, but can hold dual or even multiple on-demand or gig jobs. The job market has also become more fluid, with workers no longer tied to one company throughout their career. Job-matching platforms have, to some extent, helped with worker mobility and job upgrading but they have also facilitated more aggressive poaching and, hence, higher job turnover. To accommodate the changing nature of jobs, labour market policies need to be continuously reviewed.

Indonesia, through its Omnibus Law on Job Creation in 2022, redefined employment to accommodate the changing nature of jobs, in particular gig jobs. The law also introduced an unemployment insurance system that cushions income shocks in lieu of a severance payment system that rewards tenure. This will help workers transition up the job ladder without being punished by leaving their jobs early. Continuous support for job mobility, including helping workers to relocate, is necessary as job switching in Indonesia is still costly (Wihardja and Cunningham, 2021). Policies to support job mobility may include upgrading the national government job-matching tool and providing a stipend for workers to move jobs in occupations that are strategic for Indonesia's economy, and where workers are in high demand and short supply, including in digital technology.

Trade and investment: Indonesia could reduce restrictions or barriers to FDI in the digital sectors and sectors supporting the digital sectors. It could also reduce restrictions or barriers on importing intermediate inputs and service trade, especially regarding the movement of workers, including foreign ICT specialists.

Digital investment has contributed to Indonesia's dynamic digital economy and digital society as well as overall GDP, notwithstanding its heterogeneous impacts on labour and the need for complementary policies. In an increasingly digitally connected world, embracing digital transformation may bring more net benefits than avoiding it, as long as there are regulations and policies to minimise risks. Digital investment, even when assessed against potential risks such as those relating to the digital divide and financial instability (Rohman and Wihardja, 2022), should be encouraged.

Liberalisation of digital investment is a pro-competitive and pro-job policy in developing countries such as Indonesia if certain measures and safeguards are in place. While the positive relationship between robots and productivity has been well established (see, for example, Graetz and Michaels, 2018), the net effect on employment is ambiguous. Several studies argue that in a country at an earlier stage of industrialisation (Calì and Presidente, 2022) and lower-level automation adoption (Das et al., 2019) such as Indonesia, the employment gain from the productivity growth arising from automation offsets the employment loss due to displacement. This leads to net positive impacts for employment.

Concerns regarding job security and security in general, including national security, related to digital investment should be addressed with policies. The newly automated industries may require workers with different skills, and it is important to complement investment policies with digital education and training policies. Furthermore, national security concerns related to interventions from foreign countries may not be so relevant to Indonesia's current situation regarding automation, although cybercrimes and date leakages are rife in the country. Hence, the government needs to strengthen policies related to security, including cybersecurity measures, personal data privacy laws and regulations on the internet and digital security.

To accelerate digital transformation, the Indonesian government relaxed and removed foreign equity ownership restrictions in e-commerce, ICT, and telecommunications through the Omnibus Law and its implementing regulation (Presidential Regulation No. 49, 2021). In e-commerce, for example, 100% foreign equity ownership is now permitted. Evidence shows that removing restrictions on FDI would not only substantially increase foreign investment in Indonesia, but would also crowd in domestic investment and increase technological spillovers and productivity growth in domestic firms (Calì et al, 2022; Genthner and Kis-Katos, 2022). Hence, the government's effort in raising the foreign equity limit for digital and related investment through the Omnibus Law will help spur digital development in Indonesia.

Further down the value chain, in the manufacturing of ICT goods, Indonesia has a local content requirement policy for the telecommunication industry, requiring 30%–40% of local content for 4G/long-term evolution equipment (Negara, 2016). This means that foreign companies wishing to sell their 4G/long-term evolution products must either build a factory in Indonesia or find a local partner. This policy is intended to spur innovation in the Indonesian manufacturing industry in 4G/long-term evolution products. However, with the potentially higher costs of trade and restricted access to best quality inputs as a result of the local content requirement, Indonesia may lose competitiveness, especially amongst export-oriented 4G/long-term evolution manufacturers. Foreign investors may refrain from investing altogether. Moreover, it may be more costly for Indonesian consumers to access locally produced ICT goods.

As importantly, restrictions or barriers to service trade, especially related to the movement of personnel such as foreign ICT specialists, could be lowered to fill roles for which there is a shortage of domestic workers. Digital talent is in shortage in many countries. By 2030, there will be a digital talent shortage of 47 million workers in the Asia-Pacific region, while Indonesia needs about 600,000 every year and is still in shortage (OJK Institute, 2022). Indonesia's share of foreign labour was only 0.06% in 2016, much lower than its Asian neighbours, and although it has reformed its policy towards hiring foreign workers, there remains room for improvement to ease access to foreign talent, including digital talent (Wihardja and Cunningham, 2021).

