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DISRUPTIVE TECHNOLOGY, SKILLS, AND TASKS:

IMPLICATIONS FOR EMPLOYMENT IN INDONESIA

DISRUPTIVE TECHNOLOGY, SKILLS, AND TASKS: IMPLICATIONS FOR EMPLOYMENT IN INDONESIA

CENTRE FOR STRATEGIC AND INTERNATIONAL STUDIES

A Working Paper by
CSIS Indonesia

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Suggested Citation

Wicaksono, Teguh Yudo, and Carlos Mangunsong. 2020. "Disruptive Technology, Skills, and Tasks: Implications for Employment in Indonesia". CSIS Working Paper. Jakarta: CSIS Indonesia.

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ACKNOWLEDGEMENT

This working paper is part of the Supporting Technological Transformation in Indonesia project, funded by the Asian Development Bank.

The study is a collaboration between an interdisciplinary research team from the University of Cambridge and the Centre for Strategic and International Studies in Indonesia, with valuable guidance and support from the Fiscal Policy Agency of Indonesia's Ministry of Finance. The main output of the study, "Innovate Indonesia: Unlocking Growth through Technological Transformation" is available for download at www.adb.org.

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ABSTRACT

This paper examines relative prices of tasks following the recent and rapid adoption of new technologies in workplaces. In documenting the relationship between tasks, occupations and wages in Indonesia, we classify tasks into four groups: technological tasks; routine manual tasks; routine cognitive tasks; and non-routine interpersonal tasks. Our estimates from the labor supply model confirm the predicted relationship between tasks and wages. We found that one standard-deviation increase in the measure of non-routine tasks—i.e. interpersonal tasks—leads to a 4.1% increase in wages. On the other hand, occupations with heavy routine manual tasks saw a decline in relative wages. A one standard deviation increase in routine manual tasks leads to lower wages by 2.5%. Interestingly, we found mixed evidence on the impacts of technology on employment. Firms with high technological intensity tend to employ fewer non-production workers—i.e. a proxy for high-skilled workers—suggesting that the current adopted technology and low-skilled workers—i.e. production workers—are complementary. On the other hand, highly innovative firms are more likely to employ non-production workers, suggesting a complementarity between innovation and high-skilled workers. In general, the findings corroborate patterns on the relative prices of tasks in developed countries.

Keywords: college premium, earnings inequality, employment, occupations, Indonesia, industry 4.0, returns to schooling, skill biased technical change, skill premium, tasks, technology, wage inequality;

JEL codes: J20; J23; J24; J30; J31; O31; O33; O53

I. INTRODUCTION

A narrative that automation will wipe out jobs has been around for a long time. In the 1950s, as machinery was rapidly introduced into manufacturing, there was wariness that automation would create a joblessness economy. In 1964, the United States government even established a special commission on technology and the economy to address concerns that productivity was rising so fast that it could outstrip demand for labor (Autor 2015). Recent innovations in information and communication technology (ICT), including digital technologies, have reignited concerns that automation could make labor redundant (Brynjolfsson and McAfee 2012; Akst, 2013; Autor 2015; Acemoglu and Restrepo 2018).

Changes in technology undoubtedly have also altered types of jobs. Jobs with routine and manual tasks tend to be replaced by automation and robotics. Meanwhile, workers specializing in abstract, analytical work, or interpersonal relationships, are more shielded from automation. This could lead to "job polarization", whereby technologies replace jobs held by middle-skilled workers—where most tasks are routine—but create wage gains for workers at the top and at the bottom of income and skill distribution. This is the narrative on the impact of technological changes on employment that has emerged in the developed world (see Krueger 1993; Autor, Levy, and Murnane 2003; Goos and Manning 2007; Acemoglu and Autor 2011; Michaels, Natraj, and Van Reenen 2014; World Bank 2016; Acemoglu and Restrepo 2017). However, analysis focused on developing countries remains largely absent.

Acemoglu and Autor (2011) provide a conceptual framework to understand the impact of technologies on jobs. The very notion of the framework is that digital technologies substitute workers who carry out a limited and well-defined set of cognitive and manual activities, known as "routine tasks". Meanwhile, technology complements workers that carry out problem-solving or complex communication—described as "non-routine tasks". As this may imply, the rapid adoption of new technologies will change relative cost of tasks. Routine and manual tasks will be replaced by automation. Thus, demand for tasks will decline, resulting in lower relative prices of both routine and manual tasks. On the other hand, as demand for non-routine tasks increases, the relative price of these tasks will increase as well. Consequently, workers who perform high-level non-routine tasks could receive a significant wage premium.

In this paper we examine relative prices of tasks following the recent and rapid adoption of new technologies in workplaces. Labor market changes such as wages and employment in most periods of Indonesia's modern economy have been associated with trends in the global economy, international trade and investments. Amid weakening globalization and international trade—in part due to trade wars—new forces have emerged in which digital technologies have begun to impinge on employment and incomes. These technologies, including automation and robotics, have reshaped industries in many ways. Textile factories known for employing high numbers of workers have begun to adopt automated machines (Wicaksono and Manning 2018). As a result, they may reallocate workers to other activities and change the nature of jobs and the value of tasks.

In documenting the relationship between tasks, occupations and wages in Indonesia, we pursue the approach of Autor et al (2003) and Acemoglu and Autor (2011). Specifically, we classify tasks into four groups: technological tasks; routine manual tasks; routine cognitive tasks; and non-routine interpersonal tasks. Technological tasks require individuals to work with computers. Routine manual tasks involve physical effort, such as lifting loads or stooping. Routine cognitive tasks need intense concentration and attention. Non-routine interpersonal tasks require individuals to connect and communicate extensively with other people.

Our estimates from the labor supply model confirm the predicted relationship between tasks and wages. We found that one standard-deviation increase in the measure of non-routine tasks—i.e. interpersonal tasks—leads to a 4.1% increase in wages. The magnitude is higher than that seen in technological tasks. On the other hand, occupations with heavy routine manual tasks saw a decline in relative wages. A one standard-deviation increase in routine manual tasks leads to lower wages by 2.5%. Interestingly, routine cognitive tasks—i.e. jobs requiring a high level of concentration and attention—still offer wage premiums. Evidence suggesting a premium from routine cognitive tasks contrasts with findings from developed countries.

We found mixed evidence on the impacts of technology on employment. Firms with high technological intensity tend to employ fewer non-production workers—i.e. a proxy for high-skilled workers.[1] Another interpretation of this finding is that adopted technology and low-skilled workers—i.e. production workers—are complementary. On the other hand, highly innovative firms are more likely to employ non-production workers, suggesting a complementarity between innovation and high-skilled workers.

In general, the findings corroborate patterns on the relative prices of tasks in developed countries. That is, routine manual tasks are valued less in the labor market. Meanwhile non-routine tasks that need human judgement and analytical skills still provide relatively higher-value jobs. However, we also found evidence on complementarities between the technologies used in Indonesian institutions and the number and types of jobs in those industries. So, despite concerns about the disruptive effects on employment, new technologies can still create employment.

Our paper contributes to the literature as it is the first study that assesses the relative prices of tasks in Indonesia. In particular, we transform occupations into bundles of tasks and estimate their relative prices. Our foundational concept is that occupations consist of series of

[1] Non-production workers typically graduated at college level and above. They generally fill management positions.

tasks such as lifting objects, performing analytical work, processing information, or networking with people or customers. We simplify these tasks into categories of routine tasks (versus non-routine tasks) and cognitive tasks (versus manual tasks). We estimate the relative value through wages for these tasks.

Moreover, we also discuss changes in employment over decades, with a focus on recent waves of technology. There are potential areas for further research. However, our analyses are constrained due to the limited data covering the interplay between technologies and employment.[2] Collecting more data and information related to new technologies will be the next further step in understanding how technologies shape employment in Indonesia.

In the following section, we provide an overview of labor market trends in Indonesia. As we discuss general long-term trends of employment, we pay more attention to the relationship between recent technologies and employment. The discussion is followed by a theoretical framework for understanding mechanisms on how technologies may shape tasks and skills. We provide a more detailed discussion on constructing measures of tasks and estimating their relative price in section 4. Econometric analyses on tasks and the relationship between technological adoption and demand for labor are elaborated upon in section 5. Lastly, our final remarks are in section 6.

[2] For instance, we only use a seven-year span of data from IFLS as the information on job characteristics is available in the survey years of 2007 and 2014.

II. AN OVERVIEW OF LABOR MARKET TRENDS IN INDONESIA

Indonesia has undergone a significant labor market transformation. From the 1980s through the 1990s, Indonesia's more market-friendly policies favored foreign investment and, as a result, employment grew significantly. After the 1998 economic crisis, the policy direction was reversed, particularly on employment. Facing increased political pressure in a new democratic era, the government implemented restrictive labor policies. In the early period of democracy, labor markets did not perform well. Observers have attributed the job market struggle in the early 2000s to the 2003 Labor Law. A commodity boom starting around 2005 improved the job market outlook. Nevertheless, when the boom ended in 2012, Indonesia faced different challenges. Foreign direct investment coming into the country declined for years and pressures from overvalued exchange rates emerged (Garnaut 2015; Basri 2017).

