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ABSTRACT

This paper examines the empirical implications of technological changes for skill demand and wage inequality in Indonesia. According to the National Labor Force Survey of Indonesia, the share of educated workers and wage skill premium increased significantly over 2003–2009 for overall industry and across the region. An analysis based on demand–supply framework suggests that demand shifts favoring skilled workers during the period. The decomposition of labor demand shifts shows that they were driven not only by reallocation of labor forces between industries but also by change within industries, particularly among formal workers, suggesting evidence of skill-biased technological changes. The empirical evidence from the data of manufacturing firms suggest that diffusion of new technologies through imported materials and foreign direct investment caused greater demand for skilled labor and higher wage inequality in the manufacturing sector.

Key words: skill-biased technological change, human capital, wage inequality

JEL Classification: J24, J31, O15, O33

I. 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 increase in educational attainment and technological change for their economic growth, some economists claim that the differential effect of technological progress on wage by workers' education level can exacerbate already widening 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.[1] Since most developing economies have a dominant portion of low skilled workers, this shift in demand could cause a drastic change in their labor markets.

This assertion is based on the skill-biased technological change (SBTC) hypothesis, which argues that demand for educated and skilled workers increases when new technologies are permeated into the workplace. The SBTC thus has an effect on wage inequality by increasing the wage of more educated workers relative to less educated workers.

There is large empirical literature investigating the impact of technological changes on relative labor demand and wage inequality. Katz and Murphy (1992) used a simple supply and demand framework to explain the major changes in the wage structure in the United States (US) in the 1980s including an increase in relative earnings of college graduates, an increased premium to experienced workers among the less-educated group; and a higher inequality of earnings within narrowly defined demographic and skill groups. Their study demonstrated that there was a trend in demand growth favoring more skilled workers that could explain the movement of relative wage beyond the prediction by a simple supply–demand framework.

Berman, Bound, and Griliches (1994) confirmed the same demand growth in the 1980s. Using ASM (Annual Survey of Manufacturers) data, they found out that the increased use of non-production workers was mostly driven by increased demand within industries. They also estimated that the use of non-production workers was correlated with investment in computers and in research and development (R&D).

The spread of computers seemed to be the culprit behind the long run increase in the relative demand favoring skilled workers. According to the study by Autor, Katz, and Krueger (1998) there existed a positive effect of growth in computer utilization on skill upgrading within the industry and the relationship was accelerated during more recent decades.

Autor, Levy, and Murnane (2003) showed that the type of work was a key factor of growing demand for skilled workers. Their empirical results showed that computer utilization had a positive effect on skill upgrading in each industry. The shifts in labor input favoring non-routine tasks were concentrated in rapidly computerizing industries implying that computerization was the source of growing demand for skilled workers.

A study by Bresnahan, Brynjolfsson, and Hitt (2002) used detailed firm-level data to examine the effect of information technology and workplace organization on skill-biased

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[1] Acemoglu (2002) argues that technological development responds endogenously to its structure of labor supply. Skill-replacing machines were developed because increased supply of unskilled workers made it more profitable in the past. On the other hand, rapid increase of skilled workers in the 20th century induced the development of skill-complementary technologies as it was more lucrative.

technological change on employment of more skilled workers in the US. They claimed that the effect of information technology on employment of skilled labor became greater when technology is combined with particular workplace environments.

The evidence of skill-biased technological change is also found in other advanced countries. Machin and Van Reenen (1998) extended the analysis of Berman, Bound, and Griliches (1994) to six other Organisation for Economic Co-operation and Development (OECD) countries, finding that R&D expenditure and computer investment were associated with skill upgrading. Berman, Bound, and Machin (1998) found that skill upgrading occurred within similar industries in 12 OECD countries, suggesting pervasive skill-biased technological change.

There is also a growing empirical literature on the relationship between technology change and wage inequality in developing countries. Hur, Seo, and Lee (2005) showed that information and communications technology diffusion in Korean industrial sectors was positively correlated with skill upgrading over the 19961999 period. Berman, Somanathan, and Tan (2005) found evidence of skill-biased technological change in India in the 1990s using panel data disaggregated by industry and state. Bustos (2011) found that skill upgrading within firms increased relative demand of skilled labor in Argentina. Harrison (2008) showed the firm-level evidence supporting skill-biased technology adoption in Brazil.

This paper examines the empirical implications of technological changes for wage inequality in Indonesia. It examines how pervasive SBTC has been in Indonesia. The effects of new technologies in demand for skilled workers in Indonesia are of particular interest for a number of reasons.

Indonesia has been known for successful growth without increasing income inequality in previous literature (Alatas and Bourguignon 2005). Also, a few papers that examined skill-biased technological change reported no clear evidence supporting skill upgrading in Indonesia yet. For instance, a recent World Bank report by di Gropello and Sakellariou (2010) found there was almost no increase in the share of skilled labor in manufacturing employment or total wage bills between 1975 and 2005. It also found that most changes in labor demand shifts occurred between industries, suggesting no evidence of SBTC.

The finding in Indonesia contrasts the evidence supporting SBTC in many other developing countries such as India and Brazil. We suspect that in Indonesian industries SBTC might have occurred in more recent years when economic growth has accelerated. Using extended data sets combined with available Indonesian surveys beyond 2005, we hope to investigate the evidence of SBTC in Indonesia more thoroughly. Moreover, previous literature has not carefully considered the exact channel that skill-biased technological change takes place in developing countries. Technology is usually transferred through imported goods or foreign direct investment (FDI) in developing countries. Hence, we employ various technological change variables such as FDI and imported goods in addition to R&D investment and consider their effects on skill upgrading.

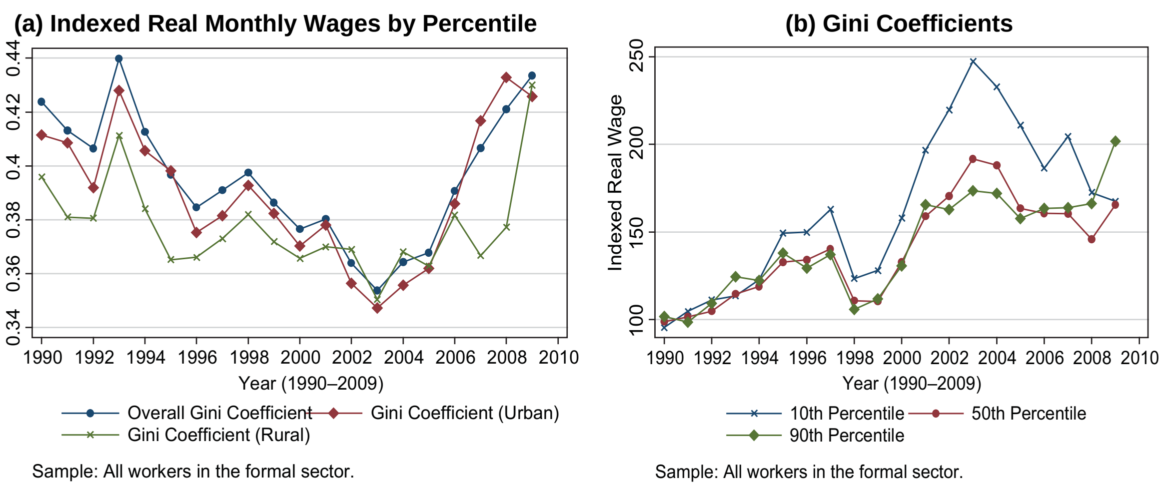
This paper is organized as follows. Section II describes trends of various wage inequality measures and overall characteristics of the Indonesian labor markets. Section III analyzes the Indonesian Labor Force Survey (Sakernas) using supply–demand framework if there occurred demand shifts favoring skilled workers. Section IV extends the analysis by adapting within/between decomposition of industry demand shifts. Section V is devoted to further exploring the existence of SBTC in the manufacturing sector whether the effect of technology innovation and diffusion on wage inequality is expected to be significant. Section VI concludes.

