Characteristics of Indonesia's large and medium scale manufacturing industries: An Exploratory Analysis.

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Declaration of Originality

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. To the best of the author's knowledge, it contains no material previously published or written by another person, except where due reference is made in the text.

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Abstract

The manufacturing sector has contributed significantly to the Indonesian economy. This sector contributed 27 per cent on average to Indonesia's GDP between 2000 and 2015, with more than 40 per cent of its value-added was contributed by large and medium scale industries. Despite the important roles of large and medium scale industries in Indonesia's economy, this sector has three major problematic characteristics that are explored by three different research papers in this thesis. These characteristics are inconsistent growth either for output or labour productivity growth, a steady increase in wage inequality, and relatively low labour absorption and labour mobility.

The first paper in this thesis aims to observe how productivity growth measured by Total Factor Productivity (TFP) growth plays a role in the production process of Indonesia's manufacturing sector. This paper estimates TFP growth and its decompositions based on varying parameter stochastic frontier analysis (VSFA) framework as this approach enables me to consider firm heterogeneity explicitly. By using datasets from Indonesia's Yearly Large and Medium Manufacturing Industries Survey over the period 2002–2014, VSFA reveals that a constant parameter stochastic frontier (SFA) overestimated mean technical efficiency (TE) and the TE rank under VSFA is more consistent than under SFA. Hence, it is logical to assume that firms should not have a constant production function response, so TFP growth is measured based on the results of VSFA. The mean TFP growth was estimated at 4.3 per cent and was mostly decomposed by technological progress. Moreover, it was estimated that labour efficiency in this sector was relatively low, at 46 per cent. This implies that technological progress had not been absorbed well by workers.

The second research paper analyses how wage inequality affects firm productivity. By implementing several econometric approaches, which are panel fixed effects, dynamic panel data estimation – Generalised Method of Moments (GMM) approach and instrumental variable estimations – two-stage least squares regression (2SLS), it is found that wage inequality significantly affects firm productivity in an inverted U-shaped relationship. This implies that when wage inequality in Indonesia's large and medium scale industries from 2000 to 2015 was relatively low, it increased firm productivity. However, if wage disparity was more than the threshold, it reduced productivity. This means that the findings support the argument of the 'tournament' model (Lazear and Rosen, 1981) rather than the 'fairness' model (Akerlof and Yellen, 1988). To increase firm productivity, relatively low wage inequality is needed to motivate workers. However, the existence of the 'hawks'- type of worker calls for caution in attempts to increase firm productivity.

The last paper examines how manufacturing jobs and labour mobility, which are measured by geographical mobility and job mobility, affect wage inequality. The findings show that manufacturing jobs and occupational mobility have an inverted U-shaped relationship with wage inequality. This implies that a relatively low level of job absorption and occupational mobility among workers will increase wage inequality. However, when this is beyond the threshold, it will reduce wage disparity. On the other hand, spatial mobility significantly affects wage inequality in a U-shaped relationship. This means that relatively low geographical mobility in the labour supply will reduce inequality. Once it is more than the threshold, it will increase wage inequality. These findings are robust across many dimensions: different types of wage inequality measurement – conditional and unconditional wage disparity; the use of different techniques such as using OLS, FE, and dynamic panel models with and without lagged independent variables, instrumental variables (IV) technique; and the use of different levels of data – industrial group and regional level data.

The three papers in this thesis provide evidence about human capital problems in Indonesia's manufacturing sector. High levels technological progress that have not been followed by labour productivity imply that workers are not ready for technological advancement. Moreover, the existence of 'hawks'-type workers who can reduce labour productivity reflects the diversity of human capital quality across industries. In addition, Indonesia still depends on low-medium technology in job absorption. Demand for labour coming from medium-high technology industries needs to be boosted to elevate the role of job creation in reducing inequality. Lastly, asymmetrical problems of workers' heterogeneity and skill mismatch are factors explaining the adverse effects of labour mobility on wage inequality. Hence, human capital improvement is an urgent matter to increase the performance of Indonesia's manufacturing sector.