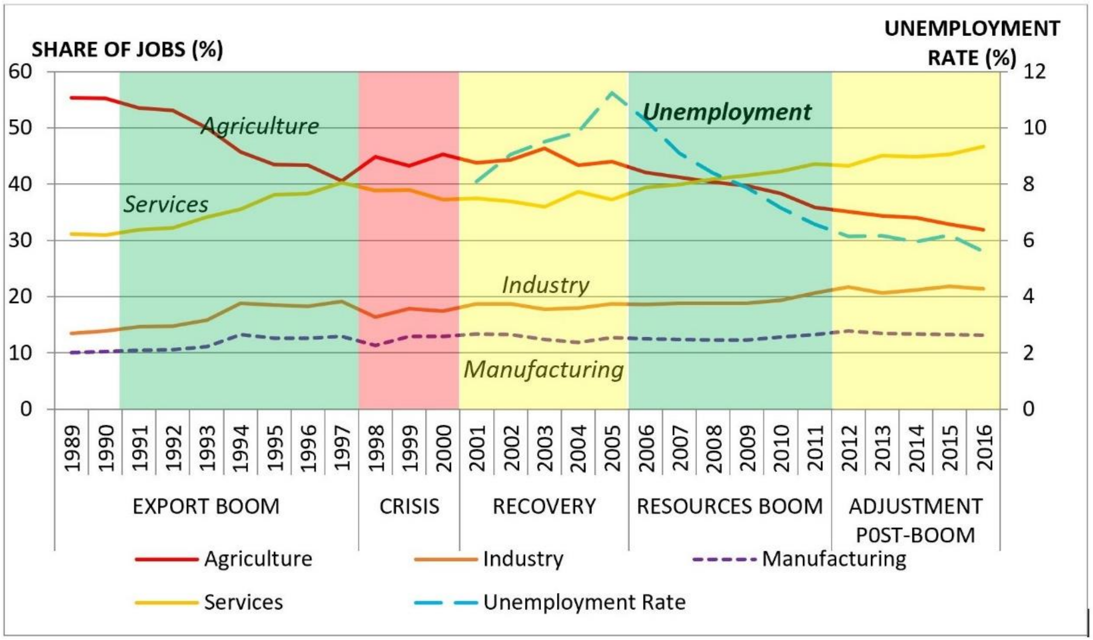
While Indonesia is becoming less attractive for foreign investment, recent technological innovations that have changed workplaces in developed economies are now shaping employment in Indonesia as well. The digital revolution, which accelerated with the widespread use of mobile phones, rapid growth of online business, 3-D printing, and the internet of things, has changed employment in service sectors. Jobs continue to grow even though labor markets have become more insulated from direct changes in the global economy than at any other time in the past half-century (Wicaksono and Manning 2018).

2.1 Employment Trends

From the 1980s through the 1990s, Indonesia's economic development shifted more toward export-oriented industrialization strategies. As Indonesia developed a competitive exchange rate and provided various incentives for promoting exports and foreign investment, the country saw a remarkable performance from exports in labor-intensive industries, mostly from textiles and garments. Over six to seven years in the 1990s, employment in these sectors almost doubled. Many young people secured jobs in the industries, which paid higher wages than rural opportunities. Thus, Indonesia saw a rapid labor transformation from the agricultural economy with low productivity to the more productive manufacturing sector.

The favorable developments in employment did not last long. The 1998 economic crisis put a brake on job creation and thus the labor transformation. During the crisis and the years shortly afterward, manufacturing output declined significantly. A plummeting exchange rate combined with hyperinflation increased the cost of manufacturing inputs. Following the crisis, employment growth in the manufacturing sector fell sharply and never really recovered. The contribution of the manufacturing sector to the increase of total employment declined from around 30% in the period before the crisis to only 12% in the 2000s (Wicaksono and Manning 2018).

Figure 1: Share of Jobs by Major Sector and Manufacturing, and Unemployment Rate, Indonesia 1989-2016



Source: Wicaksono and Manning 2018.

Pressures from other low-cost labor countries such as China and Vietnam during the period after the crisis also exacerbated Indonesia's manufacturing performance. China's entrance to the global market with its accession to the World Trade Organization (WTO) began to dominate the inflow of investment and exports of labor-intensive manufactured products—i.e. products that had created employment in Indonesia in the period before the crisis (Wicaksono and Manning 2018). The problem was compounded by meager infrastructure conditions (Basri and Hill 2011). On top of that, government policies created a less attractive business environment, such as the 2003 Labor Law, which threatened to make production less flexible and to raise wage costs (Manning and Roesad 2007).

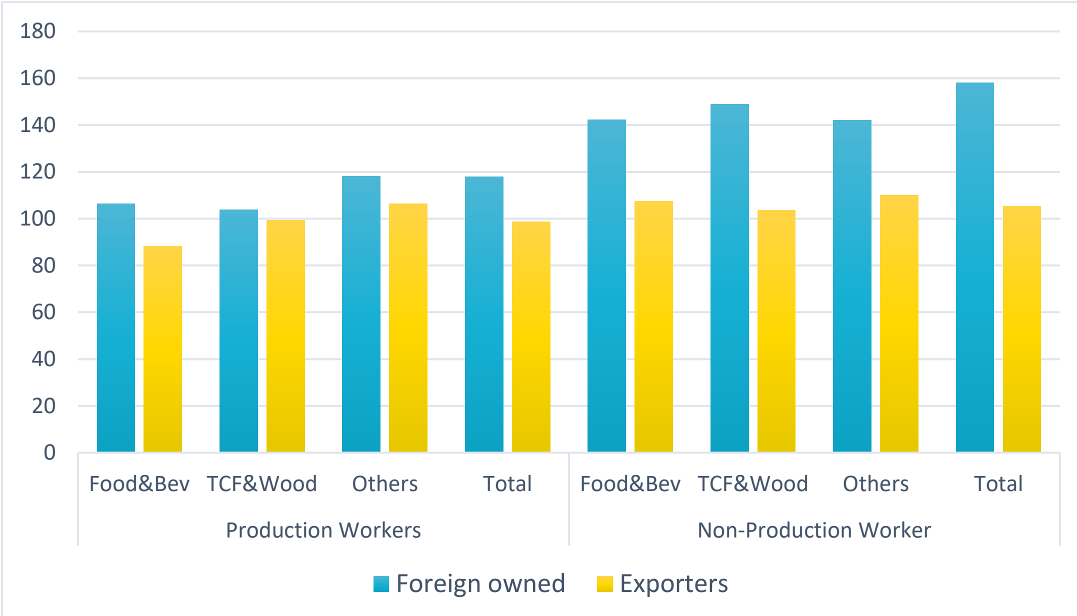
China's hunger for production inputs drove up commodity prices. The commodity boom began in 2004 and, to a large extent, improved labor market performance. As we can see in Figure 1 the unemployment rate fell dramatically from 11.2% in 2005 to 5.6% in 2016. New jobs were created in primary industries. However, the boom also induced a rapid expansion in the number of workers in the service sector. Looking deeper into the expansion in the service sector, we found that finance and business services, as well as public, social, and personal services, were two sectors within services that grew significantly. Wicaksono and Manning (2018) noted that more internationally oriented activities—such as business and tourism-related industries—featured prominently among the mainly formal sector activities that grew strongly. Workers in the rapidly growing formal sectors tended to be better educated (with a senior secondary education or higher), female and relatively young.

2.2 Wage Structure

Similar to employment trends, the dynamics of wages has been determined to a large extent by Indonesia's exposure to the global economy. During the period of rapid manufacturing growth, workers in foreign-owned firms were paid higher wages relative to domestic or even exporting firms. The higher productivity of foreign-owned firms partly explains the wage premium (Ramstetter and Sjöholm 2006; Lipsey, Sjöholm and Sun 2010). Data from a manufacturing survey carried out by Indonesia's Central Statistics Agency (BPS) in 2014 also offers evidence that foreign firms pay higher wages than domestic firms, especially in the case of non-production workers.

Figure 2 displays the relative wages of workers in foreign and exporting firms to domestic and non-exporting firms. Two salient findings can be observed from Figure 2. First is that foreign-owned and exporting firms offers higher salaries than domestic and non-exporting firms. The former tends to be larger than the latter, which may also explain the relative wages. However, this also highlights the role of global networks in wage determination. Second, the relative wages received by non-production workers—i.e. a proxy for high-skilled workers—in foreign-owned firms is much higher than the relative wage received by the same kind of workers in exporting firms. This indicates the wage premium associated with foreign firms. Meanwhile, the relative wage of non-production workers in exporting firms is similar to the relative wage of production workers in the same firms. This is different to foreign-owned firms, as non-production workers in these firms receive higher relative wage than production workers do. This figure suggests that foreign-owned firms pay a premium to non-production workers while exporting firms do not pay a premium for such skills.

Figure 2: Ratio of wages in foreign firms and exporting firms to wages in domestic owned firms and non-exporting firms, 2014



TCF = textiles, clothing and footwear.
Note: The figure is standardized with locally owned firms and non-exporting firms.
Source: Central Statistics Agency (BPS), Survey of Large and Medium Manufacturing Establishments, 2014. Adapted from Wicaksono and Manning (2018).

This finding raises a question of why skills are valued more in foreign firms than exporting firms, although both are expected to have access to international networks. It is probable that foreign firms, on average, are more likely to employ high-skilled workers than exporting firms. This results in a higher premium for high-skilled workers in foreign firms. The skill premium could also be due to foreign firms' adoption of advanced technologies. These advanced technologies and skills are complementary. As a result, high-skilled workers in the firms receive a substantial wage premium.