II. OVERVIEW OF CHANGING WAGE INEQUALITY IN INDONESIA

A. Inequality Trends in Indonesia

Wage inequality of Indonesia has been decreasing during its fast development in contrast to many other developing countries. Figure 1a demonstrates the median, 10th percentile, and 90th percentile of the real monthly wage distribution of full-time waged workers for 1990–2009. To make it easy to compare, the wages of these groups are indexed to the average wage of 1990 and 1991 normalized as 100 for all three series.

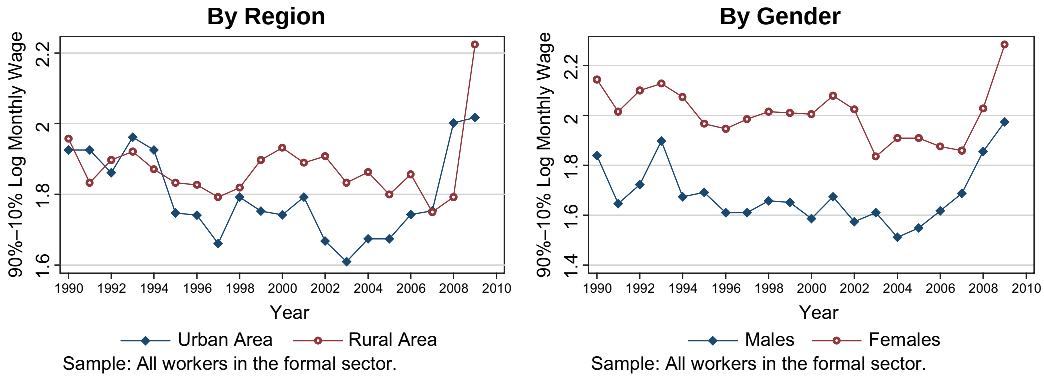
Figure 1: Overall Trends of Wage Inequality in Indonesia 2000–2009



The data presented before and after 2003 provide a clear contrast. The benefit of economic growth was the greatest for the least skilled group (proxied here by the 10th percentile) by 2003. Real wage of the 10th percentile group rose by more than 100% from 1990 to 2003 but declined sharply thereafter. For the median group, real wages rose by more than 50% 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 90th percentile rose steadily thereafter.

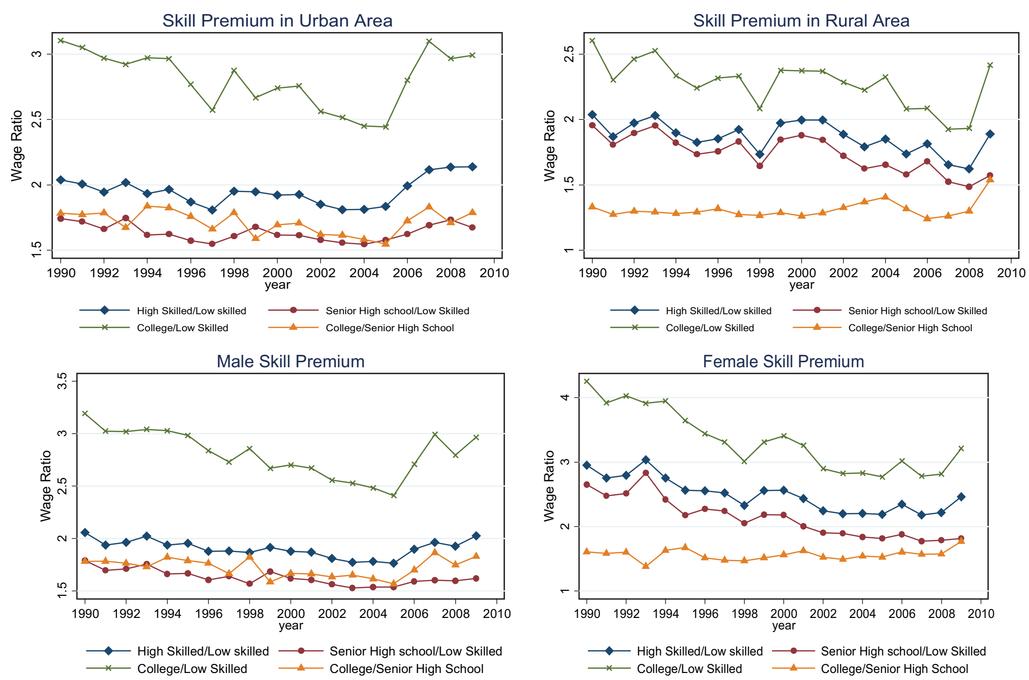
The movement of Gini coefficients also showed similar trends. Figure 1b shows that the Gini coefficient of all waged workers has sharply increased in both urban and rural areas since 2003. As real wages of the median group and least skilled group dropped, inequality level increased in recent days. Figure 2 displays the evolution of 90/10 wage inequality calculated by region and gender. All measures calculated show notable increase since 2003. For instance in urban area, 90/10 monthly wage ratio has decreased from 1990 to 2003, and increased sharply thereafter. Hence, the increase in wage inequality measured by 90/10 and Gini coefficients in recent years is a common phenomenon in both urban and rural areas.

Figure 2: Differences in Log Wages at 90th and 10th Percentile



Is the recent change in wage inequality related to the change in skill premium? We identified workers with their education level and calculated the skill premium in various ways to examine whether the change in skill premium caused wage inequality. Figure 3 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, both high school premium and college premium steadily decreased until 2008 and showed a sudden increase in 2009. These trends imply that an increase in skill premium is the source of rising wage inequality.

Figure 3: Skill Premium Changes in Indonesia, 1990–2009



Sample: All workers in the formal sector.

Note: Returns to skill is defined as wage ratio between skilled workers and unskilled workers. The workers who attained senior high school diploma or higher education (51.48% of the sample) are categorized as skilled workers. Unskilled workers are who obtained junior high school diploma at most (48.52% of the sample).

There can be other factors affecting wage inequality. We ran a regression of log monthly wage on experience (up to quartic and interacted with sex and education level dummies), and linear terms in years of schooling and got residuals. The residuals from this regression capture the dispersion of wages within each demographic group. We also calculate the difference in the log wages of those at the ninetieth and at the tenth percentiles of the distribution. Trends of overall and residual wage inequality by region and gender are shown in Figure 4.

Figure 4: Changes in Residual Wage Inequality

(a) By Region **(b) By Gender**

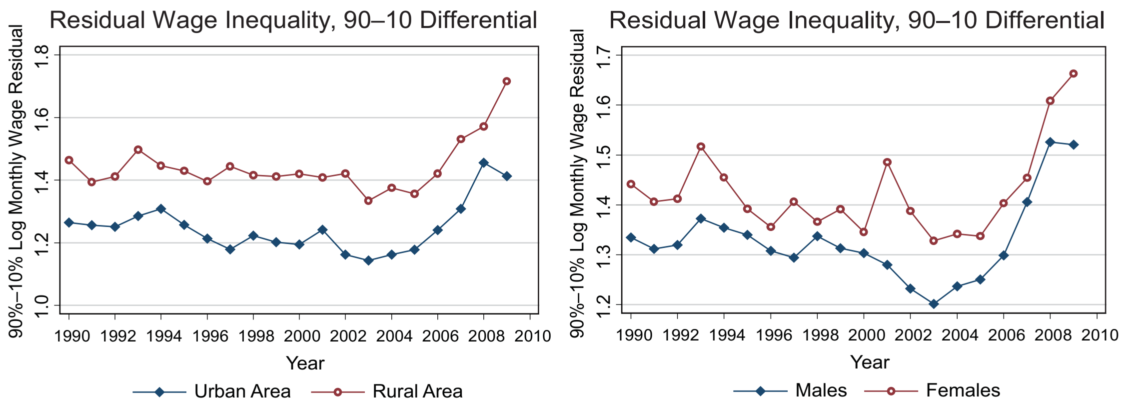


Figure 4 shows that both log wage differentials and residual wage differentials increased in all areas for both women and men from 2004 to 2009. It means not only overall wage inequality has expanded, but also within-group wage inequality has increased at the same time. Within-group wage inequality implies that the least-skilled workers within each category were lost compared to high skilled ones in recent years.

