TECHNOLOGICAL CHANGE, SKILL DEMAND AND WAGE INEQUALITY: EVIDENCE FROM INDONESIA

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ABSTRACT

This paper provides empirical evidence on the impact of technological progress on wage inequality in Indonesia. The share of educated workers and their skill premium have increased recently for overall industry. A supply and demand analysis using the labor force survey data of 1990- 2009 shows that both the between- and the within-industry shifts of labor demand favoring skilled workers contributed to widening wage inequality. The evidence from the firm-level data for manufacturing sector indicates that diffusion of foreign technologies through imports and foreign direct investment caused demand shift toward more skilled labor and increased wage inequality.

Key words: wage inequality, technology progress, globalization, foreign direct investment, Indonesia

JEL Classification: J24, J31, O15, O33

HIGHLIGHTS

- We examine the implications of technological change for wage inequality in Indonesia.
- Indonesia has experienced rising wage inequality since the early 2000s.
- The observed increase in wage inequality of Indonesia was driven by the shifts in relative labor demand within and between industries.
- International trade and foreign direct investment increase demand for skilled workers and skill premium.

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1 INTRODUCTION

What are the implications of technology and education on wage inequality? In most developing countries, educational expansion and technological progress have occurred rapidly in recent years. While these economies emphasize the positive role of educational attainment and transfer of foreign technology for their economic growth, some economists contend that the differential effect of technological progress on wage by workers' education level can exacerbate wage inequality.

They point out that there is an important channel in which technology affects relative wages by shifting labor demands away from the least skilled group. Since most developing economies have a dominant portion of low skilled workers, this shift in labor demand could cause a drastic change in their labor markets. As argued by the skill-biased technological change hypothesis, demand for educated and skilled workers increases when skill-complementary technologies are permeated into the workplace. [1]

A large body of literature investigates the impact of technological changes on relative labor demand and wage inequality in advanced countries. Though wage inequality is also a keen issue in developing countries, literature on developing countries is relatively scanty. We therefore briefly review important papers in this field and explain how our paper can contribute to the literature.

Katz and Murphy (1992) use a simple supply and demand framework to explain the change of wage structure of the United States in 1980s. Their study demonstrates that there was a trend in demand growth favoring more skilled workers that could explain the movement of relative wage beyond the prediction by the simple supply-demand framework. Berman, Bound and Griliches (1994) confirm that a greater use of non-production workers was mostly driven by increased demand within industries and this demand change was correlated with investments in computers and research and development (R&D) in the United

States. A sizeable portion of demand shift within each industry, rather than between industries, would be attributed to technology change favoring more skilled workers.

The spreading use of computers and workplace organization are pointed out as driving forces behind the long run increase in the relative demand favoring skilled workers. Autor, Katz and Krueger (1998) show that growth in computer utilization exerted a positive effect on skill upgrading within the industry and the positive relationship was accelerated in more recent decades. Autor, Levy and Murnane (2003) show the type of work as a key factor of growing demand for skilled workers and explain how the recent development of computer is associated with an increase in upper-tail (p90/p50) wage premium. The computer has three impacts on workers corresponding to their tasks. The computer complements the ones who perform non-routine tasks such as management and analysis; it replaces the ones to carry out routine tasks; it has a limited impact on manual ones. A study by Bresnahan, Brynjolfsson, and Hitt (2002) uses detailed firm level data to examine the effect of information technology and workplace organization on skill-biased technological change and shows the greater effect of information technology on employment of skilled labor with the more permeation of technology to particular workplace environments.

The evidence of technological change and associated wage inequality is also found in other advanced countries. Machin and Van Reenen (1998) extend the analysis to six other OECD countries, finding that R&D expenditure and computer investments were positively associated with skill upgrading. Berman, Bound and Machin (1998) find that, with progressing technology, skill upgrading occurred within similar industries in twelve OECD countries, suggesting pervasive skill-biased technological change.

A number of papers raise questions regarding the extents of skill-biased technological change and of its impacts on wage structure. Card and DiNardo (2002) insist that skill-biased technological change be considered an episodic event rather than a secular trend. They point out the stabilizing wage inequality in the 1990s when computer technology continued to develop. They conclude that non-market factors, such as minimum wage and labor unions, had a more important role in explaining the rising inequality.

Lee (1999) supports the claim of Card and DiNardo (2002) by showing that increasing wage inequality in the 1980s in the United States was associated with the decline in the real value of federal minimum wage. Lemieux (2006) suggests that skill-biased technological change be illusionary because of the compositional change in the labor force and measurement error in data. If unobserved skills are more dispersed among older and more educated workers, residual inequality could be higher in the labor force with more aged and educated workers. Western and Rosenfeld (2011) present a decline of union membership as a source of increased wage inequality. Their analysis shows that the decline of organized labor unionization rates from 34 to eight percent of male workers from 1973 to 2007 contributed to 20-30% of increased wage inequality in the United States.

In response to this “revisionist” literature focusing on non-market factors, Autor, Katz, and Kearney (2008) claim that skill-biased technological change is still the major source of increasing inequality over the long run. They point out that decreased overall wage inequality in the 1990s hides a strong, persistent rise in inequality in the upper half of the distribution which polarizes U.S. earnings distribution. According to their new framework, non-market factors affecting lower-tail (p50/p10) inequality cannot explain increased inequality in the upper-tail (p90/p50) inequality. Goldin and Katz (2009) further extend the supply-demand framework and examine the evolution of wage differential for far longer periods from 1890 to 2005. They claim that even with immigration flow and institutional change during the wartime in the 1940s and late 1970s, relative supply and demand for college workers were the major source of college premium in the United States.

There are a more limited but growing number of empirical studies on the relationship between technology change and wage inequality in developing countries. Berman, Somanathan, and Tan (2005) find evidence of skill-biased technological change in India in the 1990s using panel data disaggregated by industry and state. Kijima (2006) also points out the returns to skills, resulted from skill-biased technological changes within industries, as a driving force of increasing income inequality in India. Harrison (2008) shows the firm-level evidence supporting skill-biased technology adoption in Brazil. Bustos (2011) observes the positive association between skill upgrading within firms and relative demand of skilled labor in Argentina. Chen et al. (2010) also find out that wage inequality is driven by foreign direct investment in China, implying transfer of foreign technology as an important source of wage inequality in developing countries.