2.3 Skill Dynamics

As Indonesia's labor market transformation—in terms of jobs and wages—has been shaped by globalization and foreign investment, recent employment dynamics appear to be closely associated with the new wave of technologies. New technologies demand more high-skilled workers and the supply of skills will respond; that is, the workforce will become more educated. In reaching an equilibrium, as the supply of educated members of the workforce continues to increase, we may expect demand for skills to become saturated, resulting in diminishing returns to skill.[3] This prediction does not hold and, while demand for skills continues to increase, the return to skill has followed an upward pattern for a long period.

This empirical pattern—i.e. a secular increase in the return to skill—was observed after the introduction of computers to the manufacturing sector in the 1970s and 1980s in the US. Following the adoption of computers, the US economy saw rapid growth of jobs at the top of the skill ladder—e.g. professional and managerial occupations. In addition, their relative wages persistently increased for decades. On the other hand, skilled blue-collar occupations contracted rapidly, and clerical occupations reversed course (Autor 2015). This observation in the US suggests that technologies tend to favor high-skilled workers, which is known as skill-biased technical change.

Two decades after the 1998 economic crisis in Indonesia, the supply of skills grew at a dramatic pace (see Table 1). Between 2001 and 2005, the annual growth in the labor force of college graduates was around 7%. In the latter half of the commodity boom period, the supply of college graduates accelerated and grew annually by 14%. The acceleration trend continued even after the end of the commodity boom in 2012. From 2011 to 2015, the supply of high-skilled workers grew annually by 18%.

Table 1: Average Annual Growth of Labor Force by Education Level

Education	1996-2000	2001-2005	2006-2010	2011-2015
Elementary or lower	-0.2%	-1.1%	0.6%	-1.5%
Junior secondary	8.7%	8.1%	1.4%	-0.2%
Senior secondary	5.4%	4.3%	5.2%	4.8%
Diploma	7.7%	2.9%	6.1%	0.2%
Graduate (university)	8.4%	6.8%	14.2%	17.6%

Source: National Labor Force Survey (Sakernas) 2000-2015, Central Statistics Agency (BPS).

To understand how the supply of skills determines their value, we use the relative wages of workers with different education levels. In particular, the relative wages of college graduates versus senior secondary school or elementary graduates could serve as a useful, though coarse, approximation for a summary measure of the market's valuation of skills.[4] We use data from the National Labor Force Survey (Sakernas) to estimate the return to skill.

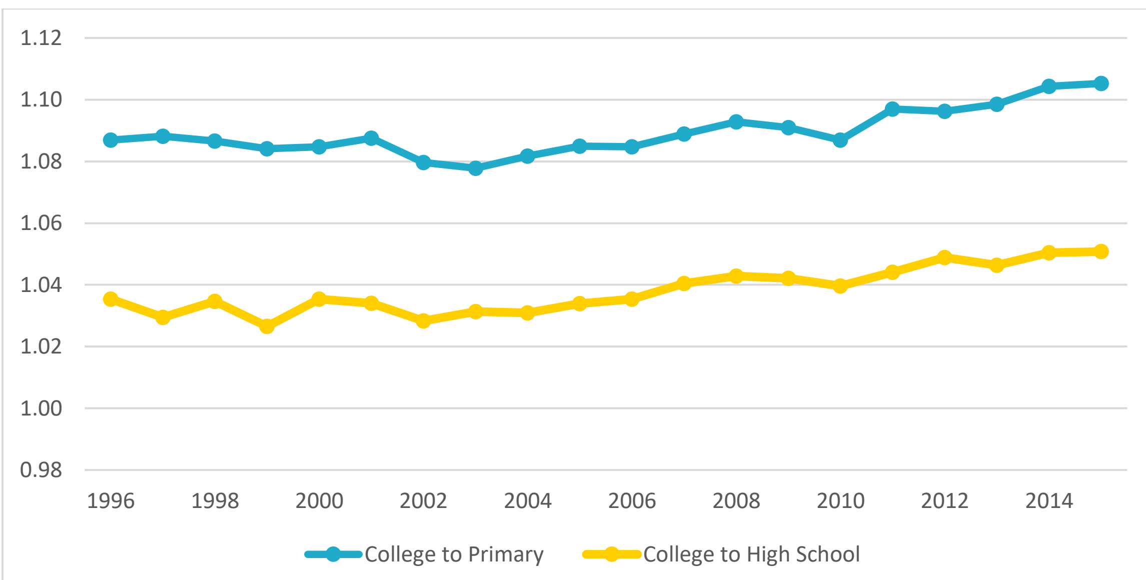
[3] Return to skill is defined here as additional income received by a worker due to an additional year of schooling, while holding other things constant.

[4] In the context of developing countries in which a substantial segment of the population may have low education levels, high school graduates are viewed as high-skilled. But here we use college degrees as a proxy for high-level skills.

Figure 3 plots the adjusted college to high school (and elementary school) natural log of monthly wage premium in Indonesia for 1992 through 2015. The natural log of monthly wage premium is defined as the estimated wage ratio of higher-educated workers to lower-educated workers. We then transform the ratio into a natural logarithm. To construct the figure, we first compute mean (predicted) log real monthly wages in each year for sex-education-experience groups. This shows mean wages for educational groups—that is, they are calculated as fixed-weighted averages of the relevant education group means.

Based on data, we saw the return to skill for college education continue to increase for decades although the supply of college graduate growth had been solid. From 1996 until just before the 1998 crisis, the return to college education relative to high school and elementary education showed a declining trend, although college graduates overall earn higher salaries. After 2002, there was a reversal trend. The return to college education rose for more than a decade and the upward trend appears to be continuing. The rapid increase in the return to college education from 2002 through 2015 happened at the same time as new technologies—such as the online economy and e-commerce—impinged upon the economy.

Figure 3: Composition Adjusted College/Senior High School (Elementary School) Log Monthly Wage Ratio, 1996-2015



Note: The plot is the predicted value gathered from the regression of natural log monthly wages in each year on gender, urban residence, region, one-digit industry, formal job, four education dummies (junior secondary, senior secondary, some diploma and college), a quartic in experience, interactions of the education dummies and experience quartic, and a full set of interactions between education, experience, and gender.

Source: National Labor Force Survey (Sakernas) 1992-2015.

Findings from Table 1 and Figure 3 suggest that the empirical patterns indicate patterns similar to developed countries. That is, the return to skill continues to increase despite a growing supply of high-skilled workers. This recent empirical development also raises concerns over deepening income inequality and, to a large extent, job polarization—in which wages of high- and low-skilled workers grow, but the wages of middle-skilled workers are stagnant. In the next subsection, we investigate changes in wages by occupation.

2.4 Job Polarization: A Precursor

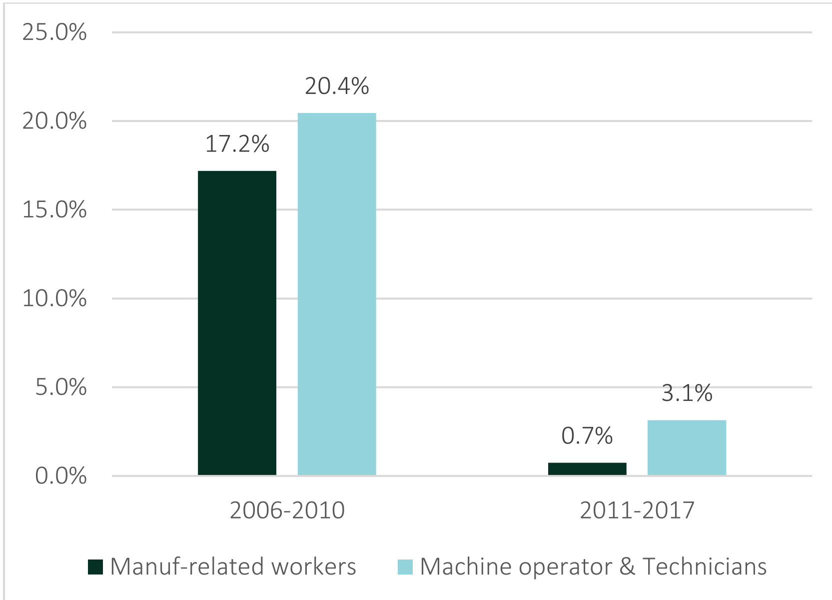
The key conjecture to Acemoglu and Autor's analysis on the impact of technologies (2011) is job polarization indicated by stagnation in both employment and wages of middle-skilled occupations. Currently there is no strong evidence suggesting a rapid decline in middle-skilled occupations. Yet some empirical developments in the last decade show a precursor that new technologies have slowed growth in jobs with a high level of routine tasks and, as a result, wage increases have slowed as well.

Data from Sakernas show that job growth in manufacturing, such as machine operators and other manufacturing-related employment, has slowed (see Figure 4). From 2006 to 2010, these jobs grew in double digits annually. Yet in the last five years, these jobs grew less than 5% annually. As these jobs mostly consist of routine tasks, they could potentially be replaced by automation and other new technologies, leading to further slowing of employment growth. These two jobs account for 20% of total employment. With this significant share, the slowing growth of employment in these occupations could have grim consequences for workers in the manufacturing sector. This may affect the overall economy as well, as the manufacturing sector is generally perceived to be a highly productive sector.