B. Overview of the Indonesian Labor Market

The Indonesian economy experienced fast growth in the 1990s until it faced the Asian financial crisis in 1997. However, due to sound crisis management, the economy started to recover since 2003 and showed steady growth since then. Table 1 shows a brief overview of the Indonesian labor market in the same period. It shows several characteristics of workers in the formal sector. The share of urban employment increased constantly during this period as in many other developing countries. On the other hand, females demonstrated relatively slow growth. The labor market was also marked by a significant increase in younger and more educated workers.

The distribution of educational attainment of employed workers drastically changed for the past two decades. 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. The proportion of workers who attained tertiary education was 7.72% in formal sector in the early 1990s, and increased to 18.15% in the late 2000s. The fraction of workers who attained high school degrees also increased constantly. The representation of young workers with better education in formal labor market was also growing during the same period. Table 1 shows that the portion of less experienced workers was increasing.

Table 1: Data Summary Statistics of Workers in SAKERNAS 1990–2009

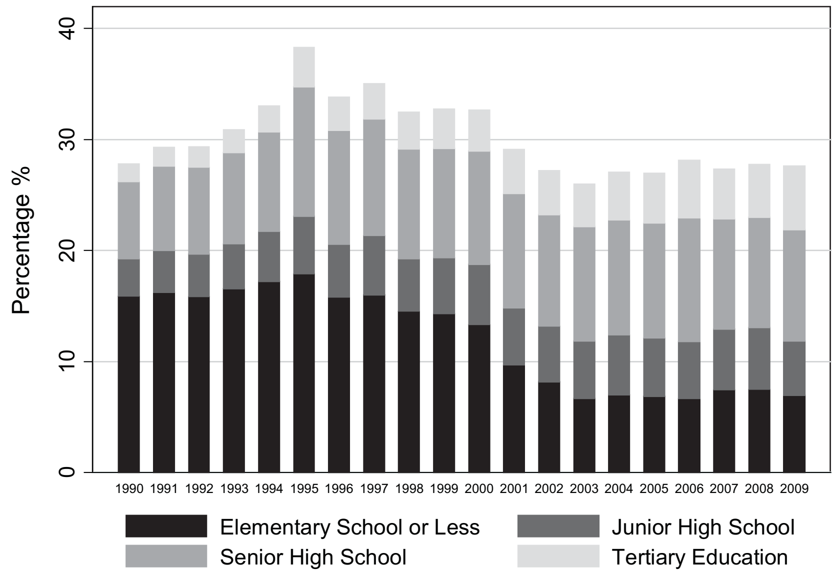
Variable	Category	1990–1996	1997–2003	2004–2009
Region	Urban	51.18%	61.56%	67.37%
	Rural	48.82%	38.44%	32.63%
Sex	Male	70.33%	68.77%	67.59%
	Female	29.67%	31.23%	32.41%
Education	Elementary Degree or Less	49.72%	37.01%	24.84%
	Junior High School	13.27%	16.22%	18.67%
	Senior High School	29.30%	34.40%	38.33%
	University Diploma or Higher	7.72%	12.36%	18.15%
Experience	≤ years	27.11%	27.99%	32.00%
	10–20 years of experience	30.59%	31.48%	31.39%
	20–30 years of experience	22.62%	22.24%	21.57%
	> 30 years	19.68%	18.29%	15.05%
Sample Size	N	378,123	202,850	283,636

Source: SAKERNAS

Note: Sample includes all formal sector employed workers aged more than 18.

In our paper, we focus our analysis on formal sector. This is because the National Labor Force Survey of Indonesia (Sakernas) only reports the wages of workers in formal sector. Using wage data of those 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 size of informal sector is sizable in Indonesia. Figure 5 demonstrates that the whole size of formal sector is less than 30% of the labor market in 2000s while it was above 30% in late 1990s. The existence of a large informal sector requires careful interpretation of our analysis.

Figure 5: Percentage of Formal Sector Workers and Their Education Level 1990–2009



Taken as a whole, the Indonesian labor market has characteristics of both developing countries and underdeveloped countries at the same time. On one hand, the sharp increase in skilled workers overall and urban sectors show the aspect of developing countries, while sizable informal sector shows a regressive aspect of the labor market.

III. SUPPLY–DEMAND FRAMEWORK

A. Sakernas and Data Construction

The data used in this section comes from the National Labor Force Survey of Indonesia (Sakernas). The survey is conducted annually and contains more than 200,000 individuals in most series. The survey also provides detailed information on employment, wages, education attainment, and demographic variables. We use 20 series of Sakernas (1990–2009) to examine the long-term trends of relative wages and relative labor supplies.

The Sakernas surveys are 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 in Indonesia. From Sakernas, we constructed two samples: a wage sample and count sample. The wage sample includes full-time workers who are reported to work more than 35 hours per week at the main job. This is based on the definition of full-time workers (40 hours of work including one hour of rest per day) in Indonesia. We excluded a small number of outliers (0.01% of total observation) based on their real wages to acquire an accurate measure of relative wage series. To calculate the measure of relative supply, count sample was 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 did 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 was divided into 64 categories by workers' gender, education level, experience level, and region. The fixed weight of average employment share for each 64 cells among all workers during the entire sample period was used when calculating aggregate measures in the wage sample, while the average relative wage of 64 cells among full-time workers was used in count sample when calculating aggregate measures.

B. Evolution of Relative Wages and Relative Supplies in Indonesia

Table 2 shows the data on full-time workers in Indonesia for the period from 1990–2009. The notable characteristics are as follows. The relative monthly real wages increased by 37% during our sample period,[2] however, growth rates decreased during the late 1990s and actually became negative in the late 2000s due to high inflation. Winners and losers were reversed between the time of fast growth and slow recovery after the Asian financial crisis. Female and less educated workers gained more than other groups in 1990s, however, their wages declined more than other demographic groups during the time of economic recovery in 2000s.

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 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.

It would be interesting to look at whether similar trends occurred in both rural and urban areas. Rural areas of Indonesia are still dominated by agriculture sector while most of manufacturing sector is concentrated in the urban area. Therefore, the movement of skill premium can be different across rural and urban areas. The simple comparison does not show notable differences. However, if we examine real wages by education-region, the least skilled group gained the most by 2003 in both regions and the most skilled group took that position from 2003 to 2009. However, the gain of the most educated group was greater in urban areas.

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

Table 2: Real Monthly Wage Changes for Full-Time Workers in Indonesia 1990–2009

Group	Changes in log average real monthly wage (multiplied by 100)			
	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	30.0	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	–1.0
Region:				
Urban	35.7	33.2	8.3	–5.8
Rural	39.1	38.6	9.3	–8.8
Education and Region:				
Region: Urban				
Elementary Degree or Less	43.4	40.7	11.0	–8.3
Junior High School	31.3	33.8	7.0	–9.5
Senior High School	32.3	30.6	7.6	–5.9
University Degree	35.8	24.5	6.4	4.8
Region : Rural				
Elementary Degree or Less	45.2	42.6	11.0	–8.4
Junior High School	32.9	34.0	7.7	–8.8
Senior High School	27.7	33.6	6.4	–12.3
University Degree	35.5	30.3	6.8	–1.7

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 were 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 entire period). All earnings are deflated by the consumer price index each year.

What caused the reversal of skill and experience premium in Indonesia? Was there a demand shift toward more skilled workers in recent days? 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. Changes in relative supply reported in Table 3 imply 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 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 whole period also implies that supply change contributed to the increase in the relative wage of these workers. However, constant increase in relative supply of workers with tertiary education in 2000s suggest that supply-side change could not explain the relative wage increase of this group and that there was demand shift toward more educated workers.

Table 3: Relative Monthly Supply Changes of Employed Workers 1990–2009

Group	Changes in log share of aggregate labor input (multiplied by 100)			
	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:				
Primary Schooling or Less	–101.0	–29.5	–66.9	–4.5
Junior High School	10.4	12.4	11.0	–13.0
Senior High School	18.3	12.2	16.6	–10.5
University Degree	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
Education and Region:				
Urban				
≤ Elementary Degree	–65.7	–29.6	–28.2	–7.8
Junior High School	18.1	12.5	18.3	–12.7
Senior High School	30.2	16.0	29.9	–15.7
University Degree	83.1	28.4	33.9	20.9
Rural				
≤ Elementary Degree	–133.5	–29.5	–104.0	–0.1
Junior High School	–4.8	12.3	–3.3	–13.8
Senior High School	–17.7	2.4	–32.7	12.7
University Degree	112.9	40.5	18.1	54.3

Notes: The numbers in Table 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 above.