This paper examines the empirical implications of technological changes for wage inequality in Indonesia, one of the largest and fastest-growing developing economies, with some 240 million people. We are especially interested in the role of foreign technology and trade on the inequality. Indonesia is a labor abundant country with relatively low wage and attracts many multinational companies around the world. Hence, it provides a good opportunity to examine the impact of trade and foreign direct investment (FDI) on demand for skilled labor. Indonesia's exposure to international trade and direct investment increased significantly in the recent decade. FDI net inflows have shown rapid growth since the Asian financial crisis, increasing from -2.8% of GDP in 2000 to 2.3% of GDP in 2012 according to the World Bank data. The country's trade share also began rising from 2003 after its collapse during the crisis. An increase in international trade and FDI is expected to have significant effects on relative demand for skilled workers and wage premium through diverse channels including the relative demand shifts across sectors and technology upgrading.

While previous literature such as Alatas and Bourguigon's (2005) highlight that Indonesia has been known for successful growth without an increase in income inequality, other papers address the reverse trend toward rising income inequality in the recent period.[2] Several factors such as increasing unemployment, changing labor market institutions, rising rice prices, and regressive fuel subsidies are pointed out as the sources for the inequality. However, there exists limited literature that analyzes the role of skill-biased technological change in the inequality.

A recent World Bank report by Di Gropello et al. (2010) examines skill-biased technological change and reports no clear evidence of skill upgrading in Indonesia. They find almost no increase in the share of skilled labor in manufacturing employment or total wage bills between 1975 and 2005. They also point out most changes in labor demand shifts occurred between industries, suggesting little evidence of demand shift toward skilled labor. It would be interesting to investigate if any significant change has occurred to the trend of wage inequality in the most recent period when the economy has promoted its exposure to foreign trade and investment.

We show evidence supporting the reversion of wage inequality trend around 2003 when all decreasing inequality indexes started to soar up. We also find, based on extended data combined with available Indonesian surveys beyond 2005, demand shift toward skilled workers occurred along with increasing wage inequality. We then carefully examine if the demand shift is related to technological progress. Our regression results using firm-level manufacturing survey data show that demand shift toward skilled labor was associated with transfer of foreign technology through FDI and imported materials. Our findings imply that trade and foreign technology transmitted to developing countries could increase wage inequality by shifting demand toward more skilled workers.

This paper is organized as follows. Section two describes trends of various wage inequality measures and overall characteristics of the Indonesian labor markets. Section three analyzes the Indonesian Labor Force Survey using a supply-demand framework and within/between decomposition of industry demand shifts. Section four is devoted to analysis of the relationship between technology transfer and skill-upgrading in the manufacturing sector. Section five concludes.

2 OVERVIEW OF CHANGING WAGE INEQUALITY IN INDONESIA

Indonesia experienced declining wage inequality during its fast development period, in contrast to many other developing countries. However, in the recent years, wage inequality has been rising. Figure 1a demonstrates the median, tenth percentile, and ninetieth percentile of the real monthly wage distribution among the full-time wage workers for the period, 1990-2009, sourced from the National Labor Force Survey of Indonesia. The survey is conducted annually. The sample size varies over time from over 65,000 in 1990 to about 299,000 households in 2009. The survey also provides detailed information on employment, wages, education attainment, and demographic variables.

<Figure 1, a & b Here>

The data provide a clear contrast in the change in wage inequality before and after 2003. The benefit of economic growth was the greatest for the least skilled group (proxied here by the tenth percentile) by 2003. Real wages of the tenth percentile group rose by more than 100 percent from 1990 to 2003 but declined sharply thereafter.[3] For the median group, real wages rose by more than 50 percent by 2003 and decreased from 2003 to 2008, recovering somewhat in 2009. The 90th percentile group moved like the median group until 2003 but unlike the median group, real wages for the ninetieth percentile rose steadily thereafter. The movement of Gini coefficients, constructed by the wage data, also showed a similar trend. In Figure 1b, Gini coefficients of the real monthly wage distribution sharply increased in both urban and rural areas since 2003.

<Figure 2, a & b Here>

We assess to what extent the recent change in wage inequality is related to the change in skill premium. We identified workers with their education level and calculated the skill premium in various ways. Figure 2 shows that both high school premium and college premium compared to the wage of those who attained junior high school or lower level education decreased from 1990 to 2004 in urban areas and significantly increased since then. In rural areas, the increasing trend of the skill premium began much later. Both the high school premium and college premium steadily decreased until 2008 and showed a sudden increase in 2009. These trends seem to imply that an increase in skill premium is a source of rising wage inequality.

However, skill premium is only one of many sources that contribute to changing wage inequality. We ran a regression of log monthly wage on experience (up to quartic and interacted with sex and education level dummies), and years of schooling to acquire residuals. The residuals from this regression capture the dispersion of wages within each demographic group. Then, we calculate the difference in the log wages of those at the ninetieth and at the tenth percentiles of the distribution.

<Figure 3, a & b Here>

Figure 3 shows that both log wage differentials and residual wage differentials increased in all areas for both women and men from 2004 to 2009. It means not only overall wage inequality expanded, but also within-group wage inequality increased at the same time. The increased within-group wage inequality implies that the least-skilled workers within each category were lost compared to the high skilled ones in recent years.

The drastic changes in the various indicators of wage inequality may result from several market and non-market factors, such as several important changes in labor market institutions and macroeconomic developments. While some market and non-market factors may contribute to the changes in labor demand and supply and wage structures, they may have a limitation in explaining the drastic increasing wage inequality in the recent decade.

The Indonesian economy experienced fast growth in 1990s until the Asian financial crisis in 1997-98. Due to sound crisis management and favorable global economic environment, the economy started to recover quickly. However, Indian Ocean Earthquake and Tsunami hit Aceh area in 2004. These macroeconomic business cycle factors could not sustain the steady increase in wage inequality from 2004 to 2009. For example, inflation should have decreased real wages of both unskilled workers and skilled workers and may not affect relative demand for skilled workers and wage premium. In fact, Figure 1 (a) shows that real wages of high-skilled workers were more stable between 2003 and 2008 and rose more quickly than the real wages of unskilled- or median-skilled workers in 2009.