We look at changes of wage levels by skill rankings. Empirically, we first rank occupation-sector groups by average wages in 2000. The occupation-sector group with high-skill ranking is defined by those with high average wages. We calculate the average wages for the same occupation-sector groups in 2017, while maintaining the rank of the occupation-sector groups in 2000. The result is displayed in Figure 5.

Figure 5 reaffirms the conjecture of Acemoglu and Autor (2011). The figure shows that low-skilled and high-skilled occupations experienced real wage growth. Meanwhile, the real wage of middle-skilled occupations was stagnant. We find that around 27.7% of employees experienced wage stagnation from 2000 to 2017. It is important to note, however, that new occupations may have appeared in 2017 that were not recorded in 2000. Thus, we may not fully account for the effect of new occupations in the evolution of wages. Yet when holding the same occupation in both periods with the same skills—i.e. holding the same level of skills as in 2000—there is a tendency for job polarization.

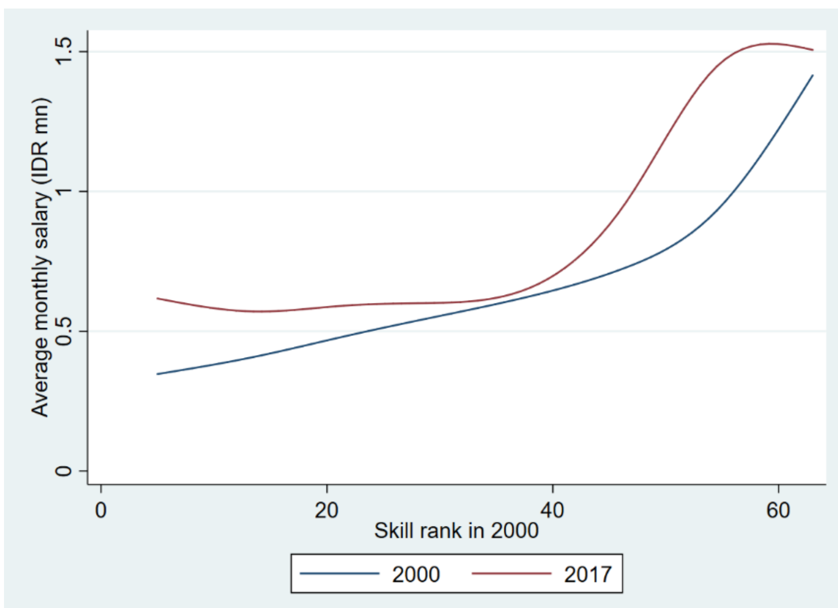
Figure 4: Annual Growth of Manufacturing Jobs, 2006 - 2016



Note: Authors' calculations.

Source: National Labor Force Survey (Sakernas) 2006-2016.

Figure 5: Average Real Monthly Salary by Skill Rank in 2000



Source: National Labor Force Survey (Sakernas) 2000 and 2017.

Figure 4 and Figure 5 highlight some important findings. First is that demand for routine tasks is in decline, leading to a slowing of job growth in some manufacturing-related jobs. Second, declining demand for some types of jobs is leading to lower wages. The wage stagnation occurs in middle-skilled occupations. Meanwhile, other high- and low-skilled roles are still experiencing wage growth. This leads to job polarization. If the trend continues, it could lead to deep income inequality.

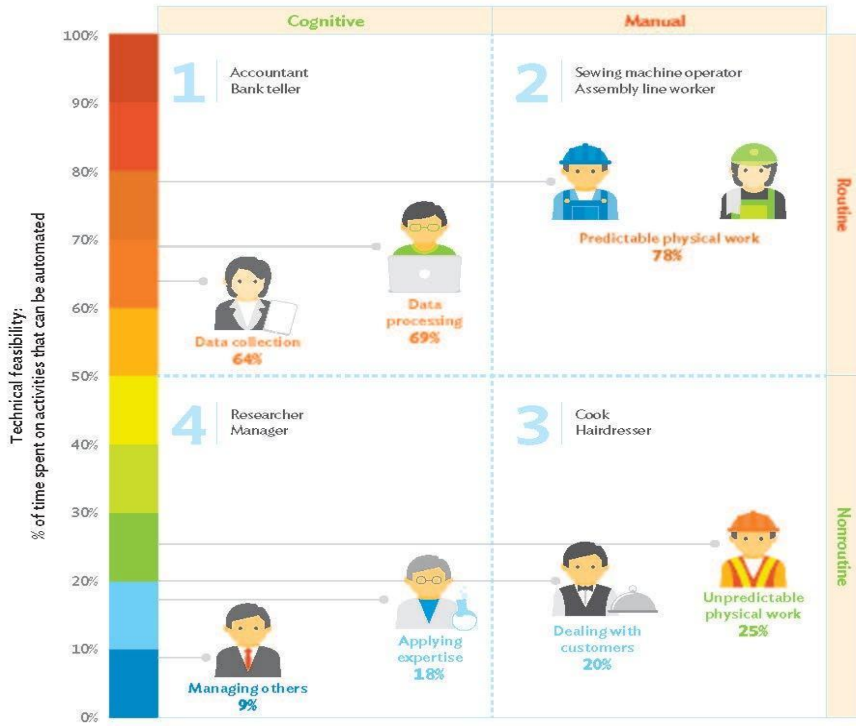
III. THEORETICAL FRAMEWORK

We borrow the framework of Acemoglu and Autor (2011) to understand the impact of new technologies on employment. In their framework, it is important to make a clear distinction between workers' skills and tasks. A skill is a worker's capability for undertaking various tasks. This endowment can be acquired through schooling and other human capital investments. A task is a unit of work activity that produces outputs. This framework—typically called a "task-based model"—highlights that skills are applied to tasks to produce outputs. Skills on their own do not directly produce outputs (Acemoglu and Autor 2011).

This framework implies that occupations consist of a bundle of tasks. Autor et al (2003) classify the bundle of tasks into two broad dimensions: manual versus cognitive, and routine versus non-routine. Figure 6 exhibits a simple illustration describing these two dimensions. As the figure shows, machine operators and assembly workers perform tasks that are mostly manual and routine. These tasks have a higher chance of being automated, resulting in the displacement of workers in these jobs. On the other hand, researchers occupy highly non-routine and cognitive jobs. This type of job is relatively difficult to automate.

The task-based framework provides insights on recent empirical developments pointing to job polarization. Routine tasks involving standardized procedures are more likely to be automated relative to other types of jobs (Autor et al, 2003; Levy and Murnane, 2004; Bartel et al, 2007). Thus, this results in lower demand for a workforce for routine work. On the other hand, jobs requiring analytical tasks, human judgement and non-routine elements are more likely to be shielded from automation. The key prediction of the framework is that technological progress affects certain types of jobs more than others. In this case, workers performing routine works have suffered the most since technology began to substitute more workers. Meanwhile, technological advances are complementary to non-routine tasks.

Figure 6: Dimensions of Jobs: Cognition and Non-Routine



Source: ADB 2018

IV. DATA AND METHODOLOGY

This section discusses the data and methodology that we use in this paper for our econometric analyses. We use data from the Indonesia Family Life Survey (IFLS), complemented by a Center for Strategic and International Studies (CSIS) and Asian Development Bank (ADB) manufacturing survey. We employ the IFLS to construct the bundles of tasks. In addition, we use the manufacturing survey to assess the impact of technological adoption at company level on demand for high-skilled workers.

To estimate the relative price of tasks, we use a Mincer-type regression model. We regress earnings on tasks, including other workers' characteristics. For the labor demand equation, we regress the share of employment by category—i.e. production versus non-production workers—at firm level on technological use and innovation intensity. The following subsections provide a more detailed discussion.

4.1 Data Sources

We use two sources of data for our regression analyses. The first data source is the IFLS, which is a longitudinal, socioeconomic and health household survey. Longitudinal data allows us to control unobserved individual characteristics that may affect decision-making for particular jobs. As we will see later, failing to control unobservable elements will bias the coefficient on variables of interest.

There have been five IFLS waves. The first wave was conducted in 1993 with a sample of 7,224 households. IFLS 1 was fielded in 13 of Indonesia's 26 provinces, representing 83% of the population in 1993. The survey collects rich information on individual respondents, their families and households. Our study uses only IFLS 4 and 5, as these two waves collected information on job tasks. For example, IFLS 4 and 5 have a question about the use of computers in daily work.

We use a sample of individuals aged 18 to 55 who were working at the time of the survey. We also exclude unpaid family workers as conceptually they do not earn an income from their jobs. Despite using panel data, we do not require individuals to be present in two periods. Thus, the data structure is an unbalanced panel, and we treat missing values as random.

To complement our analysis, we also employ a manufacturing survey—the CSIS-ADB manufacturing survey. The survey gathers information on firm characteristics such as ownership, sales, and input costs. The questions in the survey also cover topics related to research and development (R&D), such as whether a firm has an R&D unit and the amount of expenditure allocated for R&D.

An interesting theme of the survey is the adoption of recent technologies by firms. There are five new technologies on which the survey collects information: artificial intelligence, robots, 3D printing, the cloud and big data. Specifically, the survey asks about the extent of adoption of these technologies. In addition, it gathers perceptions on whether the adoption of these technologies improves outputs, increases sales, and benefits a firm's overall performance.

The survey also collects employment information. It classifies employment into two major categories: production and non-production. Questions in the employment section allow us to understand employees' education backgrounds. There are four education levels: elementary school or lower, junior high school, senior high school, and college. It also provides information on the level of employees—manager, first manager or operator—and their respective average salaries.