Regional variation in relative labor supply suggests the possibility that demands shift toward more educated workers varies across industries and occupations. The movement of relative supply of workers by education in rural areas is consistent with supply-demand framework. For instance, workers with high school diplomas decreased sharply from 1997–2003, but increased since 2003. Conversely, the relative wages of those workers in rural areas increased from 1997–2003 and decreased since 2003. On the other hand, relative wages and relative supplies mostly moved in the same direction in urban areas throughout the period, suggesting that there was a demand shift in urban areas.

C. Supply–Demand Analysis

The results in Table 2 and Table 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 divided our sample into 64 different labor groups by gender, four education levels, four experience categories, and two regions. To reduce the influence of measurement error and time trends, we aggregated our 20 years 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 calculated the inner products of the changes in these measures of wages and supplies between each pair of these five intervals.

Table 4: Inner Products of Changes in Wages with Changes in Supplies

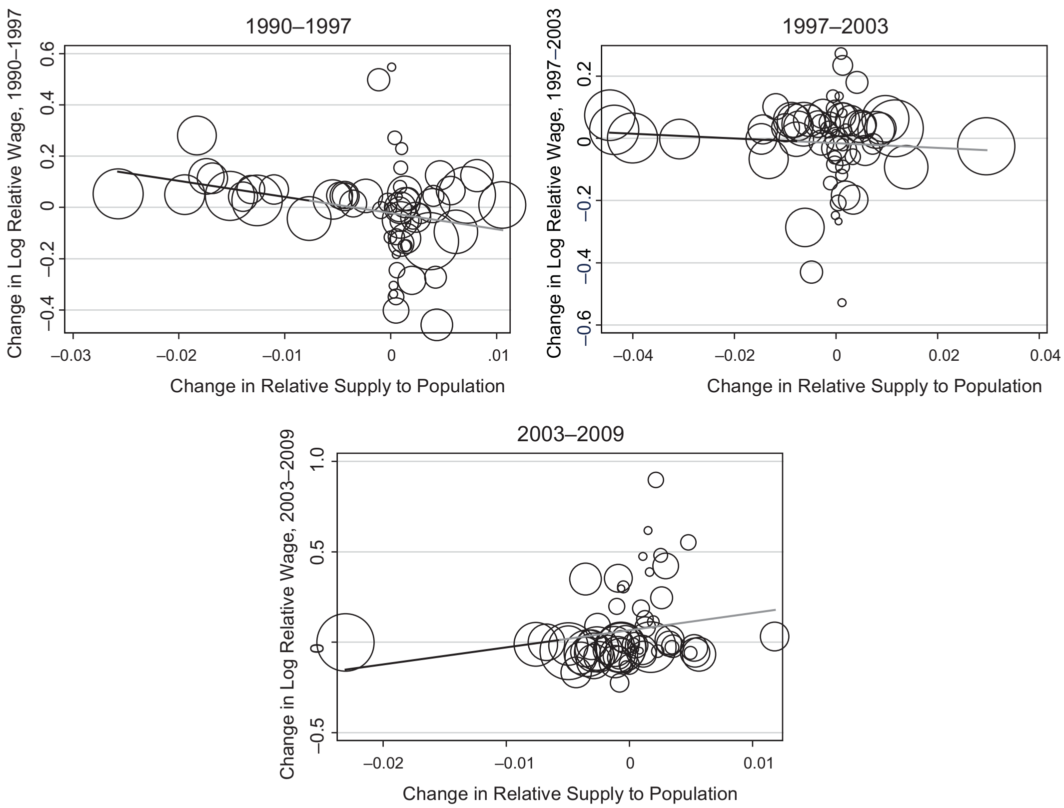
	4-year centered interval			
4-year centered interval	**1990–1993**	**1994–1997**	**1998–2001**	**2002–2005**
1994–1997	–0.0066			
1998–2001	–0.0271	–0.0074		
2002–2005	–0.0504	–0.0188	–0.0014	
2006–2009	–0.0286	–0.0041	0.0074	0.0022

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

The results of these calculations are given in Table 4. The numbers appear to be consistent with the stable demand hypothesis for 1990–2001 period. Though of small magnitude, they remain negative during this period. In contrast, the results including later periods seem to disapprove a stable factor demand hypothesis. Inner products of later periods showed positive signs indicating that a demand shift occurred in at least some sectors of the economy. Figure 6 also indicates that positive inner products of later periods in Table 4 are not a product of several outliers. The weighted scatter plot between relative wages and relative supplies from 2003–2009 shows that most of the inner products in this period fall into either upper right quadrant or lower left quadrant.

Demand–supply analysis in this chapter allows us to draw a tentative conclusion that there was a demand shift favoring more educated workers in recent views 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.

Figure 6: Relative Wage and Labor Supply Changes for 64 Groups



Note : Relative wages and relative supplies are calculated in each 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.

IV. ANALYSIS OF INDUSTRY DEMAND SHIFTS

A. Measuring Changes in the Relative Demand for Labor Using Sakernas

The previous section shows shifts in relative labor demand are necessary to explain the observed increase in wage inequality of Indonesia since early 2000s. There are several hypotheses which can explain shifts in labor demand favoring more skilled workers; changes in demand for different products, increased international competition, change in structure of trade, and skill-biased technological change. Among all the hypotheses, we are interested whether skill-biased technological change drastically altered skill demand as it did in most advanced countries. (Berman et al. 1998) Though several studies report evidence of skill-biased technological change in developing countries, there has been no convincing evidence found in Indonesia.

Table 5: Average Demographic Distributions within Each Industry and Occupation 1995–2009

	Percentage Employment Share					
Years of Schooling	**0–6**	**0–6**	**7–9**	**7–9**	**10 +**	**10 +**
Gender	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
A: Formal Workers						
Industry						
Agriculture, forestry, and fishing	52.8	17.8	14.6	2.5	10.7	1.6
Mining and quarrying	37.6	3.4	17.1	0.9	38.8	2.3
Manufacturing	21.6	14.1	15.2	9.3	28.3	11.6
Electricity, gas, and water supply	10.2	1.0	13.8	1	67.2	7.1
Construction	52.3	1.1	21.3	0.4	32.1	1.9
Wholesale and retail trade	16.6	7.4	13.8	6	34.5	21.7
Transport	31.5	0.7	23.7	0.8	37.5	5.8
Financial intermediation and real estate	5.7	0.7	8.7	1.3	58.6	25
Public service	9.7	13.1	8.2	4.6	42.2	22.2
Occupation						
Professional, managers, and armed force	3.0	0.5	5.2	1.2	57.0	33.2
Sales and service workers	27.2	19.8	12.8	7.0	23.0	10.2
Production workers	32.9	9.7	18.9	5.9	26.5	6.1
B: Informal Workers						
Industry						
Agriculture, forestry, and fishing	58.4	21.5	11.2	2.6	5.4	1.0
Mining and quarrying	63.5	12.4	14.6	1	7.9	0.7
Manufacturing	38.5	30.1	11.1	5.6	11.2	3.6
Electricity, gas, and water supply	21.7	7.3	19.8	2.7	50	4.5
Construction	60.6	1.1	20.8	0.4	16.6	0.5
Wholesale and retail trade	27.1	30.5	12	8.3	14.7	7.6
Transport	54.4	0.7	24.8	0.5	18.9	0.7
Financial intermediation and real estate	17.3	4.7	12	3.1	52.7	11.6
Public service	34	13.9	16.4	5.6	22.5	7.6
Occupation						
Professional, managers, and armed force	16.5	5.0	9.4	2.8	50.4	15.9
Sales and service workers	46.7	24.2	11.5	4.7	9.3	3.6
Production workers	48.6	13.3	18.5	2.8	14.8	2.0

Notes : The numbers in the table for each demographic group represent the average share of employment of that group in the corresponding industry or occupation with the average taken over then 1995–2009 period. Sample is all workers in the formal sector.