As Indonesia becomes more open to foreign investment and trade, it could ensure that domestic firms and workers benefit from tech spillovers of FDI and more open trade policies in the digital sectors. Policies to increase technology spillovers could include increasing the quality of human capital and domestic workers, promoting firm links and institutional partnerships between local and foreign companies, and providing incentives and advocacy to promote firm-based training.

Addressing competition issues: Indonesia could address competition issues in a network economy by sharing information, experiences, and best practices with comparator countries in promoting and enforcing competition in digital markets. We find that in digital trade and services, mean wages in a more concentrated industry may be higher than in a less concentrated industry. Moreover, a more concentrated industry in digital trade marginally increases employment. Hence, competition may work differently in the digital sectors compared with traditional sectors. However, a concentrated market is likely to eventually lead to reduced competition – hurting consumers, incoming and smaller producers, and the economy.

In a network economy, firms may require certain market shares (or a certain number of users) before reaching profit. Because of the network effect – a phenomenon by which the value or utility of a user depends on the number of users of compatible products – and the fact that technological advancement has enabled firms to produce at almost zero marginal costs but with large fixed costs, the digital sectors are susceptible to high market concentration. This could reduce competition and create unfair barriers to market entry, including for MSMEs and start-ups. Large tech players could use vertical and horizontal integration to capture and dominate the market at the expense of consumers. Furthermore, a monopsony or 'duopsony'[18]

[18] A duopsony is an economic condition in which there are only two large buyers for a specific product or service.

market structure may undermine workers' bargaining power and drive wages below competitive levels in the longer run (Ing, Anas, and Wihardja, 2022).

A case in point is the increased service fees charged by platforms on their merchants and food vendors after the promotion period ends, as well as race-to-the-bottom tariff-setting in the case of the ride-sharing ecosystem in Indonesia (Rohman and Wihardja, 2022). The OECD and others have found weaker dynamics in the platform economy in Indonesia since 2018 – increasing markups by firms, fewer start-ups, acceleration of mergers and acquisitions by digital firms, and increasing share of aggregate revenues by the largest firms (Boone, Criscuolo, and Mancini, 2019; Rohman and Wihardja, 2022).

Indonesia could amend its competition policies to address the network economy. The Secretariat of the United Nations Conference on Trade and Development (UNCTAD, 2021) elaborated on best practices in competition policy for digital markets. The European Union (EU) Digital Markets Act, which aims to provide more competition in European digital markets, could be considered a model for Indonesia (Ing, Anas, and Wihardja, 2022). This next-generation competition policy of the EU Digital Markets Act adopts an *ex-ante* not *ex-post* approach to regulating competition. The International Competition Network could also provide technical assistance to Indonesia.

Internet infrastructure: To improve internet infrastructure and maximise the benefits of digital economy, the government could improve the availability, accessibility, and quality of internet connections so that firms and students can participate more meaningfully in digital learning and training. The government could reduce internet prices by introducing cost-sharing amongst firms in internet infrastructure and implement a single, uniform licensing system for all internet services.

The theory of leapfrogging development by harnessing digital technology has been a popular but nebulous concept amongst policymakers in many developing countries, including Indonesia, and has been somewhat successful in specific contexts in some developing countries (Yayboke, Crumpler, and Carter, 2020). A case in point is China (Wong and Wihardja, 2022). Although China's remarkable development was a product of various factors, including the opening of the economy and reforms that started in the late 1970s, it leapfrogged in two major areas of the digital economy.

First, China leapfrogged traditional trade by adopting e-commerce for society as a whole. China accounted for less than 1% of global e-commerce in 1999 but nearly 50% in 2022. It is the first country in which e-commerce has surpassed traditional retail transactions and volumes. Second, China also almost leapfrogged the credit card generation altogether, moving from cash to a cashless society by adopting fintech solutions tailored towards financial inclusion. The share of cash in in-store payments in China in 2021 was 8% compared with 19% in Singapore and 51% in Japan (and on a par with developing countries in Southeast Asia) (Statista, 2023). The share of credit card payments in China in 2021 was only 18% compared with 36% in Singapore and 32% in Japan (Statista, 2023). In 2022, 90% of people in China's urban areas and 82% of people in its rural areas made digital payments, and this gap is narrowing rapidly (Statista, 2023). Other encouraging successes are Kenya's nationwide adoption of mobile money and Rwanda's nationwide 4G mobile connectivity (Yayboke, Crumpler, and Carter, 2020). These countries adopted digital technologies at a relatively low level of development.

The theory of leapfrog development through the adoption of digital technology is not a myth, but it is rare (Cirera, Comin, and Cruz, 2022) and does not happen on a blank slate. Certain preconditions can make digital transformation a success (see, for example, Melguizo, Salido Cornejo, and Welby Leaman, 2021) from a development and inclusion perspective, including public policies, close public–private relationships, and a dynamic entrepreneurial landscape (Wong and Wihardja, 2022).