Regarding the sample, the survey covers six manufacturing industries: textiles and garments; footwear; electronics; automotive; food and beverages; and rubber and plastics. It was conducted in four provinces: Jakarta; Banten; Jawa Barat and Jawa Timur. These provinces arguably have the highest concentration of manufacturers in Indonesia.

4.2 Bundling of Tasks

Key to our analysis is the bundling of tasks. Conceptually, we follow the bundles of tasks under the framework of Acemoglu and Autor (2011), who classify job tasks into five categories: routine manual; routine cognitive; non-routine manual; non-routine cognitive; and "offshorability".[5]

The routine manual category includes repetitive, production-related tasks, while routine cognitive involves repetitive clerical or customer services. The non-routine cognitive category requires abstracting, thinking creatively, analyzing and processing information, as well as tasks that need interpersonal relationships. Non-routine manual activities can cover the operation of vehicles (e.g. truck driving) or special equipment, as well as janitorial services that involve manual tasks and skills. Offshorability is any job that does not require face-to-face interaction, on-site presence or in-person care—i.e. any job that can be outsourced.

To be more precise, we construct four bundles: technological tasks; routine manual tasks; routine cognitive tasks and non-routine interpersonal tasks. Technological tasks require individuals to work with computers, while routine manual tasks require physical effort such as lifting or stooping, routine cognitive tasks need intense concentration and attention, and non-routine interpersonal tasks require working with people.

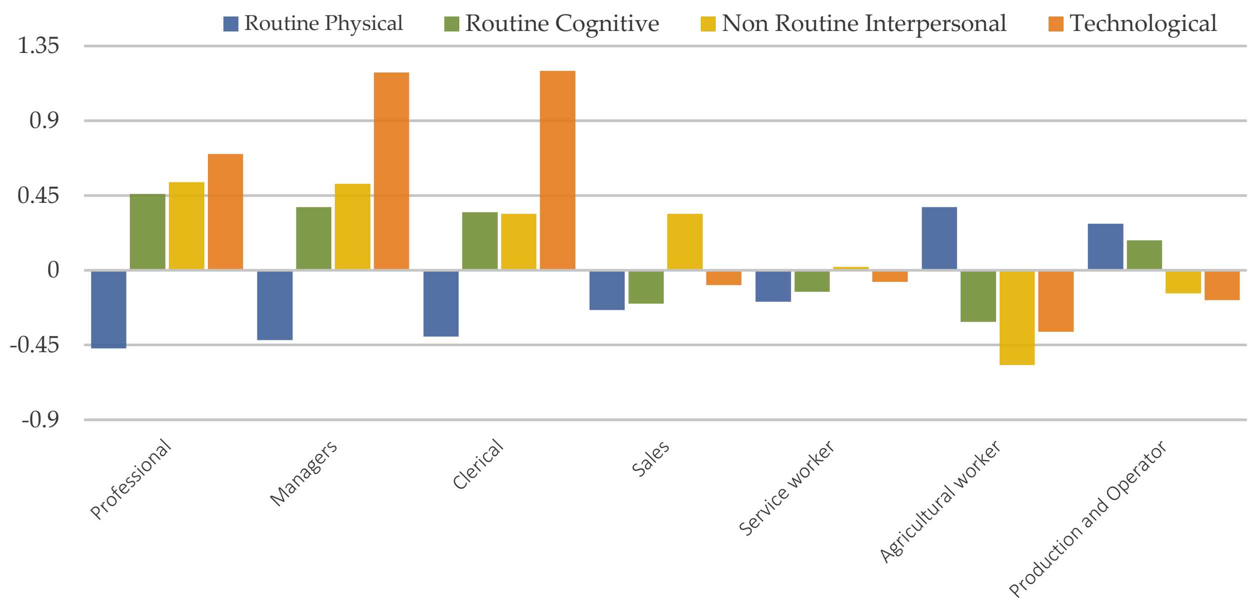
For each type of task, the IFLS asked respondents aged 15 and above Likert-type questions.[6] For example, the survey asked whether the respondent's main job required working with computers. There are four responses representing the level of intensity: all/almost all the

[5] Offshorability is the extent to which tasks/jobs can be moved or conducted overseas.
[6] Likert-type questions (or a Likert scale) represent a scale of intensity.

time; most of the time; some of the time; none/almost none of the time. We reverse these values and standardize the responses for all respondents in order to construct a z-score for each task. The standardized scores of tasks are the main variables of interest representing bundles of tasks.

Figure 7 describes the level of four types of tasks by occupation. We can observe that managers generally undertake high levels of technological and interpersonal tasks. While clerical jobs require a high level of technological skills because of high computer use in the workplace, professional occupations demand a high level of interpersonal tasks. As we may expect, agricultural jobs typically require manual activities and few technological and interpersonal tasks. Production jobs also require a high level of manual and routine cognitive tasks, with fewer lower technological and interpersonal activities. Therefore, the bundles of tasks from our estimates accurately represent the characteristics of corresponding occupations.

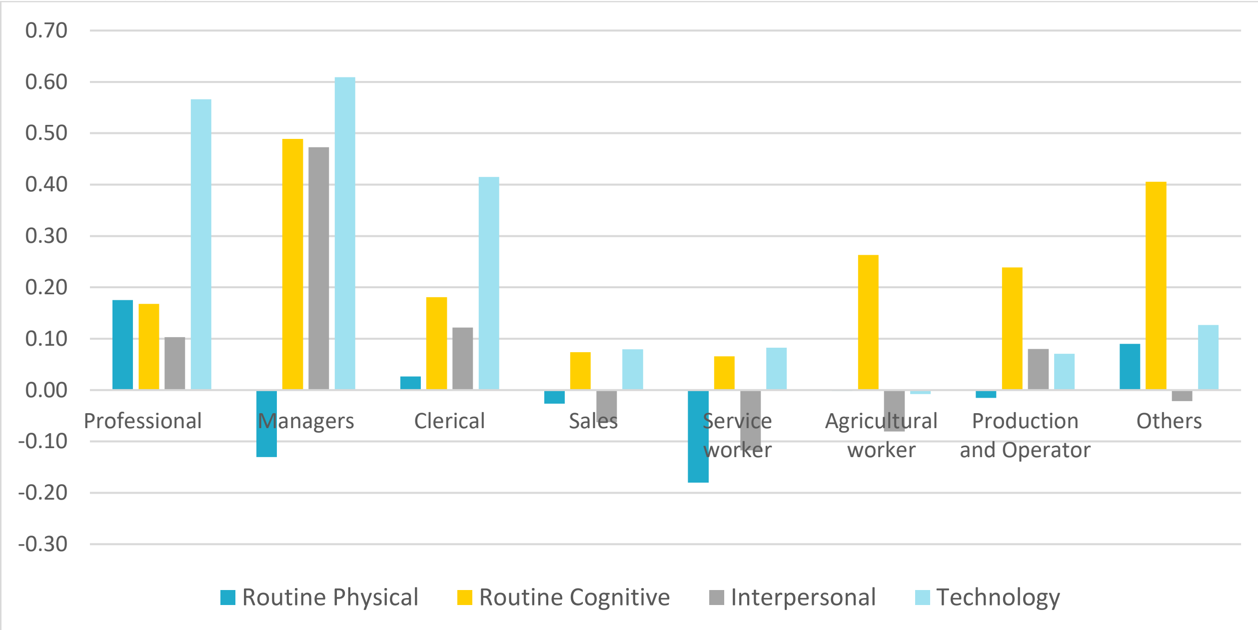
Figure 7: Tasks by Occupation



Note: Authors' calculations. The sample covers the Indonesia Family Life Survey (IFLS) 4 (2007) and IFLS 5 (2014).
Source: IFLS 4 and 5

From 2007 to 2014, tasks within occupations changed (Figure 8). Routine physical tasks declined among managerial and service-oriented occupations. Routine cognitive tasks increased in all occupations. Technological tasks increased dramatically in jobs requiring high-level skills. Managers and professionals both experienced significant growth in technological tasks.

Figure 8: Changes in Skill by Occupation Group 2007-2014



Note: Authors' calculations. The sample covers the Indonesia Family Life Survey (IFLS) 4 (2007) and IFLS 5 (2014).
Source: IFLS 4 and 5

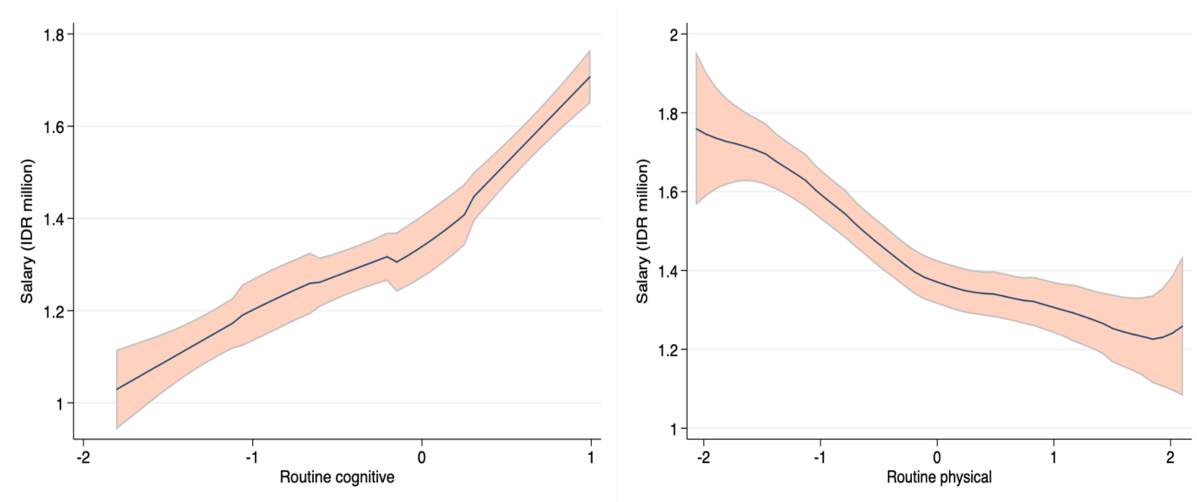
Figure 9 displays the relationship between routine tasks and real monthly wages. It describes the relative price of routine cognitive (Panel A) and manual tasks (Panel B). The difference between the two is striking. Jobs with relatively higher routine cognitive tasks are associated with higher wages. Meanwhile, a higher level of routine tasks in a job is associated with lower wages. It is important to note that the relationship is unconditional, without controlling other characteristics. Nevertheless, this gives a rough picture of how tasks are valued differently.