Implication of skill biased technological change in developing countries is crucial as many of those countries are already suffering from rising inequality caused by fast economic development. In spite of its importance, it is difficult to identify skill-biased technological change in developing countries due to lack of good data sets and existence of large informal sector. In this section, we tackle these difficulties by within/between decomposition of labor demand using the National Labor Force Survey of Indonesia. National Labor Force Survey of Indonesia provides working hours of informal workers in Indonesia. In Indonesia, there exist large shares of informal workers who are self-employed or unpaid. 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. We also treat labor demand among formal workers and informal workers separately since demand for these workers differ across industries. Table 5 shows that there is a notable difference in labor demand across industries, occupations, and job status of workers. 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 groups.

A Difference in skill distribution can cause between industry changes in demand shift. Even with no skill-biased technology, if each industry grows in different rates, skill distribution of whole labor market will be affected and reflected in between industry demand shifts. Table 6 suggests that 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 changes 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.

Table 6: Change in Employment Share by Industry and Occupation

Industry	Percentage Employment Share					
	1995 –1997	1998 –2000	2001 –2003	2004 –2006	2006 –2009	1995–2009 (% point)
Agriculture, hunting, forestry, and fishing	13.2	14.8	8.7	7.5	8.6	–3.4
Mining and quarrying	1.3	1.1	1.3	1.7	1.7	0.4
Manufacturing	22.9	24.4	29.6	28	26.3	1.2
Electricity, gas, and water supply	0.6	0.4	0.5	0.7	0.7	0.0
Construction	11.7	10.2	7.6	6.8	6.1	–5.1
Wholesale and retail trade	9.5	10.7	13.4	16.1	15.8	4.8
Transport	6.4	5.9	6.2	6.5	6.9	0.1
Financial intermediation and real estate	2.2	2.2	4.1	3.8	3.9	1.8
Public service	32.0	30.2	28.5	28.8	30.2	0.3
Occupation						
Professional, managers, and armed force	24.3	19.5	26.7	27.2	27.2	3.9
Sales and service workers	18.6	20.0	21.5	24.3	24.4	4.0
Production workers	57.1	60.8	51.8	48.5	48.4	–7.9

Notes : The numbers in the table for each demographic group represent the average share of employment of that group in the corresponding industry or occupation with the average taken over then 1995–2009 period. Sample is all workers in the formal sector.

B. Within/Between Decomposition of 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 1975, 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 (Sakernas) uses KLUI code for industry classifications. The classification system was firstly made in 1987 and went through several changes in 1995, 2000, and 2005. To construct consistent industry classification across the sample period, we aggregate detailed industry codes into 30 industry classifications.[3] For occupation code, Sakernas does not have proper occupation information in surveys constructed before 1995. Therefore, we restrict our analysis from 1995 to 2009. However, Sakernas has been using the same occupation classification (KJI: Klasifikasi Baku Jenis Pekerjaan) to identify seven

[3] Please refer appendix 1 for more information about industry codes of Sakernas.

categories of occupation throughout the sample period. We aggregate seven KJI codes into three general categories following literature.

One more remark should be made about our choice of male workers. Female workers of high education level are still not very representative in many sectors when we divide all workers by industry and occupation. 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 the index given in the following equation :

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

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 1990s, we merged tertiary education category with senior high school category to decrease bias resulting 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 given by the index in equation (1) when *j* refers to 30 industries. Within-industry demand shift index for *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 7 summarizes the decomposition of labor demand for different demographic groups across sample periods. Among formal workers, there are 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 early 2000s, but that trend has been reversed since 2003. Among formal workers, demand shift favoring more educated workers can be found in early 2000s. Though demand shift is mainly driven by between-industry, about 8% of overall demand shift 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. One final note is that the demand shift toward more skilled workers in recent days is not found among informal workers who are largely self-employed or unpaid.

The decomposition results in Table 7 are done with all industries including the private sector and public sector together. In the public sector, however, the demand for labor is not only affected by the market but also affected by political preferences. The same industry-occupation decomposition excluding the public sector is shown in Table 8. There is a noticeable change in demand for formal workers; the demand shift favoring more skilled workers became stronger. Also, the magnitude of within effect is also greater (3.5 in 03-09 period), confirming that a demand shift toward more skilled workers is driven by the private sector.

Evidence in this chapter 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 technological progress. If the evidence of skill-biased technological changes found in this chapter was driven by manufacturing sector, much skill-biased technological change is anticipated to occur in the near future. Therefore, in the next section we turn to the manufacturing sector of Indonesia, utilizing detailed information of firm-level survey and further explore evidence of skill-biased technological change in manufacturing sector and its relationship with specific technology measures.

Table 7: Industry and Occupation Based Demand Shift Measures, 1995–2009
All Workers

	Change in log relative demand for male workers (multiplied by 100)											
	Between Industry				Within Industry				Overall			
Group	1995–1999	1999–2003	2003–2009	1995–2009	1995–1999	1999–2003	2003–2009	1995–2009	1995–1999	1999–2003	2003–2009	1995–2009
Formal Workers												
years of schooling												
0–6 years	–4.2	–1.6	2.3	0.8	0.9	1.9	0.4	–0.9	–3.3	0.3	2.7	–0.2
7–9 years	–5.2	–3.6	7.1	3.8	0.3	2.5	3.0	0.9	–4.9	–1.0	10.1	4.7
10 + years	–8.8	–7.7	17.5	11.1	–3.6	0.3	1.4	–9.1	–12.4	–7.4	18.9	2.0
Informal Workers												
years of schooling												
0–6 years	3.8	3.4	–8.1	–0.4	0.5	–0.4	–0.7	3.5	4.3	3.0	–8.7	–0.9
7–9 years	3.0	1.5	–5.6	–4.0	0.4	0.1	–0.7	3.0	3.4	1.6	–6.3	–0.9
10 + years	2.2	0.8	–0.3	0.5	–0.6	–1.6	–1.5	–1.5	1.6	–0.9	–1.8	–1.0

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 $Log(1 + \Delta D_k)$.

V. INDUSTRY DEMAND SHIFTS USING THE INDONESIAN MANUFACTURING SURVEY

In previous sections, we found out that there was within-industry shifts in demand away from unskilled and towards skilled labor in Indonesia. We will further investigate the demand shifts favoring skilled workers using firm-level data from the Indonesian Manufacturing Survey (Statistik Industri). The Indonesian Manufacturing Survey 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. The data also includes detailed information of output, capital, and technology measures such as R&D investment and FDI. Detailed information of exported output and imported materials are also available on an annual base.

As we have detailed information of openness to foreign technology through FDI, export, and import, it would provide us with a good opportunity to test the existence of pervasive skill-biased technological change. According to Berman et al (1998), pervasive skill-biased technological change implies that country with abundant low-skilled labor experiences an increase in relative wage of skilled workers when it opens up to trade. This prediction is opposite to that of the Heckscher-Ohlin model. It would be interesting to find out to what extent and how pervasive skill-biased technological change has occurred in Indonesia. FDI and the share of imported materials can serve as an indicator of technology transfer from more developed countries.

Figure 7 shows the overall trends of wage bill and employment of production workers and non-production workers in the manufacturing sector. However, it is difficult to tell from these graphs if there has been a shift in demand. The aggregate employment of production workers as well as that of non-production workers does not exhibit much change during our sample period. On the other hand, the aggregate wage bill of production workers increased significantly during the sample period.[4] The aggregate wage bill of non-production workers, however, shows very smooth increase for the same period. In the following subsection, we will further investigate how relative wage bill and employment of non-production workers changed at industry level.