There was a sharp increase in minimum wages in the 1990s, partly due to international pressure (Alatas and Cameron 2008), as the level of minimum wages tripled in nominal terms and doubled in real terms. Moreover, from 2003 to 2009, the nominal level of minimum wage was on average doubled and its real value also increased significantly.[4] Alatas and Cameron (2008) indicate the sharp increase in minimum wages in the 1990s had no significantly negative effect on employment in large and medium-sized establishments. However, Comola and Mello (2011) report the possibility that some workers might have moved from formal to informal sector due to the increase in minimum wages. This suggests that wages of unskilled workers in the official sector in our sample are likely to have increased.[5] We think the decline in wage inequality in the 1990s is partly due to the increase in minimum wages and the reallocation of low-wage workers from formal to informal sector. However, considering that the size and composition of skill level of workers in the formal sector was quite constant from 2003,[6] the increases in wage inequality and skill premium from 2003 to 2009 cannot be attributed to the compositional change. In sum, the changes in minimum wages were very unlikely to cause the increasing wage inequality trend between

2003 and 2009.

We suspect that the skill-biased technological change, as it took place with rapid globalization and technological progress, was a fundamental and permanent force that contributed to the increase in skilled labor demand and wage inequality in Indonesia. Using data from the Indonesian National Labor Force Survey and Manufacturing Survey, we will analyze the the extents of skill-biased technological change and of its impacts on wage inequality in the next sections.

Table 1 shows a brief overview of the Indonesian labor market over the period, 1990-2009. The share of urban employment increased constantly during this period as in many other developing countries. The share of female employment also increased at a slow rate. The labor market is also marked by a significant increase in younger and more educated workers in the late 2000s. The sharp change in overall education attainment of workers would provide us with a good opportunity to examine the evolution of skill premium in supply-demand framework.

<Table 1 Here>

3 SUPPLY-DEMAND ANALYSES

3.1 Data Construction and Empirical Strategy

In this section we use twenty annual series of the National Labor Force Survey (1990-2009) to examine the long term trends of relative wages and relative labor supplies. The Survey is stratified into rural and urban samples. The census blocks in each stratum are geographically ordered within each regency and the regencies are geographically ordered within each province, so that systematic sampling provides implicit stratification by province and regency as well. Samples are also clustered at the two-stage level: census blocks and household level. All estimations take into account stratification and clustering, and use sample weights to calculate estimates.

We employ the methodology of Katz and Murphy (1992) to analyze the movement of relative wages and relative supplies. We construct two samples: a wage sample and count sample. The wage sample includes full-time workers who are reported to work more than 40 hours per week (which can include one hour of lunch time per day) at the main job. We exclude a small number of outliers (0.01% of total observation) based on their real wages to acquire an accurate measure of relative wage series.[7]

To calculate the measure of relative supply, the count sample is constructed using all workers in the formal sector whose wage and education level could be identified. Since we are more interested in identifying the size of labor supply of each cell, we do not restrict the count sample to full-time workers.

To examine the movement of relative supply and relative wage series of various demographic groups, the sample is divided into 64 categories by workers' gender, education level, experience level, and region. The fixed weight of average employment share for 64 cells among all workers during the entire sample period is used to construct aggregate measures in the wage sample, while the count sample uses the fixed weight of average relative wage for 64 cells.

3.2 Evolution of Relative Wages and Relative Supplies in Indonesia

Table 2 shows the change of relative wages for the period from 1990 to 2009. The notable characteristics are as follows. The relative monthly real wages increased by 37% during our sample period[8], however, growth rates decreased during the late 1990s and actually became negative in the late 2000s, partly because wage growth could not catch up inflation.[9] Winners and losers were reversed between the fast growth period and the recovery period after the Asian financial crisis. Female and less educated workers gained more, compared to other groups in the 1990s. However, their wages declined more than other demographic groups since 2003.

<Table 2 Here>

The differing relative wage trends by education level deserve attention. The least educated group benefited the most from 1990 to 2003, but the most educated group took the lead since 2003. Although all the other groups experienced a decrease in their real wages, this high skilled group maintained growth in their real earnings.

The changes in earnings by experience group showed similar trends. Young workers acquired the most gain in wage from 1990 to 1997, but the most experienced group started to enjoy their premium since 1997. In the latest period, 2003-2009, young workers lost the most compared to other groups. All these measures indicate that more educated and experienced workers are becoming a winner in the labor market of Indonesia.

<Table 3 Here>

What caused the reversal of skill and experience premium in Indonesia? Was there a demand shift toward more skilled workers in recent years? To answer to this question, we should figure out what fraction of change was caused by the change in supply side. Table 3 shows the change in relative supply of employed workers in formal sector. Table 3 implies that part of the changes in relative wages can be explained by demand-supply framework. An increasing trend of relative supply of female workers was accelerated in the 2000s suggesting that a decrease in female relative wage in 2000s can be explained by supply change to some extent. The sharp decline in relative supply of less educated workers through the whole period also implies that supply change contributed to the increase in the relative wage of these workers. However, the steady increase in relative supply of workers with tertiary education in the 2000s suggest that supply-side change cannot explain the relative wage increase of this group and that there was demand shift toward more educated workers.

The evidence from the data in Tables 2 and 3 propose the existence of demand factor increasing relative wage and employment of more educated workers at the same time. To examine this issue, we proceed to the supply-demand analysis suggested by Katz and Murphy (1992). According to supply-demand framework, the inner products of changes in relative wages and changes in relative supplies should be negative. Finding out positive inner products between relative supplies and relative wages would mean that there is demand growth factor.

We divide our sample into 64 different labor groups by gender, four education levels, four experience categories, and two regions. To reduce the influences of measurement errors and business cycle factors, we aggregate the 20 years period into five four-year intervals and computed average relative wages and average relative supplies for each of our 64 groups within these sub-periods. We then calculate the inner products of the changes in these measures of wages and supplies between each pair of these five intervals.