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Chapter 1 Introduction

The manufacturing sector has contributed significantly to the Indonesian economy. This sector contributed 27 per cent on average to Indonesia's GDP between 2000 and 2015, with more than 40 per cent of its value-added contributed by large and medium scale industries. Despite the important roles of large and medium scale industries in Indonesia's economy, this sector has three major problematic characteristics that are explored by three different research papers in this thesis. These characteristics are inconsistent growth either for output growth or labour productivity growth, a steady increase in wage inequality, and relatively low labour absorption and labour mobility.

This thesis presents evidence that total factor productivity in Indonesia's manufacturing sector varied across firms, which was decomposed into technological progress and technical efficiency. In contrast, with high levels of technological progress, labour efficiency levels, which reflect labour productivity emanating from technical efficiency, are relatively low. This may indicate that workers cannot fully absorb technological progress in the production process. Moreover, wage inequality has important effects on labour productivity. Wage inequality at relatively low levels can increase labour productivity. However, when wage inequality is too high, it will reduce productivity due to the existence of un-cooperative workers. Finally, manufacturing jobs and job mobility at a relatively high level can reduce wage inequality. By contrast, the analysis of how geographical mobility affects wage inequality reveals evidence that hiring labour from the domestic region will reduce wage inequality.

1.1 Indonesia's context

Indonesia enjoyed stable economic growth from 2000 to 2015. On average, Indonesia gained 6 per cent growth in Gross Domestic Product (GDP). This performance was in no small measure due to policy reforms implemented over this period, notably a robust macroeconomic framework. Much of the growth was domestically driven, with household consumption, in particular, providing a solid base. Labour market conditions improved, and in combination with increasingly effective poverty-alleviation programs helped to boost household incomes and confidence. The external sector also played an important role, primarily through global demand for commodity exports.

In terms of comparison with other developing countries, Indonesia and India are fairly comparable. The economies of both India and Indonesia have been reformed in the past two decades. Among other things, these economic reforms have facilitated trade, investment liberalisation, fiscal and monetary policy reforms, and infrastructural improvement (Mishra, 2011). Consequently, both economies have emerged as dynamic markets with strong economic fundamentals and a robust financial sector and manufacturing industry. The two economies have the advantage of low labour costs and have positioned themselves among the top five investment destinations in Asia. Moreover, these two countries also have enjoyed the role of exports and foreign investment as important factors for economic growth (Bhide et al., 2015).

Concerning the structure of production, like many countries in East Asia, Indonesia underwent a process of industrialisation over the period. The manufacturing sector contributed 27% on average to Indonesia's GDP from 2000 to 2015. From the entire manufacturing sectors value-added, more than 40 per cent is contributed by large and medium scale industries. By contrast, small and micro-scale industries in the same period contributed less than 10 per cent on average. Interestingly, small and micro-scale industries have an important role to play in job creation in Indonesia. This sector performed better than the medium-large scale in terms of employment. Small scale industries provided an average of 7.5 per cent of Indonesia's total employment between 2000 and 2015. In contrast, large and medium scale industries absorbed less than 5 per cent of the total Indonesian labour force.

1.2 Productivity growth

Despite the important role of large and medium industries in Indonesia's economy, this sector has experienced inconsistent growth in both output growth and labour productivity growth. The output growth of large and medium industries fluctuated from minus 10 per cent to 13 per cent during 2000-2015. The instability of output growth can be analysed by measuring the source of output growth, either due to technological factors (productivity) or input formation (Hulten et al., 2001). The objective of this study is to analyse how productivity growth plays a role in the output growth of Indonesia's manufacturing sector by estimating Total Factor Productivity (TFP) growth and its decompositions.

In this thesis, TFP growth is decomposed into technical efficiency change and technological progress. This decomposition is based on the TFP growth decomposition approach developed by Kalirajan et al. (1996). Moreover, Kalirajan and Shand (1994) argued that technical efficiency contributes mostly to the TFP of firms. Technical efficiency is important because if firms perform consistently with full technical efficiency, the more inputs they use, the larger output they achieve, the higher productivity will be gained (Grafton et al., 2004). Coelli et al. (2005) argued that the components of productivity are not only technical efficiency but also technological change and the exploitation of scale economies (Coelli et al., 2005).