The successful development of the digital economy in China comes with unique factors that might not be readily replicable in other developing countries (World Bank and Alibaba, 2020). These are mostly because of China's well-calibrated medium- and long-term plans; a light-touch policy approach encouraging investment and innovation at the beginning; investment facilitation into e-commerce and logistics, amongst others, through taxes, policies, and incentives; and the public–private symbiosis (Wong and Wihardja, 2022). In the case of Kenya and Rwanda, similar lessons can be drawn – regulatory flexibility (a deliberately hands-off approach to regulation), a willingness to embrace experimentation, and the public–private–technologist symbiosis (Yayboke, Crumpler, and Carter, 2020).

Most important of all is to remember that not all development challenges can be leapfrogged by using new digital technology. The importance of analogue complements cannot be overemphasised (World Bank, 2016). For a leapfrogging strategy to be sustainable, it must not only enable the adoption of technologies developed by other countries, but it must also drive the creation of new technological systems including through robust innovation policies (Yayboke, Crumpler, and Carter, 2020). Moreover, policymakers should adopt a bottom–up approach by starting with identifying development gaps and then asking how new technologies could help solve them, instead of starting with a digital technological solution that is often purely market-driven (Yayboke, Crumpler, and Carter, 2020).

A leapfrog strategy using digital technology should be a means and not an end. The impacts of digital transformation need to be closely monitored, and public policymaking needs to be data- and evidence-based (Rohman and Wihardja, 2022). Like any other technology, digital technology is a double-edged sword, bringing both benefits and drawbacks. Unfortunately, there are no easy methods of evaluating the externalities – both positive and negative externalities – caused by digital transformation.

7. Conclusion

The three strands of analysis show that digital transformation and digital investment have heterogeneous and differentiated impacts on different types of workers. The overall narrative is clear: workers who are more advantaged to begin with, such as high-skilled and better-educated workers, benefit more from digital transformation and digital investment than low- and mid-skilled and lower-educated workers, who are more likely to lose out. There are, however, cases where high-skilled workers may also be adversely affected. This is the case in Indonesia for the period until 2019 (2016 for the study on the effects of digital investment).

To address the digital divide potentially arising from skill-biased technological change, routine-biased technological change, and digital investment, we recommend that policies to accelerate Indonesia's digital transformation and liberalise its digital investment are accompanied by policies on education, the labour market, investment, trade (including service trade), and competition. Indonesia could improve educational outcomes and facilitate learning. Indonesia could allow flexibility in labour market policies to accommodate rapid changes in the nature of jobs as digital technologies evolve. Indonesia could reduce restrictions or barriers to FDI in the digital sectors and sectors supporting the digital sectors and on importing intermediate inputs and service trade, especially regarding the movement of workers, including foreign ICT specialists. Liberalisation of digital investment is a pro-competitive and pro-job policy in developing countries such as Indonesia. However, the government needs to strengthen certain policies including those that are related to safety and security, such as personal data privacy and cybersecurity laws and regulations. Indonesia could address competition issues in a network economy by sharing information, experiences, and best practices with comparator countries in promoting and enforcing next-generation competition policy in digital markets. Lastly, the government could improve the availability, accessibility, and quality of internet connection so that firms and students can participate more meaningfully in digital learning and training.

Our analyses, however, do not consider the effects of new and emerging digital technologies after 2019 such as generative AI. Contrary to our analysis, a study by Felten, Raj, and Seamans (2023) showed that generative AI exposes mostly highly educated, highly paid, and white-collar workers to job losses. Hence, different digital technologies may have different impacts on the labour market. Our policy recommendations shed light on the findings in this report while considering that digital technologies will continuously evolve.

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Annex

Annex 1: Industry Code-Based Definition of the Digital Sector

United Nations Statistics Division (UNSD) Information and Communication Technology (ICT) Sector

Manufacturing

2610: Manufacture of electronic components and boards

2620: Manufacture of computers and peripheral equipment

2630: Manufacture of communication equipment

2640: Manufacture of consumer electronics

2680: Manufacture of magnetic and optical media

Trade

4651: Wholesale of computers, computer peripheral equipment, and software

4652: Wholesale of electronic and telecommunications equipment and parts

4741: Retail sale of computers, peripheral units, software, and telecommunication equipment in specialised stores

4791: Retail sale via mail order houses or via internet

Services

581: Publishing of books, periodicals, and other publishing activities

5820: Software publishing

591: Motion picture, video and television programme activities

592: Sound recording and music publishing activities

60: Broadcasting and programming activities

6110: Wired telecommunications activities

6120: Wireless telecommunications activities

6130: Satellite telecommunications activities

6190: Other telecommunications activities

6201: Computer programming activities

6202: Computer consultancy and computer facilities management activities

6209: Other information technology and computer service activities

6311: Data processing, hosting and related activities

6312: Web portals

639: Other information service activities

9511: Repair of computers and peripheral equipment

9512: Repair of communication equipment

Note: Blue denotes an additional definition based on OECD (2020).