<Table 4 Here>

The results of these calculations are given in Table 4. The numbers appear to be consistent with the stable demand hypothesis for 1990-2001 periods. Though of small magnitude, they remain negative during this period. In contrast, the results from the later periods seem to disapprove a stable factor demand hypothesis. The inner products of the later periods show positive signs indicating that a demand shift occurred in at least some sectors of the economy. Figure 4 also indicates that positive inner products of later periods in Table 4 are not a product of several outliers. The weighted scatter plots between relative wages and relative supplies from 2003-2009 show that most of the inner products in this period fall into either upper right quadrant or lower left quadrant.

<Figure 4, a & b & c Here>

Demand-supply analyses in this chapter allow us to draw a tentative conclusion that there was a demand shift favoring more educated workers in recent years in Indonesia. Although it did not occur in the entire economy, widening wage differential between more skilled workers and less skilled ones in several sectors seem to be the source of rising inequality. We will examine demand shifts in detail in the next chapter by decomposing demand shifts by within/between industry demand shifts.

3.3 Within/Between Decomposition of Industry Demand Shifts

We find that the observed increase in wage inequality of Indonesia since the early 2000s was driven by the shifts in relative labor demand. The shift can be caused by not just skill-biased technological change, but other factors such as changes in industrial structure and in relative demand for products. We adopt the technique of within-/between industry decomposition of labor demand to quantitatively measure the skill-biased technological change in Indonesia.

We use decomposition of labor demand by within/between industry demand shifts according to the methodology in the literature as it has been proved to be very useful. The National Labor Force Survey of Indonesia provides working hours of informal workers as well. In Indonesia, there exist large shares of informal workers who are self-employed or unpaid. We treat labor demand among formal workers and informal workers separately since demand for these workers differ across sectors.[10] The share of skilled workers is higher among formal workers than that among informal workers, implying that demand shift toward more skilled workers can be different across the two markets.

Demand shift between industries can affect skill distribution. Even with no skill-biased technology, if each industry grows at different rates, causing between-industry demand shifts, skill distribution of whole labor market will be affected. Indonesia experienced moderate change in share of each industry during the sample period, suggesting what we observed in previous sections could have been driven by between-industry changes.

On the other hand, within-industry demand shifts can be driven by skill-biased technological change or changes in price of non-labor inputs. If there was a demand shift favoring more skilled workers within each industry, the sizable portion of demand shift would be attributed to within-industry demand shifts.

A widely used measure of the effect of between-sector demand shifts on relative labor demand in literature is the fixed-coefficient "manpower requirements" index (Freeman 1980). This index calculates the percentage change in the demand for a demographic group as the weighted average of percentage employment growth by industry where the weights are given as industrial employment distribution for the demographic group in a base period. This measure of demand shift is proved to be appropriate although it tends to understate relative demand shifts of groups with increase in relative wages.

The Labor Force Survey uses own industry classifications, KLUI (Klasifikasi Lapangan Usaha Indonesia) or Indonesian Standard Industrial Classification (KBLI). The classification system was firstly established in 1987 and improved in 1995, 2000, and 2005. To construct consistent industry classification across the sample period, we aggregate detailed industry codes into 30 industry classifications.[1 1] For occupation code, survey does not have proper occupation information in surveys constructed before 1995. Therefore, we restrict our analysis from 1995 to 2009. We aggregate original occupation classification code provided in the survey into three general categories following the literature. Finally, to prevent bias coming from measurement errors of dealing with a small sample of female workers, we decide to focus on male workers only.

According to Katz and Murphy (1992), we define our overall (industry-occupation) demand shift index for group k, ΔX_k^d, as in the following equation :

$$\Delta X_k^d = \frac{\Delta D_k}{E_k} = \sum_j \left(\frac{E_{jk}}{E_k}\right)\left(\frac{\Delta E_j}{E_j}\right) = \frac{\sum_j \propto_{jk} \Delta E_j}{E_k} \qquad (1)$$

, where index of demand shift for group k is measured relative to base employment of group k in efficiency units, E_k. ΔE_j measures total labor input as efficiency unit in cell j , where j indexes 90 industry-occupation cells. $\propto_{jk}= (\frac{E_{jk}}{E_J})$ is group k 's average share of total employment in efficiency units in cell j during the sample period. Thus, we use the average share of total employment in cell j of group k over the sample period as our measure of $\propto_{jk}$, and the average share of group k in total employment over the sample period as our measure of E_k. To make it easy to calculate, we normalize equation (1) so that total employment in efficiency units in each year sums to one. Group k is divided by workers' job status (informal/formal) and three skill levels: primary education, junior high education, and senior high education or higher. Since the share of workers who acquired tertiary education is very low in the 1990s, we merge tertiary education category with senior high school category to reduce bias from measurement error.

We also decompose this index into between- and within- industry components. The between-industry demand shift index for group k, ΔX_k^b is constructed by the index in equation (1) by summing over j when j refers to 30 industries. Within-industry demand shift index for group k, ΔX_k^w is defined as the difference between the overall demand shift index and the between-industry demand shift index (i.e., $\Delta X_k^w = \Delta X_k^d - \Delta X_k^b$). These within-industry demand shifts reflect shifts in employment within industries.

<Table 5, a & b & c Here>

Table 5 summarizes the decomposition results of labor demand for different demographic groups across three sub-sample periods—1995-99, 1999-2003 and 2003-09—and overall period. It shows several characteristics that deserve our attention. First, there is a clear contrast between the demand for formal workers and informal workers. The relative demand for informal workers has been greater than that for formal workers until the early 2000s, but that trend was reversed since 2003. Among formal workers, strong demand shift favoring more educated workers can be found in 2000s. Though demand shift is mainly driven by between-industry, about 8% of overall demand shift from 2003 to 2009 is driven within industries suggesting the existence of skill-biased technological change. Despite a small magnitude of within-industry effect, it is still a surprising result considering that more than 40% of workers belong to agriculture sector where demand for skilled worker is relatively low. However, such demand shift toward more skilled workers is not found among informal workers who are largely self-employed or unpaid.

4 TECHNOLOGY CHANGE AND LABOR DEMAND SHIFTS IN THE MANUFACTURING SECTOR

4.1 Industry Demand Shifts in Manufacturing Sector

Evidence in the previous section shows that much change was caused by between-industry effects and a demand shift toward more skilled workers is restricted to formal workers in the private sector. Nevertheless, it should be noted that Indonesia is a developing country with a low level of economic development and technological progress. If the evidence of skill-biased technological changes found in previous section was driven by manufacturing sector, much skill-biased technological change is anticipated to occur in the near future. Therefore, in this section we turn to the manufacturing sector of Indonesia, utilizing detailed information of firm-level survey and further explore the source of wage inequality in manufacturing sector and its relationship with specific technology measures.