The finding on non-routine tasks in Indonesia is in contrast to findings from developed countries. In developed countries, jobs with high routine cognitive tasks are declining. Thus, lower demand for such tasks results in lower relative wages for such jobs. This is mainly because routine tasks are being automated or replaced by machines. Our finding shows that routine cognitive tasks still pay a wage premium. This may be because adopted technologies and routine cognitive tasks are complementary, as seen in clerical jobs that require computer use.

Figure 9: Routine Tasks and Monthly Wage

A. Routine Cognitive Tasks and Wage

B. Routine Manual Tasks and Wage



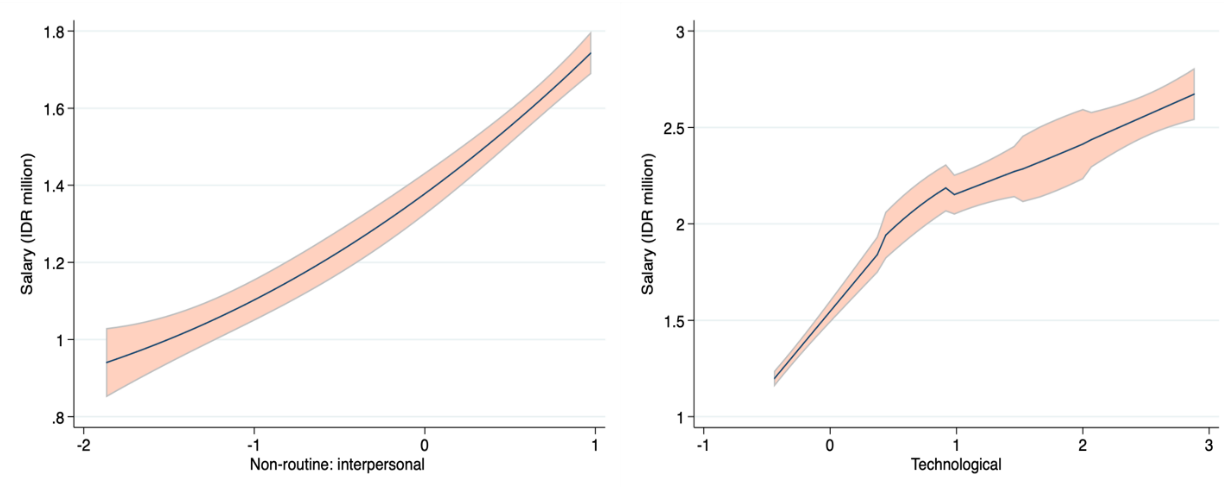
Note: Authors' calculations. Graphs are displayed using local polynomial regression between real monthly salary and standardized score of tasks. Orange shading shows the confidence interval of 95%.

Source: Indonesia Family Life Survey (IFLS) 4 and 5.

Figure 10 shows the unconditional relationship between non-routine tasks and real monthly wages. Unlike routine manual tasks, we can observe a positive association between non-routine interpersonal tasks and wages. It implies that the relative value of jobs requiring a high level of interaction with people, such as face-in-face communication or networking, is quite high. In addition, the relationship appears to be exponential, whereby the wages of jobs with very high-intensity interpersonal tasks grow exponentially. On the other hand, technological tasks in the workplace with a low level of computer use tend to offer higher premiums, to the point where computer usage is common. We can draw this as a curve representing the return to technological task showing a diminishing return—i.e. the slope of the curve is steeper when demand for computer use is low, and is gets flatter at the top level of computer use in a working environment.

Figure 10: Non-Routine Tasks and Monthly Wage

A. Non-Routine Interpersonal Tasks and Wage   B. Technological Tasks and Wage



Note: Authors' calculations. Graphs are displayed using local polynomial regression between real monthly salary and standardized-score of tasks. Orange shading shows the confidence interval of 95%.

Source: Indonesia Family Life Survey (IFLS) 4 and 5.

4.3 Technological and Innovation Intensity

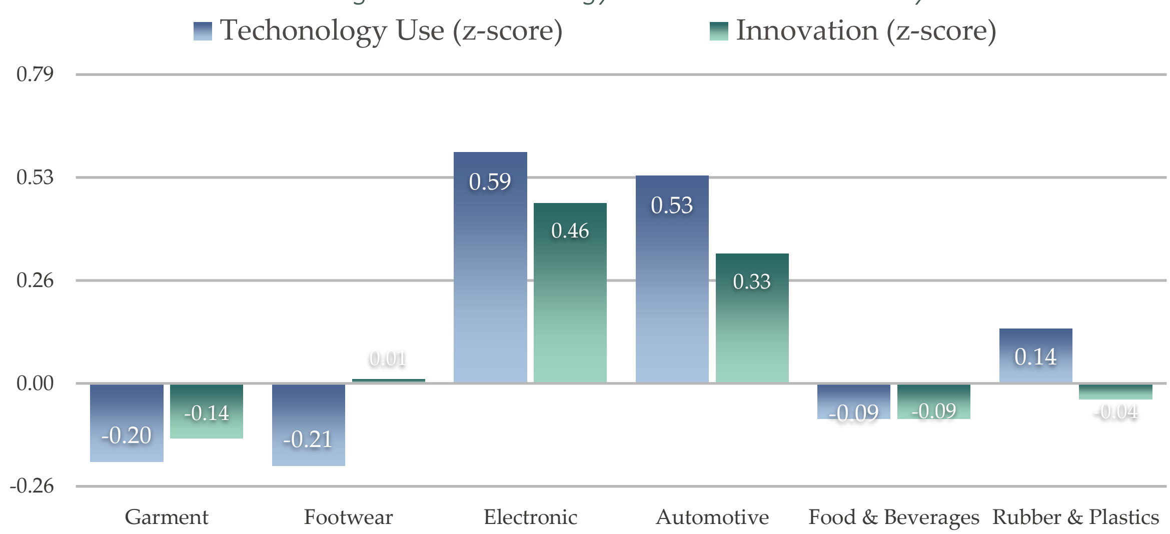
We use the CSIS-ADB manufacturing survey to assess how technological adoption at a firm level affects demand for workers, and which workers are affected the most. We construct the intensity of technology adoption and innovation at the firm level. Technological intensity is expected to capture the extent of new technology adoption by firms, while innovation intensity is aimed at describing the depth of innovation supported by firms.

Firms clearly adopt technologies that may differ vastly in terms of characteristics and sophistication. For instance, artificial intelligence (AI) technology may be more sophisticated to establish than big data or cloud computing, which are more about storage technology. To simplify our analysis, however, we impose the assumption that there is a way to map all technology usage to an outcome, which is demand for labor. As it may imply, these technologies will have equivalent values. The assumption eases our variable construction. We also impose the same assumption on innovation.

In constructing the technological intensity, we set up a composite variable that sums up all responses to questions on whether firms use AI, robots/automation, 3D printing, the cloud, and big data. We standardize the score across the full sample, resulting in zero mean and one standard deviation. The variable of innovation intensity is built with the same approach. Specifically, we sum up all innovation supported by firms in the last three years. There are four types of innovations considered in the survey, in the following spaces: product, production line, management and organizational structure, and marketing strategies

Figure 11 displays the intensity of technology and innovation. A salient finding from the figure is that innovation and technological adoption are relatively intensive in the capital-intensive sector, such as electronic and automotive companies. Relative to other sectors, rates of innovation and the adoption of the new technologies described above are among the lowest in the garment and textiles sector. A similar pattern is seen in the food and beverage sector. These two sectors have traditionally been a major source of employment creation—i.e. labor-intensive industry. Footwear firms, interestingly, support a higher rate of innovation than the average of all industries in the survey. On the other hand, technological adoption among rubber and plastics tends to be above the industry average.