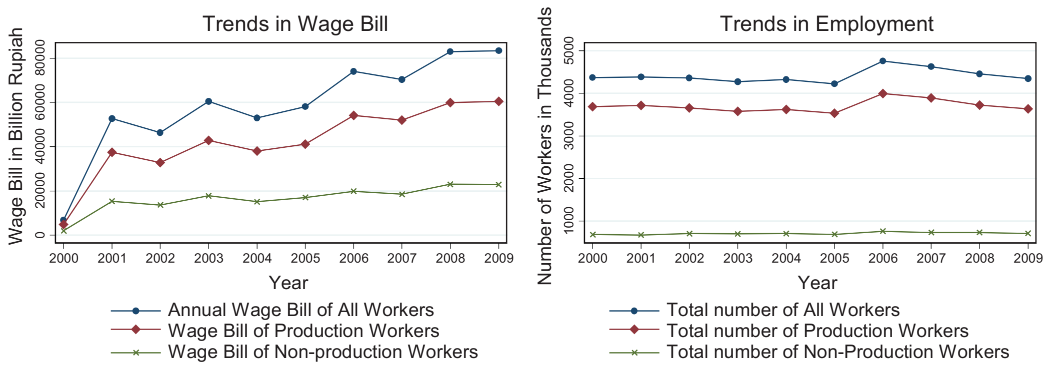
[4] The sharp increase in nominal wage bill reflects Indonesia's denomination of banknotes which took place from 2000 to 2005.

Table 8: Industry and Occupation Based Demand Shift Measures, 1995–2009
Private Sector Workers

	Change in log relative demand for male workers (multiplied by 100)											
	Between Industry				Within Industry				Overall			
Group	**1995–1999**	**1999–2003**	**2003–2009**	**1995–2009**	**1995–1999**	**1999–2003**	**2003–2009**	**1995–2009**	**1995–1999**	**1999–2003**	**2003–2009**	**1995–2009**
Formal Workers												
years of schooling												
0–6 years	–4.1	–0.5	4.0	3.6	–0.2	1.1	0.6	–2.4	–4.2	0.6	4.6	1.2
7–9 years	–4.4	–0.9	7.3	6.4	–0.7	1.5	1.6	–1.8	–5.2	0.6	8.8	4.6
10 + years	–9.1	–1.4	19.6	18.5	–4.7	1.1	3.5	–6.5	–13.8	–0.3	23.1	12.1
Informal Workers												
years of schooling												
0–6 years	2.3	0.4	–6.2	–5.8	0.6	–0.4	–0.8	1.9	2.9	0.1	–7.0	–3.8
7–9 years	2.6	0.3	–4.3	–4.0	0.7	–0.4	–1.2	1.9	3.3	–0.1	–5.5	–2.1
10 + years	3.0	0.4	–1.3	–0.9	0.0	–0.6	–0.8	1.7	3.0	–0.2	–2.1	0.8

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 $Log(1 + \Delta D_k)$. We exclude public sector in this decomposition and there are 25 industries and 3 occupation categories.

Figure 7: Trends Within Manufacturing Sector



Source: Indonesian Manufacturing Survey

Source: Indonesian Manufacturing Survey

A. Within/Between Decomposition of Demand Shift in Manufacturing Sector

We employ the following standard way of decomposing a change in industry demand shift into a term reflecting reallocation of employment between industries and another reflecting changes of proportions within industries (Berman et al. 1992) :

$$\Delta P_n = \sum_i \Delta S_i \overline{P_{n_i}} + \sum_i \Delta P_{n_i} \overline{S_i} \quad (2)$$

for i=1,....,N industries. $P_{n_i} = E_{n_i}/E_i$, is the proportion of non-production labor in industry *i* , $S_i = E_i/E$, is the share of employment in industry *i*. A bar over a term denotes an average over sample period (2000-2009). The first term on the right hand side reports the change in the aggregate proportion of non-production workers attributable to shifts in employment shares between industries with different proportions of non-production workers. The second term reports the change in the aggregate proportion attributable to changes in the proportion of non-production workers within each industry. As in Section IV, we expect that between industry shifts represent shifts in demand or trades while within industry shifts captures the effect of skill-biased technological changes.

The Indonesian Manufacturing Survey has inconsistent quality.[5] We discovered several issues in these data and believe that we resolved most of them. The original data contains a 5-digit industry classification, however, we found that at the 5-digit industry level, a large number of observations were present in some years but missing in previous or subsequent years. The Indonesian Manufacturing Survey also experienced a change in its own industry classification several times during our sample period, and some problem of miscoding seem to be caused by this change in industry classification. To avoid measurement errors in our data, we decided to use 3-digit industry level of industry aggregation in our analysis.

[5] The 2003 Statistik Industri indicates a very sharp increase in non-production workers' wage bill and sharp decrease in production workers' wage bill. The national total wage bill of non-production worker's was 13.6 trillion in 2002, but becomes 42.8 trillion in 2003 while production workers' wage bill was 32.8 trillion in 2002 and becomes 13.8 trillion in 2003. It was obvious mistake in coding and we corrected by simply reversing the coding in 2003. In the empirical analysis, we avoided to use the data of 2003 as much as possible.

Table 9: Within/Between Decomposition of Demand Shift for Non-Production Workers 3 Digit Industry Code (60)

	Employment		Wage Bill	
	Between	Within	Between	Within
	2000–2004			
Demand Shifts for Non-Production Workers	0.0035	0.0026	–0.0091	–0.0048
Total		0.0061		–0.0139
	2004–2009			
Demand Shifts for Non-Production Workers	0.0005	–0.0007	0.0071	–0.0177
Total		–0.0002		–0.0106
	2000–2009			
Demand Shifts for Non-Production Workers	0.004	0.002	–0.002	–0.0224
Total		0.006		–0.0244

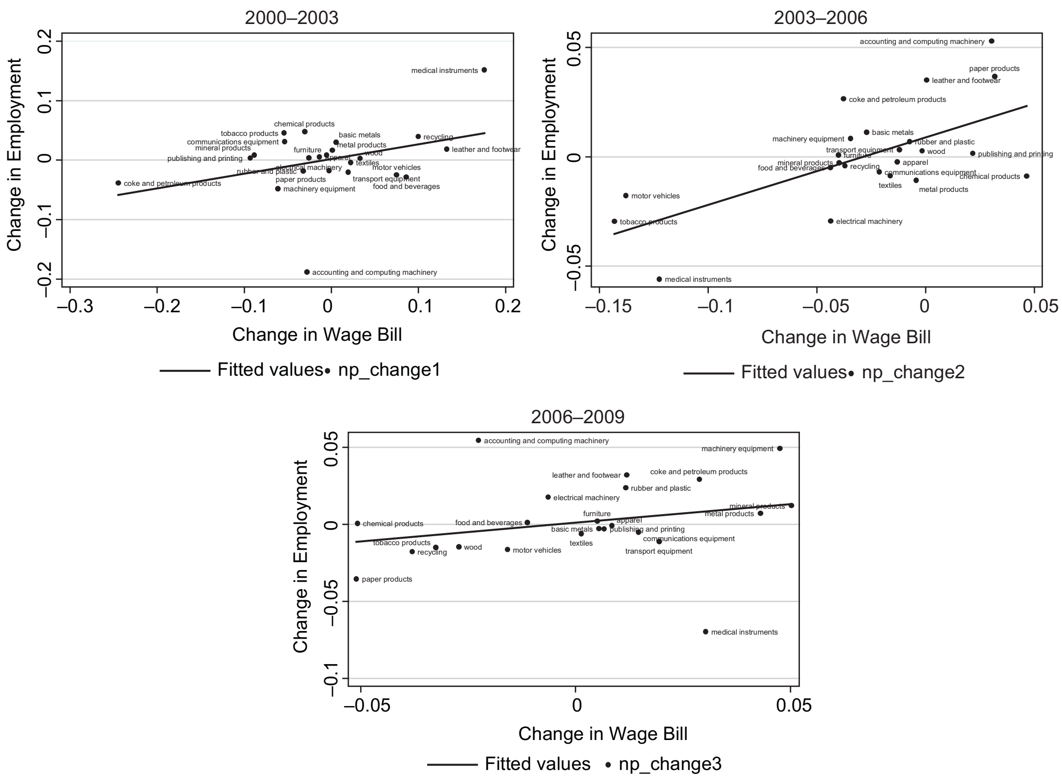
For detailed industry classification and sector classification used here, refer Appendix 2. The numbers are all annualized.

Decomposition results in Table 9 indicate that the simple decomposition now suffers from industry-specific shock or temporary shock in the manufacturing sector. In previous sections, we performed the decomposition of demand shift in the whole economy for a much longer time period; therefore, those temporary business fluctuations would not affect our results. But in this case, the results seem to be much more sensitive to those confounding factors.