The Indonesian Manufacturing Survey *(Statistik Industri)* contains information of wage bills and employment of production workers and non-production workers separately in large and medium scale firms. In the survey, non-production workers are defined as workers who supervise and manage the operation of plants. Therefore, we would take non-production workers as more skilled labor than production workers.

<Figure 5 Here>

Figure 5 show that there are positive relationships between changes in wage bill and changes in employment across different periods in the Indonesian manufacturing sectors. Also fitted lines between wage bill and employment changes are flatter than 45 degree lines, implying that industries with increased non-production workers' employment experienced a proportionally larger increase in their average wage. It implies that there was a demand shift toward non-production workers in the manufacturing sector.

We aim to examine the relationship between openness to foreign technology and labor demand shift toward non-production workers in this section. In developing countries where the level of technology is still low, the inflow of new technologies from foreign countries can affect demand for more skilled workers. A country with abundant low-skilled labor would experience an increase in relative wage of skilled workers when it opens up to trade. This argument is opposite to that of the Heckscher-Ohlin trade model, in which trade induces higher demand for low-skilled workers in labor abundant developing countries.

<Table 6 Here>

<Table 6> shows that domestic technology measures such as R&D investment share and human development share are still very low although they show sharp increases from 2000 to 2006. We employ FDI and trade measures as indicators of growth of foreign technology transferred to developing countries.

Many studies find out that foreign direct investment is an important vehicle for the transfer of technology in developing countries. Salim and Bloch (2009) study the case of Indonesia and find out that FDI contributes to productivity growth using plant-level data.

Feenstra and Hanson (1997) also find out that FDI affects skill upgrading within industries in Mexico. Evidence suggests that trade liberalization has a significant effect on wage inequality, through its impact on adoption of new skill-intensive technologies of production and organization in Latin American countries such as Argentina, Mexico and Peru (Bourguignon, Ferreira, and Lustig, 2004). We also consider export and import shares as proxies for technological changes. Though research and development investment of developing countries are often too low to lead technological development, they adopt foreign technologies by interacting with their trade partners. The more open an industry is to foreign trade, the more it is likely to absorb new technologies to compete in the global market. Coe, Helpman, and Hoffmaister (1997) also find out that foreign technology embedded in imported capital goods is an important channel of technology transfer.

The manufacturing firms in the survey actively involved in international trade. 42% of the firms were engaged in export while 19% used imported goods for production. There were also sizable FDI inflows, averaged over 6% of total investment of Indonesian manufacturing firms.

4.2 Regression Analysis

We explore the effect of technology on skill demand by employing the following regression specification which relates changes in the non-production workers' employment and wage bill shares within industry to technological measure. The share equation is driven from a translog cost function and prevalently used to measure skill-biased technological change within industry. Referring to Berman, Bound and Griliches (1994) and Machin and Van Reenen (1998), the equation for the change in the share of non-production workers’ employment and wage bills in each industry j of year t as follows,

$$Share_{jt} = \beta_j + \beta_1 \log(\mathrm{K}_{jt}) + \beta_2 \log(Y_{jt}) + \beta_3 \log\left(\frac{w^n}{w^p}\right) + \epsilon_{jt} \quad (2)$$

, where K is fixed capital stock, Y is output, and $\mathrm{w^n}$ and $\mathrm{w^p}$ are the wage rates of non-production and production workers. We take time difference of the variables in the equation (2) to get rid of industry-specific fixed effects β_j. Then, we estimate the following specification in which a measure of technological change, TECH, is added.

$$\Delta Share_{jt} = \beta_1 \Delta\log(\mathrm{K}_{jt}) + \beta_2 \Delta\log(Y_{jt}) + \beta_3 \Delta\log\left(\frac{w^n}{w^p}\right) + \beta_4 TECH_{jt} + u_{jt} \quad (3)$$

In this specification, capital-skill complementarity implies that $\beta_1 > 0$ (Krusell et al. 2000) and β_2 will be an opposite sign with the same magnitude under the constant returns to scale **(**CRS) production function.[1 2] The effects of technology measures on employment and wage bills share are captured by β_4. The specification also includes time dummies to capture macroeconomic shocks.

As discussed by Berman, Bound, and Griliches (1994), this specification has some issues to be addressed. The relative wage variable could be endogenous and also suffers from division bias as the wage bill variable used to calculate relative wage is also the dependent variable with a plausible measurement error. One way to get around this issue is running the regression without the relative wage measure, but it could cause an omitted variable bias. There is a significant variation in cross-industry difference in relative wage in our data. Hence, we decide to employ the specification (3) in our empirical investigation. In addition, as in Machin and Van Reenen (1998), we run a regression using employment share of non-production worker as a dependent variable to examine the robustness of our results as well as getting around with division bias to some extent.

The Indonesian Manufacturing Survey basically has a panel data structure with changing firm identifier every four years. However, firm-level analysis will be affected by entry and exit of each firm, causing bias in our estimate. To minimize the bias from outliers and measurement error, we decided to use 5-digit industry level aggregation[13]. We also decided to use output rather than valued added since the latter turned out to have more outliers.[14] We applied industry's output share as a weight to regressions to prevent bias coming from entry and exit of small industries.

In this regression we use two sets of difference equations over 2000-2004 and 2004-2009 to control for industry-specific characteristics. We use four-year difference equations since it takes some time for each firm to change its employment and wages. Among technology variables, *exports* and *imports* are measured by the shares in output, averaged over each period. *R&D*, *Human Development*, and *FDI* shares in investment are available only in 2000 and 2006. Therefore, we matched 2000-2004 difference equation to technology variables in 2000, and 2004-2009 difference equation to technology variables of 2006. By using this specification, we can also get around the potential reverse-causality problem. Time trends are included to control the impact of business cycles and other macro shocks. We also excluded outliers using Hadimvo procedure based on technology variables.