Technical efficiency in Indonesia's manufacturing sector, which is argued above to be an important factor decomposing TFP, has been measured in many studies (Pitt & Lee, 1981; Hill & Kalirajan, 1993; Timmer, 1999; Margono & Sharma, 2006; Ikhsan, 2007; Suyanto &

Bloch, 2009; Margono et al., 2011; Prabowo & Cabanda, 2011; Suyanto & Salim, 2011; Suyanto & Bloch, 2014; Sari et al., 2016). However, heterogeneity between individual firms was not treated explicitly in these studies as it is assumed that frontier production functions shift neutrally from the actual production function. This assumption may result in a misspecification bias when time-varying unobservable factors exist. To address this limitation, this paper applies a varying parameter stochastic frontier analysis framework to decompose the sources of TFP (Kalirajan and Obwona, 1994). To the best of the author's knowledge, studies assuming varying production responses in measuring technical efficiency and total factor productivity are scarce.

The results indicate that technical efficiency estimated by constant stochastic frontier is higher than under the assumption of varying parameter stochastic frontier analysis (VSFA). TE ranks, estimated by VSFA are more consistent over the periods. By arguing that TE measured through VSFA considers firm's heterogeneity properly, total factor productivity is measured based on this approach. VSFA reveals that TFP growth during 2002–2014 in Indonesia's large and medium scale industries varied across firms with an average growth of 4.3 per cent, which is mainly decomposed by technological progress. Moreover, labour efficiency is relatively low, at 51 per cent on average between 2002 and 2014. This may imply that technological progress has not been absorbed well by workers. The results suggest that pursuing equal opportunity for industrial technology development and preparing workers for technology development by enhancing human capital in each industrial division is arguably crucial.

1.3 Wage inequality and firm productivity

It is found in the first paper that labour efficiency, which reflects labour productivity in Indonesia's manufacturing sector, is relatively low. Hence, it is crucial to investigate what factors affect labour productivity. It has been argued that wages, relative wages particularly, are an important factor affecting workers' effort and productivity (Lallemand et al., 2004). Two leading theories explain how relative wages can affect firm productivity; the 'fairness' theory developed by Akerlof and Yellen (1988) and the 'tournament' model established by Lazear and Rosen (1981) and Lazear (1989). In the fairness theory, it is argued that more compressed wages will generate more productivity. On the other hand, according to the 'tournament' model, a certain level of wage disparity is required to boost workers' efforts to work more productively.

According to the above theories and wage inequality levels in Indonesia's manufacturing sector, which grew significantly from 2000 to 2015, the second paper in this thesis aims to analyse how wage inequality affects firm productivity, which is measured by labour productivity. To answer this question, I implement both wage inequality measurements, conditional and unconditional wage inequality, which have rarely been observed in previous studies. Conditional wage inequality is estimated by the standard error of wage regression (Winter-Ebmer and Zweimüller, 1999). Moreover, the Gini Index and maximum-minimum wage ratio measure unconditional wage inequality. The results from various and robust estimation approaches: panel data-fixed effects model, dynamic panel data-system (Generalised Method of Moments – GMM), two-stage least squares (2SLS) and different level of datasets reveal that wage inequality significantly affects firm productivity in an inverted U-shaped relationship. This means that wage dispersion increases firm productivity at a relatively low level. However, if wage inequality is above the optimum level, firm productivity will decrease. Hence, this paper supports the argument of the 'tournament' model rather than the 'fairness' model. However, the existence of the 'hawks' or 'uncooperative' type of worker that can reduce productivity suggests a need for caution.