Overall employment decomposition is consistent with our previous results. Though within-effect is negative from 2004 to 2009, the magnitude is very small and does not affect overall results. In 2000s, employment of non-production workers has increased in the manufacturing sector and the size of within-effect is 50% of between-effect. This result confirms that demand for non-production workers in the manufacturing sector was a leading factor of demand shift in our previous section.

On the other hand, the decomposition of wage bill shows inconsistent results over the whole sample period. We suspect that temporary shock or existence of outliers might have caused them. Figure 8 shows there are indeed several outlier sectors in each period that experienced sharp declines in wage bill. It implies that some temporary shocks on those businesses caused sharp decline in within-industry demand for non-production workers' wage bill. However, all these graphs show that there is a positive relationship between change in wage bill and change in employment. 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 proves that there was demand shift toward non-production workers in the manufacturing sector. Therefore we proceed to regression analysis in the next section to examine skill-biased technological changes controlling detailed conditions of each industry and time trends.

Figure 8: Change in Non-production Wage-bill Shares and Employment Shares



B. Regression Analysis

The previous section shows the possibility that skill upgrading is confounded with many other factors affecting demand for non-production workers within industry. Moreover, within/between decomposition does not provide shifts in skills demand caused by technology changes. To further explore the effect of technology on skill upgrading, we employ the following regression specification which relate changes in the non-production workers' employment/wage bill share in a given industry to observable measures of technology (Berman, Bound, and Griliches, 1993). Under the assumptions of translog cost function, cost minimizing firms, and constant returns to scale, we can derive the following "share" equation in first difference form. For the change in the share of non-production employment in each industry *j* of year *t* :

$$\Delta S_{jt}^{n} = \beta_0 + \beta_1 \Delta \ln\left(\frac{W_{jt}^{n}}{W_{jt}^{p}}\right) + \beta_2 \Delta \ln\left(\frac{K_{jt}}{Y_{jt}}\right) + \varepsilon_{jt} \quad (3)$$

where *n* and *p* indicate non-production and production labor. W_{jt}^{n} and W_{jt}^{p} denotes the wages of non-production workers and production workers separately, while K_{jt} represents fixed capital and *Y* represents value added. In this specification, capital-skill complementarity implies that $\beta_2 > 0$ while β_0 is a measure of the cross-industry average bias in technological change. We use the same specification for the wage bill of non-production workers.

Before we proceed to regression results, we would like to make several remarks about our empirical work. The Indonesian Manufacturing Survey basically has a panel data structure. We can keep track of each plant for four years since its identifier changed during the sample period. However, firm-level analysis will be affected by entry and exit of each firm, causing bias in our estimate. To minimize bias from outliers and measurement error, we decided to use 5-digit industry level aggregation.

We also use variable *output* rather than *value added* since the latter one turned out to have more outliers. Output is conventionally used instead of value added because of lack of proper value added deflator. We also applied industry share of output as a weight to regressions to prevent bias coming from entry and exit of small industries.

The measure of technological change should be our main concern. Table 10 shows the list of variables we used to capture technological change of each industry. In studies about the United States, people used the measure of computerization (Autor, Levy, Murnane 1993 and Berman, Bound, Griliches 1994). However, it is difficult to have such a measure in developing countries. At the same time, the level of technology is still low in many developing countries, so the measure of computerization may not be a proper indicator of technology.

Our first choice of technological measure is research and development investment share. Table 10 shows that the average of R&D investment share is doubled from 2000 to 2006 while the level of R&D investment is still very low (0.2%). Human development investment share is expenditure mainly spent for training of workers. The level and increase of human development investment share is similar to that of R&D investment share.

The more interesting measure would be FDI concerning that Indonesia is still a developing country. Many studies found out that foreign direct investment is an important vehicle for the transfer of technology in developing countries (Borensztein, Gregorio, and Lee 1998). Average of FDI investment[6] is marginally increased from 6.3% in 2000 to 6.8% in 2006.

Table 10: 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 unit of observation is 5-digit industry level.

6 We treated missing values of FDI as zero in our data.

We also consider export and import shares as proper proxies for technological changes. In a world with international trade in goods and services, technological progress depends not only on domestic technology investment but spillovers of foreign technologies by interacting with trade partners. The more export-led an industry is, the more it is likely to absorb new technologies to compete in the global market. Imported material shares can also be a good indicator of technology since most technologies are embedded in imported machines in developing countries.[7]

In this regression we use two sets of difference equations: 2000–2004 difference equation and 2004–2009 difference equations. We use four-year difference equations since it takes some time for each firm to change it's employment and wages. Among technology variables, R&D, human development, and FDI investment shares 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.

Table 11: Change in Non-production Workers' Share in Employment

2000–2004, 2004–2009 Combined					
Change in Non-production Workers' Share in Employment: $\Delta E_j^n/E_j^p$					
Equation	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$\Delta ln(Kapital/Output)$	0.0063 (0.0026)**	0.0061 (0.0027)**	0.0063 (0.0026)**	0.0068 (0.0026)***	0.0072 (0.0025)***
$\Delta ln(output)$	–0.0021 (0.0037)	–0.0018 (0.0037)	–0.0022 (0.0037)	–0.0021 (0.0037)	–0.0030 (0.0036)
$\Delta ln(w_j^n/w_j^p)$	–0.0414 (0.0047)***	–0.0415 (0.0050)***	–0.0414 (0.0047)***	–0.0417 (0.0046)***	–0.0411 (0.0045)***
R&D/Investment		0.9744 (1.3442)			
HD/Investment			0.0887 (1.5504)		
FDI/Investment				0.0485 (0.0252)*	
Export/Output					–0.0330 (0.0181)*
Import/Output					0.0510 (0.0154)***
Constant	–0.0194 (0.0059)***	–0.0195 (0.0067)***	–0.0154 (0.0053)***	–0.0185 (0.0052)***	–0.0226 (0.0068)***
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.2307	0.1967	0.2283	0.2497	0.2738
N	351	351	351	351	350

Source: Author's tabulations based on the Indonesian Manufacturing Survey.

Sample: About 200 five-digit manufacturing industries. Outliers are eliminated by Hadimvo procedure.

Note: Equations weighted by average share of industry output in manufacturing.

7 We used Hadimvo procedure to get rid of outliers in technology variables. Our result is robust to different criterion.

Estimation of equation (3) with technology variables are presented in Table 11 and Table 12. The regression (1) of Table 11 shows estimation of basic cost function derived in equation (3) using employment share of non-production workers as a dependent variable. The significant effect of 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 coefficient for output is insignificant confirming that production function is constant returns to scale.

The effect of R&D and human development investment shares on non-production workers' employment share is estimated in regression (2) and (3). Estimates show no significant effect of R&D or human development investment controlling time trends and other factors. It may reflect that Indonesia has very low level of R&D or human development investment and growth rates. The highest growth rate of R&D investment share between 2000 and 2006 is only 1.8 percentage point, indicating that domestic technological progress is yet too small to influence the labor market of Indonesia.

On the other hand, indicators of foreign technological changes show evidence of skill-biased technological changes. In regression (4), the estimated coefficient of FDI share is 0.0485 and is also of significant size. In 2000, average fraction of FDI was 0.0634. Multiplying 0.0485 by 0.0634 gives 0.0031, or 52.5% of the shifts that occurred in the employment share from 2000 to 2009. The positive coefficient of imported material share in regression (5) also implies that demand shifts away from production worker could have been much larger if all the other factors were controlled.

It should be noted that the coefficient of export share in regression (5) is negative, which is opposite to our anticipation. However, the negative effect of export on demand for more skilled workers is consistent with the finding of other previous studies about Indonesia (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 or textiles. On the other hand, firms 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 driven by foreign technology rather than domestic ones.