<Table 7 Here>

The estimation of specification (3) is presented in Table 7. The regression (1) of Table 7 shows estimation of the basic cost function derived in specification (3) using employment share of non-production workers as a dependent variable. The significant effect of fixed capital on employment share indicates that there exists capital-skill complementarity. The magnitude and significance of capital-skill complementarity is consistent across other specifications as well.

The effect of R&D and human development investment shares on non-production workers' employment share is estimated in regressions (2) and (3). Estimates show no statistically significant effect of domestic technology investment controlling time trends and other factors. These results may indicate that domestic technological creation is yet too small to influence the labor market of Indonesia.

On the other hand, indicators of foreign technological changes show expected effects on skill upgrading. In regression (4), the estimated coefficient of FDI share is positive and statistically significant with considerable size; if a domestic firm has an increase of FDI inflows by 10% point of its total investment, the share of non-production workers would increase by 5.2% point.

The coefficient of imported material share in regression (5) is also positive and statistically significant. The estimate shows the sizable impact of imported goods: an increase of import share, controlling other factors fixed, by 10% point leads to an increase in the share of non-production workers by 4.5% point. Manufacturing firms that produce medical instruments, computing machinery, and non-metallic mineral products are heavily dependent on imported materials. As skill-oriented industries are import oriented, we can conclude that demand shift toward skilled workers is influenced by foreign technologies embedded in imported equipment.

The negative coefficient of export share in regression (5) is opposite to our anticipation, but not implausible.[15] This finding is also consistent with that of previous studies about Indonesia (Di Gropello et al, 2010). It is because export-oriented industries of developing countries specialize in labor-intensive products which rely more on production workers rather than non-production workers. Indeed, most of the export-oriented industries in Indonesia produce food and beverages, apparel and textiles. We conjecture that exports have a negative direct effect on wage inequality, but a positive indirect effect by inducing skill-biased technologies.

<Table 8 Here>

<Table 8> shows the regression results of specification (3) which employs wage bill share of non-production workers as a dependent variable. The estimated coefficient on fixed

capital variable is positive, supporting capital-skill complementarity, but becomes statistically insignificant. It may reflect that more skilled workers are young and relatively inexperienced, so their wage bill shares do not increase as much as their employment shares.

The main results regarding the relationship between technology measures and skill upgrading are confirmed in this specification. The effects of FDI and imported material are positive, though statistically significant at the 10% level, consistent with our previous findings in Table 7. On the whole, the estimated positive relationship between technology measures and wage bill confirms that demand shift toward skilled workers are driven by within industry demand shift and that skill-biased technology change has increased wage inequality of Indonesian manufacturing industries. The estimated positive relationship between foreign technologies and demand for skilled workers in the regressions controlling time trends shows that macroeconomic shocks were not a critical factor of rising wage inequality in 2000s.

The positive effect of technological changes on demand for skilled workers seems to support the implication of the task model developed by Autor, Levy, and Murnane (2003). According to their model, technological advancement complements high-skilled workers while it replaces average-skilled workers performing routine tasks. Our results show that demand for skilled workers increases with exposure to foreign trade and direct investment. With the exposure, firms necessitate high-skilled workers who can exercise non-routine tasks such as communicating with foreign trade partners and better selling and persuasion techniques using computers. However, replacement of middle-skill group with advanced technology is less likely to happen in the country where a plenty of relatively cheap labor force exists. Therefore, the task model provides a good explanation for the positive association between foreign technologies and demand for more skilled workers even in Indonesia’s labor-intensive industries.

6 CONCLUSIONS

In this paper, we examined the source of rising wage inequality in Indonesia. Indonesia achieved fast development with narrowing inequality until its reversal in wage inequality trend in the early 2000s. Wage inequality increased across demographic groups as well as within the groups, implying that the rising wage gap cannot be simply explained by change in the level of education or experience. Using nationally representative labor force survey, we found out that there have been labor demand shifts favoring skilled workers since the early 2000s. Our empirical analysis confirmed that while most demand shifts were driven by between-industry reallocation of labor forces, about 8% was resulted from the change within industry.

We further investigated what drove within-industry demand shift in Indonesia. As Indonesia is a developing country with a low level of own technology innovation, we focused on the role of trade and foreign direct investment in transferring advanced technology into Indonesia. Our regression analysis showed that foreign technology embedded in imported material and FDI increased employment and wage bill shares of non-production workers within 5-digit industries. The sizable magnitude of estimated effects predicted that further imports of foreign technology can accelerate the skill-biased technological change in Indonesia.

Although there must be other important market and non-market factors that can explain change in skilled labor demand and wage inequality in Indonesia, we suspect skill-biased technological change as a significant contributing factor for the inequality in the late 2000s. Our analyses clearly showed that increased demand for skilled workers within industry results from globalization and technological progress.

Understanding the impact of technological changes induced by trade and foreign investment on labor demand shifts and wage inequality is of both academic and policy interest. Design and implementation of deliberate policies toward promoting international trade and investment, combined with appropriate labor and social policies would be important for more inclusive economic growth in Indonesia. The key policy to reducing wage inequality should be providing better education and training for unskilled workers, rather than building trade barriers, that can protect the workers from being replaced with new technology. The government should respond to the challenges with policy measures that enhance social safety nets and financial access for those who need further accumulation of human capital without hampering economic growth.

Our research identifies the possible factor for rising wage inequality, but there still remains the question on the exact channels through which globalization and technological progress influence wage structure and income distribution in developing countries. More in-depth investigation of detailed interactions between foreign technologies and country-specific environment, using longer time series data across economies, would be helpful to design more effective policies in individual countries.

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Table 1: *Data summary statistics of workers in the labor force, 1990-2009*

Variable	Category	1990-1996	1997-2003	2004-2009
Region	Urban	51.2%	61.6%	67.4%
	Rural	48.8%	38.4%	32.6%
Sex	Male	70.3%	68.8%	67.6%
	Female	29.7%	31.2%	32.4%
Education	Elementary degree or less	49.7%	37.0%	24.8%
	Junior high school	13.3%	16.2%	18.7%
	Senior high school	29.3%	34.4%	38.3%
	University diploma or higher	7.7%	12.4%	18.2%
Experience	≤ years	27.1%	28.0%	32.0%
	10-20 years of experience	30.6%	31.5%	31.4%
	20-30 years of experience	22.6%	22.2%	21.6%
	> 30 years	19.7%	18.3%	15.1%
Sample Size	N	378,123	202,850	283,636

Notes: The sample includes all workers aged over 18 years old employed in the formal sector. Data are sourced from the National Labor Force Survey (SAKERNAS), 1990-2009.