Annex 2: Methodological Note: RIF Regression

In standard regression models, such as the ordinary least squares (OLS) estimator, the goal is to provide estimates of the regression coefficients that reflect the average relationship between the independent variables and the dependent variable. However, in social welfare analysis, one might be interested not only in the average effect of a variable or policy on point estimates, but also on the distributional effect of the variable (e.g. how a policy could impact the value of the first decile of income distribution, how it influences income inequality as captured by the Gini). The recentred influence function (RIF) regression allows for linear regression models to capture the impact of covariates on many distributional statistics. The method achieves this by leveraging influence functions, which measure the sensitivity of model parameters to changes in individual observations, popularised by Firpo, Fortin, and Lemieux (2009).

Following Rios-Avila (2020), the RIF regression steps are:

1. Defining the (recentred) influence function of statistics of interest

   The influence function (IF) represents the directional derivative indicating how the distributional statistic $v()$ changes in response to a minute alteration in the distribution F_Y along the H_{y_i} direction. Formally:

$$\text{IF }\{y_i,\ v(F_Y)\} = \lim_{\varepsilon\to 0} \frac{v\{(1-\varepsilon)F_Y + \varepsilon H_{y_i}\} - v(F_Y)}{\varepsilon} = \frac{\partial v(F_Y \to H_{y_i})}{\partial \varepsilon}$$

   It can also be understood as the impact that observation y_i has on the estimation of the distributional statistic $v()$. The function can then be recentred around its mean:

$$\text{RIF}\{y_i,\ v(F_Y)\} = v(F_Y) + \text{IF}\{y_i,\ v(F_Y)\}$$

2. Defining the impact of changes in distribution of covariates

   The unconditional distribution of variable Y (and any counterfactual distribution G) and all covariates X can be defined as:

$$F_Y(y_i) = \int F_{Y\,|X}\,(y_i|\mathbf{X} = \mathbf{x})dF_X(\mathbf{x})$$

$$G_Y = \int F_{Y\,|X}\,(y_i|\mathbf{X} = \mathbf{x})dG_X(\mathbf{x})$$

   The statistics $v()$ from distribution Y (or G) can be rewritten based on their RIF, such as:

$$v(F_Y) = \int \text{RIF}\,\{y, v(F_Y)\}\,dF_{y\,|X}\,(y|\mathbf{X} = \mathbf{x})dF_X(\mathbf{x})$$

$$v(F_Y) = \int E[\text{RIF}\{y, v(F_Y)\}|\mathbf{X} = \mathbf{x}]dF_X(\mathbf{x})$$

This led to the implication that when the distribution of the covariate X changes from F_X to G_X, with the assumption that the conditional distribution $F_{y|X}$ remains constant, this transforms the unconditional distribution of Y from F_Y to G_Y. Consequently, there will be a corresponding change in the distributional statistic $v(F_Y)$ to $v(G_Y)$:

$$v(G_Y) - v(F_Y) = \int E[\mathrm{RIF}\{y,\ v(F_Y)\}|\mathbf{X} = \mathbf{x}]d(G_X - F_X)(\mathbf{x})$$

which describes how changes in the distribution of X may impact the statistics $v()$.

3. Estimating the impact of covariates X to distributional statistics of interest

Based on the approach proposed by Firpo, Fortin, and Lemieux (2009), a straightforward method to estimate RIF regressions involves assuming a linear relationship between $RIF\{y, v(F_Y)\}$ and the explanatory variables X. By making this assumption, we can employ OLS to fit a linear model that captures the influence of small changes in the distribution of the independent variables X on $v(F_Y)$.

$$\mathrm{RIF}\{y,\ v(F_Y)\} = \mathbf{X}'\beta + \varepsilon_i,\ E(\varepsilon_i) = 0$$

The distinction from the standard OLS model is that in RIF-OLS, the $RIF\{y, v(F_Y)\}$ values for each observation y_i in the data set serve as the dependent variable, while all the relevant variables of interest are regressed against it. Thus, coefficients from the RIF–OLS regressions would be interpreted as the expected changes in distributional statistics $v()$ given one unit change in the distribution of covariate X.