Table 12 shows similar results for wage bill of non-production workers. Though evidence of capital-complementarity is somewhat enervated, other main results remain the same. The effect of R&D and human development is meaningless or only marginally significant. In contrast, the effect of FDI and imported material is significant and sizable, consistent with our previous results. The coefficient of import share is 0.0518 and if we multiply average fraction of import in 2000, it is 0.0146. It is of magnitude which can offset decrease in wage bill in the same period by 60%. The estimated positive relationship between technology measures and wage bill confirms that the negative within-effect found earlier is confounded with other factors.

Table 12: Change in Non-production Workers' Share in Wage Bill

2000–2004, 2004–2009 Combined					
Change in Non-production Workers' Share in Wage Bill: $\Delta WB_j^n/WB_j^p$					
Equation	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$\Delta ln(Kapital/Output)$	0.0041 (0.0026)	0.0043 (0.0028)	0.0038 (0.0027)	0.0048 (0.0024)*	0.0045 (0.0025)*
$\Delta ln(output)$	–0.0029 (0.0039)	–0.0039 (0.0040)	–0.0044 (0.0040)	–0.0028 (0.0037)	–0.0039 (0.0038)
$\Delta ln(w_j^n/w_j^p)$	0.1257 (0.0038)***	0.1222 (0.0048)***	0.1237 (0.0042)***	0.1247 (0.0034)***	0.1239 (0.0037)***
R&D/Investment		2.4253 (1.4139)*			
HD/Investment			2.5020 (1.5462)		
FDI/Investment				0.0904 (0.0265)***	
Export/Output					0.0145 (0.0176)
Import/Output					0.0518 (0.0157)***
Constant	–0.0277 (0.0046)***	–0.0264 (0.0056)***	–0.0383 (0.0053)***	–0.0476 (0.0031)***	–0.0365 (0.0049)***
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.8495	0.6911	0.7788	0.9785	0.9082
N	351	351	351	351	350

Source: Author's tabulations based on the Indonesian Manufacturing Survey.

Sample: About 200 five-digit manufacturing industries. Outliers are eliminated by Hadimvo procedure.

Note: Equations weighted by average share of industry output in manufacturing.

The regression analysis supports the skill-biased technology argument in Indonesia that technological change has been an important factor contributing to increased demand for more skilled workers in 2000s. Though we failed to find the significant effect of domestic technological measures on demand shift for skilled workers, we found out that foreign technology transferred by imported materials or FDI are major driving forces behind the story. Evidence found in this section confirm pervasive skill-biased technological changes hypothesis suggested by Berman, Bound, and Machin (1998) that skill-biased technological changes occur simultaneously in countries which open up to trade.

VI. CONCLUSIONS

In this paper, we examined the source of rising inequality in Indonesia, the largest and leading economy in Southeast Asia. Indonesia achieved fast development with narrowing inequality until it experienced trend reversal in wage inequality in early 2000s. Wage inequality increased across demographic groups as well as within narrowly defined demographic groups implying rising income gap between winners and losers among workers with similar backgrounds. Using nationally representative labor force survey, we found out that there occurred demand shifts favoring skilled workers since early 2000s. Though most demand shifts were driven by between industry reallocation of labor forces, about 10% was driven by change within industry.

We further investigate what drove within-industry demand shift in Indonesia. In advanced countries, it is found that technological changes such as computerization and R&D investment facilitate within-industry demand shift. As Indonesia is a developing country with a low level of technology, we focus on the role of trade and foreign direct investment in transferring advanced technology into Indonesia. Our regression analysis suggests that foreign technology embedded in imported material and FDI increases employment and wage bill of non-production workers within 5-digit industries. The sizable magnitude of estimated effects predicts that further import of foreign technology can accelerate the skill-biased technological change in Indonesia.

APPENDIX

A.1: Comparison of Industry Classification Codes : Our Data vs. Sakernas

Industry Classification of Our Data	KLUI 1995 (1995–1999)	KBLI 2000 (2000–2007)	KBLI 2005 (2008–2009)
1. Agriculture and Husbandry	11, 12, 13, 14	11, 12, 13, 14, 15	1111–1502
2. Forestry	15	20	2011–2059
3. Fisheries	16, 17, 18	50	5011–5056
4. Mining and Quarrying	21-26	101–102, 111–112, 121, 131, 132, 141–142	10101–14299
5. Food, Beverages, and Tobacco	31	151–155, 160	15111–16009
6. Textile, Clothes, and Leather Industry	32	171–174, 181, 182, 191, 192	17111–19209
7. Wooden Commodities and Furniture	33	201–202, 361, 369	20101–20299, 36101–36109
8. Paper, Printing and Publishing	34	210, 221–223	21011–22302
9. Chemicals, Rubbers, and Plastic	35	231–233, 241–243, 251–252	23100–25209
10. Non-Metallic Minerals	36	261-269	26111–26900
11. Basic Metals	37	271–273	27101–27320
12. Metal Products, Machinery, and Equipment	38	281, 289, 291-293	28111–29309
13. Other Industry Process	39	300, 311-319, 321–323, 331–333, 341–343, 351–359, 371, 372	30001–35990, 36911–37200
14. Electricity, Gas, and Drinking Water Supply	41, 42, 43	401, 402–403, 410	40101–41003
15. Construction	51, 52	451–455	45100–45500
16. Trading	61, 62	501–505, 511–519, 521–526, 531–539, 541–549	50101–54900
17. Accommodation	64	551	55111–55190
18. Restaurants	63	552	55211–55260
19. Land Transportation and Pipeline	71	601–603	60110–60300
20. Water Transportation	72	611–612	61111–61226
21. Air Transportation	73	621–622	62111–62390
22. Storage and Supporting Transport	74	631–639	63100–63900
23. Post and Telecommunication	75	641–642	64110–64430
24. Financial Agents and Insurance	81, 82	651–652, 660, 671–672	65110–67209
25. Real Estate, Rental, and Business Services	83	701–703, 711–713, 721–729, 731–732, 741–749	70101–74990
26. Government, Defense, and Education	91	751–753, 801–809	75111–75300, 80111–80929
27. Health and Social Services	92	851–853, 900	85111–85322
28. Social and Organizational Activities	93	911–919	90001–91990
29. Entertainment and Culture	94	921–924, 930	92111–93094
30. Personal Household Services	95	950	95000

A.2: Industry Code Classification in Indonesian Manufacturing Survey

Industry Classification	Industry Share (%)	Non-production Employment (%)	Non-production Wage bill (%)
15. Manufacture of food products and beverages	22.54	22.10	32.10
16. Manufacture of tobacco products	4.13	9.70	24.10
17. Manufacture of textiles	9.46	12.30	20.70
18. Manufacture of apparel	9.83	9.00	16.50
19. Tanning and dressing of leather, manufacture of footwear	2.61	11.90	19.50
20. Manufacture of wood	6.42	13.70	21.50
21. Manufacture of paper and paper products	1.84	21.90	30.90
22. Publishing, printing, and reproduction of recorded media	2.78	23.50	30.40
23. Manufacture of coke, refined petroleum products	0.27	26.20	40.80
24. Manufacture of chemicals and chemical products	4.54	32.40	47.20
25. Manufacture of rubber and plastic products	6.71	17.90	28.10
26. Manufacture of other non-metallic mineral products	7.20	18.10	34.90
27. Manufacture of basic metals	1.00	19.60	31.50
28. Manufacture of fabricated metal products	3.91	17.30	29.30
29. Manufacture of machinery and equipment	1.87	18.80	32.20
30. Manufacture of office, accounting, and computing machinery	0.04	9.30	9.60
31. Manufacture of electrical machinery and apparatus	1.09	16.70	28.40
32. Manufacture of radio, television, and communication equipment	0.85	14.40	26.20
33. Manufacture of medical, precision and optical instruments	0.25	22.30	26.50
34. Manufacture of motor vehicles, trailers, and semi-trailers	1.18	19.60	32.90
35. Manufacture of other transport equipment	1.44	19.70	28.00
36. Manufacture of furniture	9.63	11.50	21.00
37. Recycling	0.42	14.30	23.50

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Technological Change, Skill Demand, and Wage Inequality in Indonesia

What is the implication of technology on rising wage inequality in developing countries? Employing rich data set of Indonesia, we found out that there is within-industry demand shift toward non-production workers. Our analysis shows that the demand shift was related to technology transferred through imported goods or foreign direct investment.

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