1.4 Manufacturing jobs, labour mobility and wage inequality

Considering that wage inequality has significant effects on determining productivity, the following question is, what factors can determine wage inequality? Many factors affect wage inequality. However, numerous studies have found that job absorption and labour mobility play an important role in determining wage inequality. Manufacturing jobs can reduce wage inequality because of wage compression (Lambson, 1991; Kremer, 1993; Davis and Haltiwanger, 1995; Lallemand and Ryck, 2006; Sun, 2014; Barth et al., 2014). By contrast, some studies have argued that job absorption would increase wage inequality due to workers' heterogeneity (Oi, 1983; Dickens and Katz, 1986; Fox, 2009; Song et al., 2019). In terms of labour mobility, both spatial and job mobility, these factors can affect wages inequality either negatively (Pissarides and McMaster, 1990; Kanbur and Rapoport, 2005; Dorantes and Padial, 2007 and Belley et al., 2012) or positively (Burda and Wyplosz, 1992; Feser and Sweeney, 2003; Elhorst, 2003; Südekum, 2005; Epifani and Gancia, 2005; Partridge and Rickman, 2006; Østbye and Westerlund, 2007; Francis, 2009; Kambourov and Manovskii, 2009; Hoffmann and Shi, 2011; Soria et al., 2015; Stijepic, 2017; Park, 2019).

As there has no consensus on how manufacturing jobs and labour mobility affect wage inequality and the unique conditions in Indonesia's manufacturing industries regarding job absorption and labour mobility, I raise the question of how manufacturing jobs labour mobility affect wage inequality. To answer this question, I apply various approaches: different types of wage inequality measurement, conditional and unconditional wage disparity, various econometric techniques such as OLS, FE, dynamic panel models with and without lagged independent variables, and instrumental variables (IV) techniques; and the use of different levels of data such as industrial group and regional level data. The results reveal robust relationships between manufacturing jobs and wage inequality in an inverted U-shaped pattern. Moreover, two types of labour mobility measurements, which are spatial and job mobility, affect wage inequality in different patterns, an inverted U–shaped pattern for job mobility and a U-shaped form for geographical mobility.

The above results imply that demand for high-medium technology industries needs to be boosted as these industries fall in the area below the optimum level. Moreover, skill mismatch and asymmetrical problems due to worker heterogeneity can explain why labour mobility increases wage inequality. These implications can be drawn to the conclusion that human capital quality needs to be improved in all industry groups to elevate the role of manufacturing jobs and labour mobility in decreasing wage inequality.

The third paper contributes to the body of knowledge in the following way. First, this paper provides empirical evidence in the context of a developing country, Indonesia, which has rarely been observed for the related topic. In fact, cases of developing countries are relatively unique and interesting. In terms of methodology, this paper applies various dimensions and techniques, including simultaneous analysis of manufacturing jobs and labour mobility, which had not been explored in previous studies. Furthermore, this paper also explores possible reasons behind the relationship between manufacturing jobs, labour mobility and wage inequality by providing descriptive data gathered from rich datasets.

1.5 Organisation

The thesis has five chapters. Chapters 2 to 4 present the core research about characteristics of Indonesia's large and medium scale manufacturing sector. Chapter 2 analyses how total productivity growth is decomposed by implementing a varying-parameter stochastic frontier analysis approach. Chapter 3 investigates the effects of wage inequality on firm productivity, measured by labour productivity. Chapter 4 provides an analysis of how manufacturing jobs and labour mobility affect wage inequality. Lastly, key findings and their implication are summarised in Chapter 5.

Chapter 2 The Decomposition of Total Factor Productivity Growth: Varying parameter stochastic frontier analysis framework

Abstract

Generating output growth by adding more input into the production process may not be beneficial for the economy, given limited resources. On the other hand, if productivity growth dominates the production process, it will generate more output without excessive increase in input use. Hence, this paper aims to analyse how productivity growth takes a role in the production process of Indonesia's manufacturing sector by estimating productivity growth and its decompositions. Productivity growth will be measured by Total Factor Productivity (TFP) and decomposed into technological progress and technical efficiency within the framework of varying parameter stochastic frontier analysis (VSFA). An empirical application is demonstrated using Indonesia's Yearly Large and Medium Manufacturing Industries Survey data over the period 2002–2014. The results indicate that mean technical efficiency (TE) measured by constant parameter stochastic frontier analysis (SFA) is overestimated compared to VSFA. Moreover, the TE rank of sub-sectors is more consistent under VSFA with the best performer being the sub-sector of repair and installation of machinery and equipment (ISIC 33). By arguing that it is logical to assume that firms should not have a constant production function response, the TFP is measured based on the results of VSFA. The mean TFP growth during the period 2002-2014 was estimated at 4.3 per cent and was mostly contributed by technological progress experienced by firms. Considering sub-sector performance, the sub-sector that gained the highest TFP growth was the manufacture of tobacco products. The value of TFP growth is widely divergent among sub-sectors, showing that the degree of technological development among industries is very diverse. Moreover, the low level of human capital has remained a challenge in this sector reflected by the relatively low labour efficiency at 51 per cent.