Table A5.1: Wage Regression

Control Variable	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90	(11) Gini
New investment project	0.002***	0.002***	0.003***	0.003***	0.003***	0.003***	0.003***	0.002***	0.001***	0.000	−0.000
(Lag 1)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Digital manufacturing	0.560***	0.481***	0.623***	0.688***	0.795***	0.988***	0.908***	0.976***	1.001***	0.047	0.007*
	(0.066)	(0.093)	(0.079)	(0.062)	(0.050)	(0.044)	(0.057)	(0.034)	(0.109)	(0.084)	(0.004)
Digital trade	−0.041	0.016	−0.009	−0.004	−0.004	−0.014	−0.029	−0.013	−0.049	−0.035	0.002
	(0.056)	(0.064)	(0.057)	(0.052)	(0.053)	(0.050)	(0.045)	(0.048)	(0.048)	(0.068)	(0.003)
Digital services	−0.026	0.019	−0.030	−0.014	0.015	0.007	0.039	0.087	0.113	0.204	0.010***
	(0.119)	(0.080)	(0.101)	(0.111)	(0.110)	(0.121)	(0.109)	(0.116)	(0.129)	(0.168)	(0.003)
Digital manufacturing x	−0.002	−0.023***	−0.020***	−0.019***	−0.019***	−0.019***	−0.006**	0.009***	0.024***	0.054***	0.001***
new investment project (Lag 1)	(0.001)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.006)	(0.004)	(0.000)
Digital trade x new investment	0.004	−0.017	−0.004	0.009	0.023	0.025	0.029	0.025	0.021	0.019	0.001*
project	(0.023)	(0.010)	(0.013)	(0.014)	(0.015)	(0.020)	(0.020)	(0.026)	(0.021)	(0.035)	(0.001)

Control Variable	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90	(11) Gini
(Lag 1)											
Digital services x new investment project (Lag 1)	−0.002	−0.011	−0.011	−0.010	−0.009	−0.007	−0.003	−0.001	0.003	0.003	0.000**
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.009)	(0.009)	(0.008)	(0.000)
Herfindahl-Hirschman Index – high	−0.093	−0.081	0.005	0.050	0.082	0.105**	0.112***	0.128***	0.136***	0.095*	0.014***
	(0.079)	(0.106)	(0.080)	(0.062)	(0.051)	(0.045)	(0.037)	(0.039)	(0.047)	(0.051)	(0.005)
High Herfindahl-Hirschman Index x new investment project (Lag 1)	0.001	0.001	0.000	−0.000	−0.001	−0.001	−0.001	−0.000	−0.000	0.001	−0.000*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Digital manufacturing x high Herfindahl-Hirschman Index	−0.095	−0.102	−0.181**	−0.225***	−0.283***	−0.399***	−0.312***	−0.458***	−0.625***	0.113	−0.011**
	(0.081)	(0.113)	(0.086)	(0.069)	(0.059)	(0.053)	(0.070)	(0.066)	(0.125)	(0.113)	(0.005)

Control Variable	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90	(11) Gini
Digital trade x high Herfindahl-Hirschman Index	0.288***	0.219**	0.307***	0.215***	0.223***	0.264***	0.231***	0.132**	0.230***	0.037	−0.009**
	(0.078)	(0.098)	(0.078)	(0.066)	(0.063)	(0.060)	(0.056)	(0.062)	(0.070)	(0.088)	(0.004)
Digital services x high Herfindahl-Hirschman Index	0.351**	0.171	0.163	0.117	0.128	0.168	0.161	0.200	0.242	0.289	−0.013**
	(0.153)	(0.108)	(0.122)	(0.133)	(0.127)	(0.141)	(0.135)	(0.150)	(0.174)	(0.226)	(0.006)
Digital manufacturing x high Herfindahl-Hirschman Index x new investment project (Lag 1)	−0.001	−0.001	−0.007	−0.007	−0.001	−0.004	−0.020**	−0.001	−0.011	0.033*	−0.000
	(0.003)	(0.013)	(0.007)	(0.008)	(0.008)	(0.006)	(0.010)	(0.010)	(0.010)	(0.018)	(0.001)
Digital trade x high Herfindahl-Hirschman	−0.007	0.013	−0.002	−0.013	−0.026*	−0.027	−0.028	−0.024	−0.023	−0.019	−0.001
	(0.023)	(0.010)	(0.013)	(0.014)	(0.015)	(0.020)	(0.020)	(0.026)	(0.021)	(0.035)	(0.001)