Figure 11: Technology and Innovation Intensity



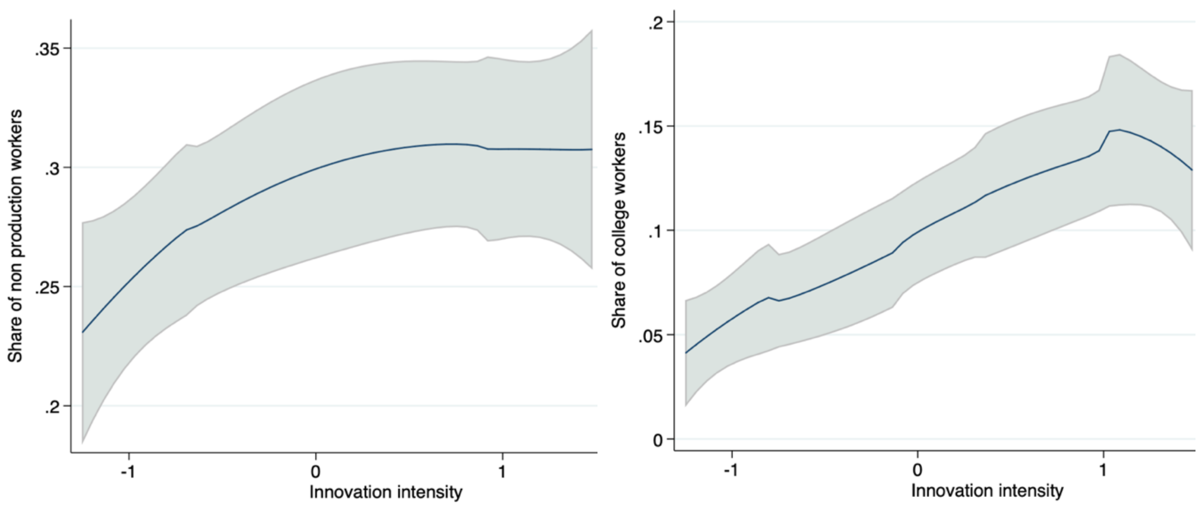
Source: Center for Strategic and International Studies-Asian Development Bank manufacturing survey 2019

Figure 4.5 describes the relationship between innovation intensity and demand for high-skilled workers, represented by non-production workers and college graduate workers. Demand for non-production workers increases dramatically when firms with a low level of innovation start to innovate. For firms with above-average innovation intensity, demand for non-production workers tends to flatten. While this is an unconditional relationship between innovation and demand for non-production workers, it describes the extent to which innovation and non-production workers are complementary. On the other hand, the share of college graduates monotonically increases with the intensity of innovation.

The distinct difference between Figure 12.A and Figure 12.B shows the characteristics of tasks within firms. Non-production workers typically carry out administrative and management tasks in firms, including both college graduates and non-college graduates. However, firms with a high level of innovation may embark on innovations in their management and organizational structure. Thus, some routine tasks carried out by these workers are no longer needed in highly innovative firms and, as a result, demand for this type of workers tends to remain flat.

Figure 12: Innovation Intensity and High-Skilled Workers

A. Innovation and non-production workers B. Innovation and college workers



Note: Graphs are displayed using local polynomial regression between share of employment—i.e. non-production workers and college graduates and standardized score of technology and innovation intensity.

Source: Center for Strategic and International Studies-Asian Development Bank manufacturing survey 2019.

4.4 Econometric Models

For our labor supply model, we use a Mincer-type regression model. In particular, we estimate the following simple log-linear wage equations. Suppose that worker i $(i = 1, \dots N)$ works in an occupation j $(j = 1, \dots, J)$ and industry k $(k = 1, \dots, K)$ at a given time t $(t = 1, \dots, T)$. The relationship between earnings and tasks can be described as:

$$lnWage_{ijkt} = \alpha_i + Task_{ijkt}\delta + X_{ijkt}\beta + v_j + u_k + \varepsilon_{ijkt} \tag{1}$$

Where $lnWage_{ijkt}$ is the natural log of gross monthly earnings, $Task_{ijkt}$ is the intensity of tasks (i.e. routine cognitive, routine manual, non-routine interpersonal and technological tasks). $Task_{ijkt}$ is a vector of tasks with standardized values with zero mean and one standard deviation. X_{ijkt} refers to a vector consisting of demographic variables: years of schooling, tenure, age, age squared, hours worked, union status, marital status, job status, firm size, a dummy variable indicating the formal sector, a dummy variable on urban residence and a dummy indicating the year. The error term is denoted by ε_{ijkt}, where we allow conditional heteroscedasticity in the model.

The model includes time-invariant individual heterogeneity denoted by α_i. This reflects unmeasured individual job productivity that leads to higher skills, which potentially includes an innate ability to perform particular tasks, and more productive workers for specific tasks. The model also includes v_j and u_k that control unobserved heterogeneity stemming from occupations *j* and industry *k*, which potentially affect relative wages. Controlling unobserved heterogeneity at individual, occupation and industry levels is important as failing to control this leads to bias on the relative price of tasks.

Panel Data Estimator

The key identification challenge in equation 1 is that unobserved individual, occupation, and industry heterogeneity—i.e. a_i, v_j and u_k—potentially correlates with earnings and tasks; e.g. technological tasks could correlate with unobserved ability, productivity or firm characteristics. The advantage of using the IFLS is that its longitudinal nature of data allows us to sweep out all time-invariant individual and occupation-industry effects.

There are two standard panel-data estimators allowing us to control for latent heterogeneity through person, occupation and industry-specific intercepts in equation 1: deviations from the time-mean (within or fixed effects), and the time-difference (first-difference) estimators. In short panel data, as we currently have (i.e. T = 2), both estimators yield identical results.[7] However, the first-difference model offers a more flexible approach to the structure of the model. Hence the model of 1 becomes:

$$\Delta lnWage_{ijkt} = \Delta Task_{ijkt}\delta + \Delta X_{ijkt}\beta + \Delta\varepsilon_{ijkt} \tag{2}$$

Δ denotes a difference (e.g. $\Delta lnWage_{ijkt} = lnWage_{ijkt} - lnWage_{ijkt-1}$). From

[7] Short panel data are data that collect the same observations—i.e. same individuals—for a short period of time or a small number of years. This is in contrast with long panel data that collect the information of individuals for many years. Our data cover only two survey years and thus fall into the short panel data category.

equation 2, is clear that the equation above reduces any biases arising from unobserved characteristics assumed to be time-invariant. We use first-difference to estimate model 2.

Data from the manufacturing survey is cross-sectional. Hence, we use ordinary least square (OLS) to estimate the relative demand for types of workers. For firm i $(i = 1, \dots N)$ in industry k $(k = 1, \dots, K)$, we estimate a labor demand function as follows:

$$ShrEmp_{ij} = \alpha + Tech_{ij}\beta + X_{ij}\gamma + \varepsilon_{ij} \tag{3}$$

$ShrEmp_{ij}$ is the share of types of workers—i.e. non-production workers, college graduate workers, non-production female workers, non-production college workers, and female workers. $Tech_{ij}$ is a vector of technology and innovation. The vector consists of technology-use intensity, innovation intensity, a dummy indicating whether the firm has an R&D unit, and a dummy indicating whether or not the firm adopts a high level of technology. Moreover, X_{ij} is a vector of firm characteristics, such as the year of establishment, ownership status, location (within industrial zones and bonded zones), natural log of value added, and an indicator of whether the firm is classified as part of the labor-intensive industry.

V. EMPIRICAL RESULTS

This section discuses findings from labor supply—i.e. the IFLS and labor demand, or the manufacturing survey. Our analyses begin with estimates from a labor supply model that estimates relative prices of tasks. This is followed by the analysis of labor demand at firm level.

5.1 Evidence from Household Survey

Table 2 displays summary statistics of variables for our analysis. The mean of natural log of hourly earnings, our dependent variable, is 8.52 (around Rp 5,000 per hour). Job tasks—routine physical and cognitive, interpersonal, and technological—are standardized with mean zero and one standard deviation. The length of schooling is 9.48 years, suggesting that a large number of individuals in our sample completed senior high school. Around 80% are married and the average age is around 35 years old. In total there are 28,396 year-person observations.

Table 2: Summary Statistics from Indonesia Family Life Survey (2007-2014)

Variable	Mean	Std. Dev
Log of hourly earnings	8.52	1.15
Routine physical	0.00	1.00
Routine cognitive	0.00	1.00
Non-routine: interpersonal	0.00	1.00
Technology	0.00	1.00
Years of schooling	9.48	4.31
Marital	0.79	0.41
Age	35.38	9.70
Male	0.61	0.49
Union participation	0.11	0.31
Location in urban area	0.61	0.49
Hours worked	45.24	23.78
Formal sector	0.64	0.48
Employment size	1.88	1.06
Total year-person observation	28,396	

Source: Indonesia Family Life Survey (IFLS)

We begin with an analysis of skills that use first-difference models. Table 5.2 displays the results of the models. Columns 1 to 4 of the table display the result for the model that regress monthly earnings on specific tasks, while controlling for all personal characteristics. Column 5 shows the result with full specifications, in which we include all tasks together in the model. In each model, we control for years of schooling, tenure, age, age squared, hours worked, union status, marital status, job status, firm size, a dummy variable indicating the formal sector, a dummy variable for urban residence and a dummy indicating the year. We also use fixed effects on occupations and industries to control for unobserved heterogeneity stemming from job characteristics.

Estimates from the model provide striking confirmation of the predicted relationship between tasks and wages. From the model controlling for all tasks, we find higher relative wages for workers who specialized in non-routine and technological tasks. One standard-deviation increase in the measure of non-routine tasks leads to a 4.1% increase in wages, which is statistically significant at a conventional 99% significance level. The magnitude is higher than technological tasks, in which an increase of one standard deviation leads to higher wages by 3.4%.