2. 1 Introduction

Output growth can be achieved through growth in productivity and/or large increases in inputs used. Productivity growth is a crucial factor at firm or industry level since it allows the firm or industry to compete with other sectors of the economy for limited resources and even improve its competitiveness in the marketplace. The benefits of productivity growth can be distributed in several ways, such as through better wages and conditions for labour, lower prices for consumers and increased tax payments to the government, which can be used to fund social and economic programs (Parham, 2011). Although using more inputs in production can be one way to increase outputs, adding more inputs will not increase the income earned per unit of input. It is likely to result in lower average wages and lower rates of profit.

Nevertheless, when output growth is achieved through productivity growth, with existing inputs, more output and income can be generated. If income per unit of input rises, additional resources are also attracted to production and can be profitably employed. Hence, it is crucial from the policy perspective to analyse the sources of output growth since it is important to observe whether output growth is due to input growth or productivity driven.

The objective of this study is to analyse how productivity growth takes a role in the output growth of Indonesia’s manufacturing sector by estimating TFP growth and its decompositions. In this research, productivity is measured by total factor productivity (TFP). TFP recognises that all inputs are scarce and productivity growth comes from all combined inputs, not just one input. To analyse the source of productivity growth, TFP in this study is decomposed into two components, technological progress and technical efficiency change. Technological progress which comes from technological inventions (Hulten et al., 2001) cannot be the only the source of TFP as long as firms are not operating on the production possibility frontier that shows the maximum potential output (Kalirajan et al., 1996). A firm's capability and willingness to produce the maximum potential output is defined as technical efficiency (TE). On the other hand, technical inefficiency is ‘a gap that normally exists between a firm’s actual and potential maximum possible levels of output’ (Kalirajan and Shand, 1994, p. 4). Technical efficiency is influenced by institutional organisation improvement and shifts in social attitudes (Hulten et al., 2001). It is vital for a firm to consistently perform efficiently to achieve higher productivity (Kompas et al. 2004).

Indonesia is an interesting case to study for TFP analysis. First, Indonesia’s economic structure has changed significantly in the recent decades. Before the 1980s, Indonesia depended heavily on the agricultural sector. During the 1950s and 1960s, the Indonesian government focused on promoting agricultural self-sufficiency programs by implementing several policies. However, with the declining oil price in the 1980s, the Indonesian government diversified its exports from exporting oil toward exporting manufacturing goods. Since that decade, manufacturing has contributed significantly to Indonesia's economy. In terms of the size of the industry, large and medium-sized firms have contributed most to manufacturing's value-added, which is 40 per cent of the total manufacturing GDP. Second, despite the importance of large and medium scale industries to Indonesia’s economy, these industries have experienced unstable and low output growth in the recent decades.

The decomposition of TFP into technological progress and change in technical efficiency is crucial from a policy perspective to improve Indonesia’s manufacturing performance. The decomposition provides more information about how technology has been applied by firms in the production process. This analysis provides knowledge about whether technology has been improved over time and whether technology has been used to its full potential. If technology is not utilised to its full potential, the introduction of new technology into the production process will not be beneficial. Moreover, technical efficiency analysis also provides information about whether inputs are being used at their full potential. This means that through this analysis, it can be seen whether there is still room for output growth without adding more inputs in Indonesia's manufacturing sector.