Control Variable	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90	(11) Gini
Index x new investment project (Lag 1)											
Digital services x high Herfindahl-Hirschman Index x new investment project (Lag 1)	0.002	0.001	0.001	0.002	0.001	0.004	0.002	−0.000	0.001	−0.008	0.000
	(0.011)	(0.009)	(0.009)	(0.011)	(0.009)	(0.010)	(0.009)	(0.014)	(0.017)	(0.014)	(0.000)
Age	0.072***	0.058***	0.053***	0.049***	0.048***	0.053***	0.053***	0.059***	0.062***	0.061***	−0.001***
	(0.008)	(0.008)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.007)	(0.007)	(0.000)
Age ^2	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.382***	0.591***	0.562***	0.480***	0.400***	0.362***	0.296***	0.256***	0.208***	0.186***	−0.007***
	(0.035)	(0.073)	(0.059)	(0.048)	(0.041)	(0.037)	(0.028)	(0.024)	(0.018)	(0.022)	(0.002)
Urban	0.164***	0.174***	0.164***	0.157***	0.143***	0.150***	0.137***	0.131***	0.124***	0.125***	−0.002*
	(0.022)	(0.032)	(0.025)	(0.020)	(0.018)	(0.018)	(0.016)	(0.015)	(0.017)	(0.020)	(0.001)
Years of education	−0.015	0.062***	0.050***	0.039***	0.024**	0.007	−0.015	−0.045***	−0.090***	−0.141***	−0.003***
	(0.013)	(0.012)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.013)	(0.018)	(0.001)

Control Variable	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90	(11) Gini
Years of education ^2	0.006***	−0.001	0.000	0.001*	0.002***	0.004***	0.005***	0.008***	0.011***	0.015***	0.000***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Employee	0.077	0.018	0.019	0.037	0.016	−0.001	−0.042	−0.062	−0.006	0.012	−0.007
	(0.080)	(0.115)	(0.086)	(0.066)	(0.054)	(0.051)	(0.044)	(0.050)	(0.064)	(0.085)	(0.005)
Casual worker in agricultural	0.417*	−0.021	−0.360***	−0.390***	−0.358***	−0.328***	−0.283***	−0.253***	−0.206***	−0.184***	−0.050***
sector	(0.246)	(0.160)	(0.106)	(0.075)	(0.057)	(0.050)	(0.040)	(0.040)	(0.041)	(0.048)	(0.017)
Casual worker in non-agricultural	0.161*	−0.076	−0.080	−0.046	−0.060	−0.089	−0.138***	−0.165***	−0.142***	−0.050	−0.019***
sector	(0.095)	(0.124)	(0.131)	(0.118)	(0.095)	(0.078)	(0.047)	(0.035)	(0.031)	(0.031)	(0.005)
Formal_new	0.344**	0.110	0.078	0.081	0.100*	0.114**	0.122**	0.138***	0.113*	0.078	−0.018*
	(0.150)	(0.119)	(0.087)	(0.068)	(0.056)	(0.055)	(0.049)	(0.053)	(0.058)	(0.076)	(0.009)
High-skilled worker1	−0.440***	−0.427***	−0.339***	−0.262***	−0.211***	−0.187***	−0.141***	-0.097***	−0.027	0.098**	0.028***
	(0.139)	(0.145)	(0.097)	(0.069)	(0.053)	(0.045)	(0.037)	(0.037)	(0.043)	(0.048)	(0.009)
Constant	11.239***	10.608***	11.077***	11.462***	11.695***	11.785***	12.003***	12.099***	12.291***	12.784***	0.078***
	(0.234)	(0.233)	(0.170)	(0.139)	(0.127)	(0.136)	(0.140)	(0.170)	(0.232)	(0.293)	(0.011)

Control Variable	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90	(11) Gini
N	1.5e+06	1.5e+06	1.5e+06	1.5e+06	1.5e+06	1.5e+06	1.5e+06	1.5e+06	1.5e+06	1.5e+06	1.5e+06
r2	0.154	0.088	0.151	0.193	0.215	0.224	0.235	0.242	0.255	0.213	0.057

KBLI = Klasifikasi Baku Lapangan Usaha Indonesia (Standard Classification of Indonesian Business Fields), RIF = recentred influence function, Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Notes: * p<0.1, ** p<0.05, *** p<0.01. Controls for year-specific and industry-specific fixed effects. Data are at the individual level. Run using the RIF regression approach. Standard errors are clustered at the KBLI level.
Sources: Sakernas; investment data from the Ministry of Investment (2020); authors' calculations.

Table A5.2: Employment Regression

Control Variable	(1) Total Employment	(2) Female	(3) Male	(4) Primary Education	(5) Secondary Education	(6) Tertiary Education	(7) Low-skilled	(8) High-skilled	(9) Blue-collar	(10) White-collar
L.Total new investment Project	0.002***	−0.001	0.002***	0.002	0.002**	−0.001	0.002***	−0.001	0.003**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Digital manufacturing x L.Total new investment project	−0.005***	−0.012***	0.000	−0.041***	−0.003*	−0.028***	−0.004***	−0.010***	−0.009***	0.010***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)
Digital trade x L.Total new investment project	−0.041***	−0.085***	−0.014**	−0.083***	−0.025	−0.083***	−0.035**	0.361***	0.149***	−0.059***
	(0.015)	(0.016)	(0.006)	(0.009)	(0.016)	(0.019)	(0.017)	(0.028)	(0.010)	(0.020)
Digital services x L.Total new investment project	0.004	0.008	0.003	−0.029*	−0.007	0.016	0.003	−0.011	−0.001	0.004
	(0.006)	(0.008)	(0.006)	(0.018)	(0.012)	(0.013)	(0.007)	(0.014)	(0.014)	(0.007)
Formal sector	−0.226	0.125	−0.232	−0.457**	0.508	1.574***	0.181	1.222**	−0.748**	1.402***
	(0.313)	(0.266)	(0.345)	(0.219)	(0.363)	(0.377)	(0.219)	(0.548)	(0.353)	(0.285)