Occupations involving heavy routine manual tasks saw a decline in relative wages. Specifically, one standard-deviation increase in manual tasks leads to lower wages by 2.5%, and the relationship is significant at a 10% level. On the other hand, routine cognitive tasks—jobs requiring a high level of concentration and attention—offer a wage premium. Evidence suggests that premiums from routine cognitive tasks contrasts with findings from developed countries, probably because the content of tasks still involves human judgment and abstract work, which are paid a premium.

The extent of unobserved heterogeneity affecting the relationship between tasks and relative wages can be observed by comparing Table 3 and Table 4. Table 4 presents results from pooled ordinary least squares (POLS). As it becomes clear, the comparison between two estimators—first difference and POLS—highlights the magnitude of latent heterogeneity correlated with tasks and wages. This comparison also underscores the extent of the bias in premiums from task measures when particular econometric issues are not handled appropriately.

Table 3: Estimates of Tasks and Wages: First-Difference Model

Variables	1	2	3	4	5
Routine physical	-0.00878				-0.0245*
	(0.012)				(0.013)
Routine cognitive		0.0290***			0.0250***
		(0.008)			(0.009)
Non-routine: interpersonal			0.0458***		0.0411***
			(0.009)		(0.010)
Technology				0.0405***	0.0344***
				(0.013)	(0.013)
Years of schooling	0.0404***	0.0399***	0.0395***	0.0392***	0.0384***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Constant	0.147*	0.143*	0.162*	0.142*	0.157*
	(0.085)	(0.085)	(0.085)	(0.085)	(0.084)
Observations	6934	6934	6934	6934	6934
Adjusted R-squared	0.065	0.066	0.068	0.066	0.069

Notes: Dependent variable is natural log of hourly earnings. Standard errors are in parentheses. Standard errors are robust to heteroscedasticity and clustered in industry-occupation groups. Included variables not shown are tenure, age, age squared, hours worked, union status, marital status, job status, firm size, a dummy variable indicating the formal sector, a dummy variable on urban residence and a year dummy, one-digit industry code and one-digit occupation code. *** significant at 1%, **5%, *10%.

Source: Indonesian Family Life Survey (IFLS) 4 and 5

Unlike other tasks, unobserved individual heterogeneity leads to an upward bias in the coefficient on routine physical tasks. This could be because more productive individuals will specialize more in non-physical tasks that pay higher wages. Failure to control for unobserved heterogeneity tends to lead to an upward bias on the coefficients of other task measures. In general, the bias reaches between 0.5 (non-routine interpersonal) and 2.37 (technological tasks), higher than estimates controlling for unobservables.

Table 4: Estimates of Tasks and Wages: POLS Model

Variables	1	2	3	4	5
Routine physical	0.0014				-0.0191*
	(0.012)				(0.010)
Routine cognitive		0.0741***			0.0569***
		(0.009)			(0.009)
Non-routine: Interpersonal			0.0835***		0.0627***
			(0.010)		(0.009)
Technology				0.128***	0.116***
				(0.011)	(0.011)
Years of schooling	0.0652***	0.0631***	0.0615***	0.0572***	0.0530***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	10.85***	10.90***	10.91***	10.97***	11.03***
	(0.165)	(0.167)	(0.170)	(0.162)	(0.167)
Observations	28396	28396	28396	28396	28396
Adjusted R-squared	0.317	0.321	0.322	0.326	0.332

Notes: Dependent variable is natural log of hourly earnings. Standard errors are in parentheses. Standard errors are robust to heteroscedasticity and clustered in industry-occupation groups. Included variables not shown are tenure, age, age squared, hours worked, union status, marital status, job status, firm size, a dummy variable indicating the formal sector, a dummy variable on urban residence and a year dummy, one-digit industry code and one-digit occupation code. *** significant at 1%, **5%,*10%.

Source: Indonesian Family Life Survey (IFLS) 4 and 5

5.2 Evidence from Manufacturing Survey

Table 5 shows summary statistics from the manufacturing survey. From the survey, 24% of workers are non-production workers—e.g. in a managerial position. Of non-production workers, on average, 39% are women. On average, women accounted for 30% of employees at firms. The share of college-graduate workers in a firm is very low, at around 10% of workers on average. We standardize technology and innovation intensity with mean zero and a standard deviation of one. Around 37% of firms we interviewed said they had an R&D division and around 6% adopted a high level of technology, as defined by the survey.

Table 5: Summary Statistics from CSIS-ADB Manufacturing Survey

Variable	Obs	Mean	Std. Dev
Share of non-production workers	342	0.24	0.24
Share of female non-production workers	317	0.39	0.30
Share of female worker	392	0.30	0.28
Share of college workers	392	0.10	0.17
Share of college-graduate non-production workers	312	0.07	0.12
Technological intensity	502	0.00	1.00
Innovation intensity	502	0.00	1.00
Research & development	502	0.37	0.48
High technology adoption	502	0.06	0.24
Has a website	502	0.42	0.49

Note: Authors' calculations.

Source: Center for Strategic and International Studies-Asian Development Bank manufacturing survey 2019.

Table 6 displays the OLS results from estimates on technological and innovation intensity. Each column in the table shows an estimated coefficient from regressions with various types of employment as the dependent variables. All models control for firms' characteristics—e.g. ownership, year of establishment, and location—and also sectors.

As shown in the table, the impacts of technology and innovation on employment are rather mixed. Firms with a high intensity of technology tend to employ fewer non-production workers—i.e. a proxy for high-skilled workers. The other side of the coin is that the adopted technology in our sample and production workers—i.e. low-skilled workers—are complementary. On the other hand, highly innovative firms are more likely to employ non-production workers, suggesting a complementarity between the two.

Moreover, firms with an R&D division are associated with a higher share of college-graduate workers. Comparing the coefficient on R&D for the model of all college workers and of college workers in non-production roles reveals an interesting finding. An R&D division in the former model—i.e. all college graduate workers—is associated with 8 percentage points higher in the share of college-graduate workers. Meanwhile it is associated with only 5.7 more percentage points in the share of non-production workers with college degrees. This implies that an R&D division is associated more with production workers who graduated from college. It seems to suggest that firms investing in R&D demand more college-graduate workers for production activities. It is important to note that our sample is all manufacturing sectors, in which the share of production workers is substantial.

Table 6: Estimates of Technological, Innovation and Employment

Variable	Shr. Non-Prod Worker	Shr. College Worker	Shr. College Non-Prod. Worker
Technological intensity	-0.0399**	0.00491	-0.00702
	(0.016)	(0.015)	(0.009)
Innovation intensity	0.0374***	0.00117	0.00779
	(0.014)	(0.009)	(0.007)
R & D	-0.00116	0.0820***	0.0570***
	(0.031)	(0.027)	(0.017)
High technology adoption	0.0559	-0.0408	-0.0207
	(0.081)	(0.050)	(0.030)
Has a website	-0.00834	0.0358**	0.0188
	(0.030)	(0.018)	(0.013)
Constant	0.175*	0.0205	-0.0529
	(0.096)	(0.094)	(0.042)
Observations	342	392	312
Adjusted R-squared	0.008	0.164	0.146

Notes: Dependent variables are share of non-production workers, share of female non-production workers, share of female workers, share of college workers, and share of college non production workers. Standard errors are in parentheses. Standard errors are robust to heteroscedasticity. Included variables not shown are duration of establishment, bonded zone location, natural log of value added and an indicator of whether the firm is part of a labor-intensive industry. *** significant at 1%, **5%,*10%.

Source: Center for Strategic and International Studies-Asian Development Bank manufacturing survey 2018

VI. CONCLUDING REMARKS

In this study we examine the relative value of tasks following the recent and rapid adoption of digital technologies in workplaces. We document the relationship between tasks, occupations and wages in Indonesia by pursuing the approach of Autor et al (2003) and Acemoglu and Autor (2011). Specifically, we construct bundles of tasks and classify them into technological tasks, routine manual tasks, routine cognitive tasks, and non-routine interpersonal tasks. Technological tasks cover jobs that require individuals to work with computers. Routine manual tasks involve any activities that require physical effort, lifting or stooping. Routine cognitive tasks cover any work that needs intense concentration and attention. Non-routine interpersonal tasks require employees to work with people.

Our estimates from the labor supply model confirm the predicted relationship between tasks and wages. We find that one standard-deviation increase in the measure of non-routine tasks—interpersonal tasks—leads to a 4.1% increase in wages. The magnitude is higher than for technological tasks. On the other hand, occupations using heavy routine manual tasks saw a decline in relative wages. Using the manufacturing survey, we find that the impacts of technology and innovation on employment are rather mixed. Firms with high-intensity technology tend to employ fewer non-production workers—i.e. a proxy for high-skilled workers. The other side of the coin is that the adopted technology in our sample and production workers—low-skilled workers—are complementary. On the other hand, highly innovative firms are more likely to employ non-production workers, suggesting a complementarity between the two.

All in all, the findings corroborate patterns on the relative prices of tasks in developed countries. That is, routine manual tasks are valued less in the labor market. Meanwhile, non-routine tasks that need human judgement and analytical skills still provide relatively higher-value jobs. However, there is also a complementarity between the technologies used in Indonesian establishments and the number and types of jobs in those industries. Thus, despite concerns about the disruptive effects on employment, new technologies can create employment.

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