Several studies have analysed Indonesian manufacturing productivity (Pitt & Lee, 1981; Hill & Kalirajan, 1993; Timmer, 1999; Margono & Sharma, 2006; Mohamad Ikhsan, 2007; Suyanto & Bloch, 2009; Margono et al, 2011; Prabowo & Cabanda, 2011; Suyanto & Salim, 2013; Suyanto & Bloch, 2014; Sari et al., 2016). Most of these studies also estimated TFP growth by decomposing into technological progress and technical efficiency. However, it is argued in the above-cited studies that the difference between a firm's actual and potential maximum outputs solely results from the difference in intercept coefficients, though the slope parameters may also vary across firms due to their existing level of technical efficiency. In other words, heterogeneity between individual firms was not treated explicitly in the previous studies since it is expected that firm' production behaviour, which varies across firms, will shift the frontier production function neutrally from the actual production function. This may result in a misspecification bias when time-varying unobservable factors exist. To address this limitation, to decompose the sources of TFP, this paper applies a varying parameter stochastic frontier analysis framework (Kalirajan and Obwona, 1994). This approach enables us to predict the frontier production function to estimate firm-specific TE when the function moves non-neutrally from the observed production function. This paper will estimate TE change as a movement in the production function and treat the total input growth as the residual. On the other hand, output growth will be treated using an accounting approach. The main benefit of treating input growth as a residual factor is the ability to avoid problems in measuring productivity such as omitted important inputs and adjustment for changes in input quality (Kalirajan and Obwona, 1994). To provide comparison analysis, TE that results from constant production response SFA is also presented in this paper.

This research contributes to the existing literature on productivity analysis in the following way. To the best of the author's knowledge, studies assuming varying production response in measuring technical efficiency and total factor productivity are scarce. Focusing on the Indonesian manufacturing sector, most previous studies on efficiency performance in the Indonesian case have followed the assumption of a neutral shift in the production frontier, which assumes that all firms have constant production response from inputs. Thus, this gap will be filled by applying varying production response to consider firm's heterogeneity in estimating technical efficiency and total factor productivity.

The results indicate that when production function responses are assumed to be constant under stochastic frontier analysis (SFA), technical efficiency (TE) is higher than under the assumption of varying parameter stochastic frontier analysis (VSFA). Since the assumptions are different between SFA and VSFA, the TE rank between SFA and VSFA may differ. However, the TE rank under VSFA is more consistent over the periods. By arguing that TE measured through VSFA considers firm's heterogeneity properly, total factor productivity is measured based on this approach. VSFA reveals that TFP growth during 2002 – 2014 in Indonesia's large and medium scale industries was 4.3 per cent which is mainly decomposed by technological progress. Due to the fact that TFP growth is contributed mostly by technological progress, pursuing equal opportunity for industrial technology development is crucial to boosting productivity in the Indonesian manufacturing sector. Moreover, preparing labourers for technology development by enhancing human capital in each industrial divisions is also arguably crucial. Labour efficiency is estimated to be relatively low, which is 51 per cent on average from 2002 to 2014. This may imply that technological progress has not been absorbed well by workers.

The rest of the paper is organised as follows. Section 2 summarises the literature review on Indonesian manufacturing analysis as well as stochastic frontier analysis. After describing the data and methodology used in the study in Section 3, empirical results and discussion are presented in Section 4. Section 5 concludes the paper with policy suggestions.

2.2 Theoretical framework

2.2.1 Stochastic frontier analysis and technical efficiency

One of many ways to measure a firm's production performance is through calculating the ratio of output to input. The higher the ratio is the better firm performance is indicated. The measurement of productivity by dividing output and input is a trivial method when the firm only uses one input and produces one output. However, when a firm utilises more than one input, a single index of inputs must be applied to generate a productivity ratio. In this research, productivity is discussed as total factor productivity, which captures productivity that results from all production factors.

The terms productivity and efficiency have been used interchangeably to describe the production performance indicators of a firm. However, these interchangeable terms are not fully accepted because they are not precisely the same indicators. Productivity shows the amount of output generated per unit of input utilised. On the other hand, efficiency demonstrates the distance between the production frontier and actual production function. A production frontier illustrates the maximum output that can be obtained by a firm using a certain level of inputs at the current state of technology. If firms produce at their production frontier, they are fully technically efficient. On the other hand, if firms operate below the frontier, they are inefficient in the sense that outputs can be increased by using the same level of inputs.