Control Variable	(1) Total Employment	(2) Female	(3) Male	(4) Primary Education	(5) Secondary Education	(6) Tertiary Education	(7) Low-skilled	(8) High-skilled	(9) Blue-collar	(10) White-collar
High Herfindahl-Hirschman Index x L.Total new investment project	−0.002*	0.002	−0.002*	−0.002	−0.001	0.002	−0.002**	0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Digital manufacturing x high Herfindahl-Hirschman Index x L.Total new investment project	0.004	−0.078	0.067	0.098	−0.049	0.280***	−0.015	0.333***	−0.040	0.071
	(0.066)	(0.087)	(0.062)	(0.112)	(0.099)	(0.029)	(0.062)	(0.014)	(0.068)	(0.056)
Digital trade x high Herfindahl-Hirschman Index x L.Total new investment project	0.029*	0.059***	0.005	0.082***	0.014	0.066***	0.023	−0.356***	−0.148***	0.049**
	(0.015)	(0.016)	(0.006)	(0.009)	(0.016)	(0.019)	(0.017)	(0.028)	(0.010)	(0.020)
Digital services x	−0.023	−0.043	0.026	0.066**	0.031	−0.041	-0.039	0.079	−0.012	0.004
	(0.058)	(0.041)	(0.044)	(0.030)	(0.038)	(0.056)	(0.056)	(0.055)	(0.033)	(0.057)

Control Variable	(1) Total Employment	(2) Female	(3) Male	(4) Primary Education	(5) Secondary Education	(6) Tertiary Education	(7) Low-skilled	(8) High-skilled	(9) Blue-collar	(10) White-collar
High Herfindahl-Hirschman Index x L.Total new investment project										
Constant	11.085***	9.300***	10.732***	10.457***	9.472***	7.162***	10.403***	7.714***	10.468***	8.668***
	(0.223)	(0.189)	(0.245)	(0.156)	(0.258)	(0.276)	(0.157)	(0.403)	(0.252)	(0.206)
N	1,980	1,891	1,972	1,918	1,957	1,751	1,950	1,591	1,895	1,900
r2	0.057	0.062	0.044	0.035	0.075	0.154	0.040	0.042	0.039	0.073

KBLI = Klasifikasi Baku Lapangan Usaha Indonesia (Standard Classification of Indonesian Business Fields), Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Notes: * p<0.1, ** p<0.05, *** p<0.01. Controls for year-specific and industry-specific fixed effects. Data are at four-digit KBLI industry code level. Robust standard errors are reported.
Sources: Sakernas; investment data from the Ministry of Investment (2020); authors' calculations.

Table A5.2: Employment Regression (2)

Control Variable	(11) Youth, Primary or Below	(12) Youth, Secondary	(13) Youth, Tertiary	(14) Adult, Primary or Below	(15) Adult, Secondary	(16) Adult, Tertiary	(17) Elder, Primary or Below	(18) Elder, Secondary	(19) Elder, Tertiary
L.Total new investment project	0.003	0.000	0.002**	0.001	0.002**	−0.002	0.002	0.000	0.004
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.005)
Digital manufacturing x L.Total new investment project	−0.092***	−0.010***	0.151***	−0.008***	−0.002	−0.034***	−0.082***		
	(0.003)	(0.002)	(0.015)	(0.002)	(0.002)	(0.003)	(0.007)		
Digital trade x L.Total new investment project	−0.179***	−0.047***	0.009	−0.051***	−0.019	−0.111***	−0.498***	−0.008***	0.213***
	(0.012)	(0.015)	(0.007)	(0.005)	(0.014)	(0.017)	(0.107)	(0.002)	(0.069)
Digital services x L.Total new investment project	0.019	−0.017	−0.043*	−0.022	−0.006	0.018	−0.014	−0.047	0.110***
	(0.011)	(0.015)	(0.025)	(0.015)	(0.015)	(0.012)	(0.027)	(0.085)	(0.012)
Formal sector	0.724**	1.111***	0.448	−0.603**	0.384	1.376***	−1.158***	−0.004	1.244
	(0.362)	(0.316)	(0.641)	(0.249)	(0.360)	(0.412)	(0.346)	(0.527)	(0.816)
Herfindahl-Hirschman Index	−0.002	0.000	−0.002	−0.001	−0.001	0.002	−0.003**	−0.000	−0.002