Table 2: *Real monthly wage changes for full-time workers in Indonesia, 1990-2009*

	Changes in log average real monthly wage (multiplied by 100)			
Group	1990-2009	1990-1997	1997-2003	2003-2009
All	37.0	35.3	8.7	-6.9
By Gender :				
Male	33.8	32.5	7.5	-6.2
Female	44.7	41.9	11.4	-8.6
By Education :				
Elementary degree or less	44.4	41.7	11.0	-8.3
Junior high school	31.8	33.8	7.3	-9.3
Senior high school	31.1	31.3	7.3	-7.5
University degree	35.6	25.7	6.5	3.4
Experience : (Men Only)				
1-10 years	38.5	39.9	8.9	-10.3
11-20 years	30	29.8	5.7	-5.5
21-30 years	30.3	30.8	6.2	-6.6
≥ 30 years	38.4	28.8	10.6	-1
Region :				
Urban	35.7	33.2	8.3	-5.8
Rural	39.1	38.6	9.3	-8.8

Notes: The numbers in the table represent log changes in average monthly wages using SAKERNAS for 1990-2009. Average monthly wages for full-time workers in each of 64 sex-education-region-experience cells are computed in each year. Average wages for broader groups in each year are weighted averages of these cell averages using a fixed set of weights (the average employment share of the cell for the entire period). All earnings are deflated by the consumer price index each year.

Table 3: *Relative monthly supply changes of employed workers, 1990-2009*

	Changes in log share of aggregate labor input (multiplied by 100)			
Group	1990-2009	1990-1997	1997-2003	2003-2009
Gender :				
Men	-9.0	-1.3	-2.1	-5.6
Women	28.3	4.8	7.1	16.4
Education :				
Elementary degree or less	-101	-29.5	-66.9	-4.5
Junior high school	10.4	12.4	11	-13
Senior high school	18.3	12.2	16.6	-10.5
University diploma or higher	87.8	30.2	31.6	26.1
Experience : (Men Only)				
1-10 years	-3.6	1.0	-8.8	4.1
11-20 years	-11.3	-2.4	9.7	-18.6
21-30 years	-2.5	1.1	-1.1	-2.5
≥ 30 years	-20.7	-5.4	-17.9	2.6
Region :				
Urban	24.5	7.5	20.4	-3.4
Rural	-50.9	-11.9	-50.2	11.3

Notes: The numbers represent log changes in each group's share of total monthly labor supply measured in efficiency units (annual working hours times the average relative wage of the group for the sample period) using SAKERNAS. Supply measures include all workers in the count sample described in the text.

Table 4: *Inner products of changes in wages with changes in supplies*

4-year centered interval	4-year centered interval			
	1990-1993	1994-1997	1998-2001	2002-2005
1994-1997	-0.0066			
1998-2001	-0.0271	-0.0074		
2002-2005	-0.0504	-0.0188	-0.0014	
2006-2009	-0.0286	-0.0041	0.0074	0.0022

Notes: The numbers represent inner products between changes in relative wages and changes in relative supplies of 64 cells. The inner product is calculated using changes in each column and row period. The relative wage measure is constructed from the sample of full time workers in the formal sector while the relative supply is calculated from the sample of workers in the formal sector.

Table 5: *Industry- and occupation-based demand shift measures, 1995-2009*

A. Formal workers				
Period	1995 -1999	1999 -2003	2003 -2009	1995 -2009
0-6 years of schooling				
Between industry	-4.2	-1.6	2.3	0.8
Within industry	0.9	1.9	0.4	-0.9
Overall	-3.3	0.3	2.7	-0.2
7-9 years of schooling				
Between industry	-5.2	-3.6	7.1	3.8
Within industry	0.3	2.5	3.0	0.9
Overall	-4.9	-1.1	10.1	4.7
10+ years of schooling				
Between industry	-8.8	-7.7	17.5	11.1
Within industry	-3.6	0.3	1.4	-9.1
Overall	-12.4	-7.4	18.9	2.0

B. Informal workers				
Period	1995 -1999	1999 -2003	2003 -2009	1995 -2009
0-6 years of schooling				
Between industry	3.8	3.4	-8.1	-4.4
Within industry	0.5	-0.4	-0.7	3.5
Overall	4.3	3.0	-8.7	-0.9
7-9 years of schooling				
Between industry	3.0	1.5	-5.6	-4.0
Within industry	0.4	0.1	-0.7	3.0
Overall	3.4	1.6	-6.3	-1.0
10+ years of schooling				
Between industry	2.2	0.8	-0.3	0.5
Within industry	-0.6	-1.6	-1.5	-1.5
Overall	1.6	-0.8	-1.8	-1.0

Note: The overall and between-industry demand shift measures for each demographic group k are of the form $\Delta D_k = \sum_j a_{jk}(\Delta E_j/E_k)$ as shown in equation (1). The reported numbers are of the form $Log(1 + \Delta D_k)$.

Table 6: *Summary statistics of technology variables*

	2000	2006
R&D/Investment	0.0011	0.0022
	(0.0020)	(0.0040)
HD/Investment	0.0010	0.0019
	(0.0015)	(0.0028)
FDI/Investment	0.0634	0.0680
	(0.1622)	(0.1674)
Export/Output	0.2260	0.2425
	(0.2621)	(0.2437)
Import/Output	0.2817	0.2358
	(0.2912)	(0.2587)

Note: The figures are mean values with standard-deviation in parentheses. The unit of observation is 5-digit industry level.