A frontier production function that can be estimated by using either a deterministic or stochastic approach represents the maximum possible output that can be produced by a firm using given input sets and the chosen technology in the best practice scenario. In the deterministic method, statistical errors are not considered, which means that all deviations from the production frontier are measured as technical inefficiency. On the other hand, in stochastic frontier analysis, the difference between actual and potential outputs can be differentiated as due to external random factors or firm-specific production behaviour. Hence, stochastic frontier analysis (SFA) is followed in this study.

SFA has been developed step-by-step to provide a robust estimation. In 1972, Afriat argued that a frontier production function is also a function of multiplicative error. He further proposed that the error is assumed to be a random variable with values from 0 to 1 and distributed under the Beta distribution. Under this assumption, he argued that the maximum likelihood estimator could be defined and the model could be evaluated. In order to complement Afriat, Richmond (1974) estimated the frontier model by applying the Cobb-Douglas production function with an assumption of zero expectation in the error terms. To result in a better estimation of the intercept term, he applied the corrected OLS by predicting the moments of the error distribution. He argued that the residuals of the Cobb-Douglas model could follow the Beta distribution.

Schmidt (1976) argued a specific distributional assumption for the disturbance term and derived estimated parameters using the maximum likelihood technique. He argued that when the disturbance terms are identical, independently distributed and uncorrelated with the explanatory variables, OLS is unbiased and consistent except for the intercept. Subsequently, Aigner et al. (1977) decomposed the error term into two parts, of which one is the difference between the actually observed production behaviour of economic decision-making units (EDMU) and the other is the best practice method, which yields the maximum possible output (-u); and statistical error and other random factors (v). Moroever, Aigner et al. (1977) assumed that the non-positive u followed a half-normal distribution and the random factors were distributed normally. Meanwhile, Meeusen and Van den Broeck (1977) assumed that technical efficiency has an exponential distribution.

The stochastic frontier production function can be written as follow

$$q_i = \exp(\beta_0 + \beta_1 \ln x_i) * \exp(v_i) * \exp(-u_i) \qquad (2.1)$$

$$q_i = \text{deterministic component} * \text{noise} * \text{inefficiency term} \qquad (2.2)$$

If there were no inefficiency effects, then the so-called frontier outputs would be this

$q^*_i = \exp(\beta_0 + \beta_1 \ln x_i + v_i)$ (2.3)

Frontier output is beyond the deterministic component when the noise effect is non-negative. On the other hand, the actual output will be below the deterministic component because the combination of noise and inefficiency terms is less than zero ($u - v < 0$). An unobserved frontier output is most likely to be distributed beyond and underneath the deterministic part of the frontier. However, observed output tends to be below the deterministic part of the frontier. The output can only be above the deterministic component when the noise is more than zero and bigger than the inefficiency term. Technical efficiency (TE) can be measured as the ratio of actual output to the corresponding stochastic frontier potential output (Battese and Coelli, 1995). This measurement can be written like this

$$TE_i = \frac{q_i}{\exp(x_i'\beta + v_i)} = \frac{\exp(x_i'\beta + v_i - u_i)}{\exp(x_i'\beta + v_i)} = \exp(-u_i) \qquad (2.4)$$

where

$E(v_i) = 0$,

$E(v_i^2) = \sigma_v^2$,

$E(v_i v_j) = 0$ for all $i \neq j$,

$E(u_i^2) =$ constant,

$E(u_i u_j) = 0$ for all $i \neq j$,

U follows a half-normal distribution.

Regarding the data set used to measure technical efficiency, a cross-sectional data set is argued to be inconsistent in measuring firm' efficiency. Therefore, in much research, panel data is preferred because of its ability to estimate efficiency over different times rather than only in one-time data.

Schmidt and Sickles (1984) argued that estimating the production frontier using panel data has three main benefits. First, panel data does not require a specific distributional specification of efficiency term to estimate consistent parameters. Second, the assumption that efficiency term and inputs level are independent is relaxed by using a panel data set. And lastly, panel data has the ability to specifically identify error terms that measure technical inefficiency and statistical noise in the individual-level data. Hence, the production frontier will be estimated using a panel data set in this study.