Control Variable	(11) Youth, Primary or Below	(12) Youth, Secondary	(13) Youth, Tertiary	(14) Adult, Primary or Below	(15) Adult, Secondary	(16) Adult, Tertiary	(17) Elder, Primary or Below	(18) Elder, Secondary	(19) Elder, Tertiary
high x L.Total new investment project									
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.005)
Digital manufacturing # high Herfindahl-Hirschman Index x L.Total new investment project	0.020	−0.099***		−0.135*	0.037	0.342***			
	(0.068)	(0.005)		(0.076)	(0.082)	(0.065)			
Digital trade x high Herfindahl-Hirschman Index x L.Total new investment project	0.176***	0.026*	0.009*	0.051***	0.011	0.096***	0.480***		−0.245***
	(0.012)	(0.015)	(0.005)	(0.005)	(0.014)	(0.017)	(0.107)		(0.069)
Digital services x high Herfindahl-Hirschman Index x L.Total new investment project	0.043***	0.032	0.159***	0.054	0.051	−0.053	2.341***	0.259***	−0.165***
	(0.016)	(0.027)	(0.029)	(0.042)	(0.039)	(0.064)	(0.075)	(0.085)	(0.016)

Control Variable	(11) Youth, Primary or Below	(12) Youth, Secondary	(13) Youth, Tertiary	(14) Adult, Primary or Below	(15) Adult, Secondary	(16) Adult, Tertiary	(17) Elder, Primary or Below	(18) Elder, Secondary	(19) Elder, Tertiary
Constant	7.944***	7.673***	6.629***	10.267***	9.246***	7.149***	8.887***	6.797***	5.679***
	(0.247)	(0.229)	(0.499)	(0.176)	(0.255)	(0.302)	(0.230)	(0.362)	(0.588)
N	1,616	1,793	984	1,888	1,947	1,727	1,610	1,289	754
r2	0.042	0.101	0.165	0.029	0.059	0.149	0.101	0.133	0.161

Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Notes: * p<0.1, ** p<0.05, *** p<0.01. Controls for year-specific and industry-specific fixed effects.
Sources: Sakernas; investment data from the Ministry of Investment (2020); authors' calculations.

Table A5.3: Descriptive Statistics of Gig Workers

Workers' Characteristics	Non-internet-using, Other Sector	Non-internet-using, Transport	Non-internet-using, Trade	Non-internet-using, Services	Internet-using, Other Sector	Internet-using, Transport	Internet-using, Trade	Internet-using, Services	Gig Worker, Transport	Gig Worker, Trade	Gig Worker, Services
Age											
2019	40.73	39.88	39.72	39.55	35.57	34.14	32.91	36.79	35.34	36.52	38.15
2020	41.19	40.38	39.78	40.13	35.89	33.98	33.49	37.19	36.65	36.40	38.52
2021	41.56	41.01	40.40	40.86	36.28	34.27	34.00	37.49	37.39	37.09	39.23
2022	42.24	40.58	41.05	40.11	36.68	34.19	34.37	37.36	37.37	38.52	39.67
Male											
2019	0.67	0.97	0.46	0.50	0.74	0.80	0.59	0.54	0.93	0.52	0.65
2020	0.66	0.97	0.44	0.51	0.74	0.82	0.55	0.52	0.93	0.48	0.64
2021	0.66	0.97	0.43	0.50	0.74	0.84	0.55	0.51	0.92	0.48	0.61
2022	0.66	0.96	0.43	0.47	0.75	0.85	0.56	0.53	0.93	0.50	0.61
Years of education											
2019	7.25	8.57	8.64	10.24	11.23	12.33	11.70	14.07	11.18	10.85	11.73
2020	7.47	8.72	8.79	9.67	10.71	11.86	11.37	13.47	11.07	10.85	11.46
2021	7.46	8.68	8.75	9.62	10.60	11.99	11.35	13.95	10.96	10.78	11.50
2022	7.27	8.73	8.45	9.83	10.27	11.83	11.13	13.74	10.88	10.48	11.34
Urban											
2019	0.35	0.64	0.64	0.67	0.72	0.84	0.81	0.74	0.87	0.75	0.82
2020	0.34	0.66	0.65	0.68	0.66	0.80	0.77	0.72	0.85	0.73	0.79
2021	0.34	0.66	0.64	0.68	0.65	0.80	0.76	0.72	0.83	0.73	0.78
2022	0.33	0.66	0.63	0.66	0.63	0.81	0.77	0.75	0.82	0.73	0.82

Sakernas = Survei Angkatan Kerja Nasional (National Labor Force Survey).
Sources: Sakernas; authors' calculation.

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