Table 7: *Regressions for change in non-production workers' share in employment*

	(1)	(2)	(3)	(4)	(5)
	Pooled Data, 2000-2004 and 2004-2009				
	Dependent variable: Change in non-production workers' share in employment: $\Delta E_j^n/E_j^p$				
$\Delta ln(Capital)$	0.006** (0.003)	0.005** (0.003)	0.006** (0.003)	0.007*** (0.003)	0.006** (0.003)
$\Delta ln(Output)$	-0.003 (0.004)	-0.002 (0.004)	-0.004 (0.004)	-0.004 (0.004)	-0.004 (0.004)
$\Delta ln(w_j^n/w_j^p)$	-0.075*** (0.008)	-0.074*** (0.009)	-0.076*** (0.008)	-0.078*** (0.008)	-0.071*** (0.009)
R&D		0.344 (1.349)			
HD			-0.041 (1.459)		
FDI				0.052** (0.026)	
Export					-0.037** (0.019)
Import					0.045*** (0.016)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.30	0.22	0.37	0.40	0.24
N	357	357	357	357	356

Notes: All regressions include time-period dummies. Equations are weighted by average share of industry output in manufacturing. The sample consists of about 200 five-digit manufacturing industries. Outliers are eliminated by Hadimvo procedure. Standard errors are in parentheses. Asterisks denote the following significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: *Regressions for change in non-production workers' share in wage bill*

Pooled Data, 2000-2004 and 2004-2009					
Dependent variable: Change in non-production workers' share in wage bill: $\Delta WB_j^n/WB_j^p$					
	(1)	(2)	(3)	(4)	(5)
$\Delta ln(Capital)$	0.001 (0.003)	0.001 (0.005)	0.001 (0.003)	0.002 (0.003)	0.002 (0.003)
$\Delta ln(Output)$	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.004 (0.004)	-0.004 (0.004)
$\Delta ln(w_j^n/w_j^p)$	0.156*** (0.008)	0.173*** (0.009)	0.151*** (0.008)	0.147*** (0.007)	0.158*** (0.008)
R&D		0.515 (1.462)			
HD			-0.046 (1.534)		
FDI				0.052* (0.028)	
Export					-0.022 (0.019)
Import					0.031* (0.017)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.58	0.49	0.65	0.71	0.58
N	357	357	357	357	356

Notes: All regressions include time-period dummies. Equations are weighted by average share of industry output in manufacturing. The sample consists of about 200 five-digit manufacturing industries. Outliers are eliminated by Hadimvo procedure. Standard errors are in parentheses. Asterisks denote the following significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Captions for Figures

*

(a) Real monthly wages by percentile (b) Gini coefficients

Figure 1: Overall trends of wage inequality in Indonesia 1990-2009

Notes: Real wages are indexed with the average wage of 1990 and 1991 normalized as 100 for all three percentiles. The sample consists of all workers in the formal sectors. Data are from the National Labor Force Survey (SAKERNAS).

*

Figure 2: Skill premium changes in Indonesia 1990-2009 Notes: The sample includes all workers in the formal sector. Data are sourced from the National Labor Force Survey (SAKERNAS). Return to skill is defined as wage ratio between skilled workers and unskilled workers. The workers who attained senior high school diploma or higher education (51.5% of the sample) are categorized as skilled workers. Unskilled workers are the ones who obtained junior high school diploma at most (48.5% of the sample).

*

(a) By Region (b) By Gender

Figure 3: Changes in residual wage inequality

*

Figure 4: Relative wage and labor supply changes for 64 groups

Notes : Relative wages and relative supplies are calculated in each of 64 different labor groups by gender, four education levels, four experience categories, and two regions. Markers in these scatter plots are weighted by average relative supply of each cell.

*

Figure 5: Change in non-production workers' wage-bill shares and employment shares

Note: Changes in wage bill and changes in employment of non-production workers are calculated across different periods for 2-digit Indonesian manufacturing industries. Data are sourced from the Indonesian Manufacturing Survey (Statistik Industri)

[1] Tinbergen (1975) emphasizes the interaction between educational expansion and technology progress that raises the relative demand for more educated workers. A number of studies including Katz and Murphy (1992) and Autor, Katz and Krueger (1998) have developed theoretical frameworks with different skill groups and skill-biased technological change to explain the changes in the returns to skills. Acemoglu (2002) argues that technological development responds endogenously to its structure of labor supply as a rapid increase of skilled workers induces the development of skill-complementary technologies as it is more lucrative. Autor, Levy, and Murnane (2003) propose a model that distinguishes between skills and tasks. Acemoglu (2011) provides a survey of the recent developments in this topic.

[2] See Miranti et al. (2013). The income Gini coefficients increased from 29.7 in 2002 to about 34.0 over 2005-2008 according to the Standardized World Income Inequality Database, constructed by Solt (2011).

[3] We focus our analysis on formal sector because the National Labor Force Survey of Indonesia only reports the wages of workers in the formal sector. Using wage data of self-employed or unpaid workers is mostly avoided in analysis of wage inequality in advanced countries as well. However, it should be noted that the informal sector is sizable in Indonesia. According to the National Labor Force Survey, the whole size of the formal sector is less than 30% of the labor market in the 2000s. We consider the informal sector in analyzing relative demand shifts in section 3.

[4] Since 2003, when the decentralization of government organizations began, each province has set its own minimum wage every year.

[5] This implies that in consideration of the increased minimum wage and the sample selection into the formal sector, the actual skill premium could have been larger than the observed ones,

especially in the 1990s.

[6] The working paper version of this paper (Lee and Wie, 2013) shows that the size of the formal sector decreased from 1997 to 2003 and remained constant for years thereafter.

[7] The results do not change qualitatively in the analyses with inclusion of the outliers.

[8] We use the approximation that 100 times log changes is percentage changes.

[9] Inflation rate in Indonesia was on average 8% from 1990 to 1997 and increased to 45% in 1998 and 18% in 1999 during the Asian financial crisis. After the crisis, in the 2000s,, inflation rate was on average 7.7%.

[10] Lee and Wie (2013) shows that there is a notable difference in labor demand across industries, occupations, and job status of workers in Indonesia.

[11] Please refer to Lee and Wie (2013) for more information about industry codes of SAKERNAS.

[12] Machin and Van Reenen (1998) examine whether estimation produces different results with and without CRS condition imposed. All our results remain strong in the specifications that include capital/output ratio instead of capital and output variables.

[13] For detailed information about industry code, please refer Lee and Wie (2013).

[14] Our regression results remain qualitatively the same when we replace output with value added.

[15] If we include import share and export share variable independently in the regression, import share remains positive and statistically significant, while export share is statistically insignificant.