2.2.2 Varying-parameter stochastic frontier analysis and technical efficiency

The stochastic frontier analysis explained above is based on the assumption of the constant production response and variable-intercept approach to estimate the frontier production function. This means that a firm that follows the best practice technological technique and a firm that does not use the best practice technology will both enjoy the same input response to the output, which contradicts the theoretical definition of technical efficiency. If a firm follows the best practice approach, its potential output will be determined by the technique of utilising the input, regardless of input levels. Moreover, empirical evidence indicates that different levels of outputs can be achieved by implementing different techniques with the same level of inputs and technology. This implies that different approaches to utilising different input levels will differently affect the output produced by the firm. The impact of the method of utilising input level on output can be reflected in the magnitude of the parameter of the production function response. Hence, different methods in each firm for applying inputs will lead to a different magnitude of the parameter from the estimated production function across the firms. In this case, the conventional stochastic frontier analysis that follows the constant-slope approach will not be able to show variation in the firm's methods of applying inputs (Kalirajan and Obwona, 1994).

To address the limitation of constant-slope SFA, Kalirajan and Obwona (1994) developed varying-parameter stochastic frontier analysis[1]. This model is drawn from the random coefficient regression model (RCRM) proposed by Swamy (1970). RCRM allows for estimating heterogeneity in functional relations between dependent and independent variables. Consider the model:

$$y_i = x_i\beta_i + u_i \qquad (2.5)$$

where $y_i = (y_{i1}, y_{i2},\ldots, y_{iT})$ is an observation's T x 1 sized-vector on the left-hand side variable; x_i is an observations' matrix with sized of T x K matrix of observations on the right-hand side variables where K is the number of ranks. In terms of panel data, this matrix will be represented as x_{itk} (t = 1,2,…, T; k = 0,1,…, K-1); β_i is a coefficients' K x T-vector which is turned into β_{iK} (t = 1, 2, …, T; K = 0, 1,…, K-1) for panel data estimation; and $u_i \equiv (u_{i1,} u_{i2}, \ldots u_{iT})$ is an unobserved random vector. There are T observations on each of n individual units.

The model above follows the assumptions given below:

1. The sample sizes (n and T) have to be larger than the number of ranks (K)

[1] Similar discussion on the varying coefficients estimation but not in the context of stochastic frontier production function has been done by Ackerberg et.al. (2015),

2. The left-hand side variables are non-stochastic (X_{i-}), and are fixed in repeated samples on y_i.
3. The unobserved random vector (u_i) is independently distributed with an expected mean of zero ($Eu_i = 0$) and a variance-covariance matrix of u_i is $\sigma_{ii}I_T$.
4. The coefficient vectors β_i (i = 1,2,…, n) are independent and identically distributed (iid) with $E\beta_i = \bar{\beta}$ and $E(\beta_i - \bar{\beta})(\beta_i - \bar{\beta})' = \Delta$, which is non-singular.
5. The vectors u_i and β_i are independent for every i = 1,2,…, n.

Assumption 3 implies that the disturbance is both contemporaneously and serially uncorrelated. Assumption 4 suggests that the vectors of estimated coefficients (β_i) are random drawings from the same non-singular multivariate distribution with mean $\bar{\beta}$ and variance-covariance matrix Δ.

The coefficients to be estimated are $\bar{\beta}\Delta$ and σ_{ii}. These parameters can be predicted by assuming

$$\beta_i = \bar{\beta} + \delta_i \qquad (i = 1, 2,\ldots,n) \qquad (2.6)$$

where δ_i is a random element's K x1 vector. Drawing from assumption 4, random elements are iid with zero mean and variance-covariance matrix Δ. Now, Equation 2.5 can be written as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ . \\ y_n \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ . \\ x_n \end{bmatrix} \bar{\beta} + \begin{bmatrix} x_1 & 0 & \ldots & 0 \\ 0 & x_2 & \ldots & 0 \\ . & . & \ldots & . \\ . & . & \ldots & . \\ . & . & \ldots & . \\ 0 & 0 & \ldots & x_n \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \\ . \\ . \\ . \\ \delta_n \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ . \\ . \\ . \\ u_n \end{bmatrix} \qquad (2.7)$$

or more compactly as,

$$y = X\bar{\beta} + D(X)\delta + u \qquad (2.8)$$

where $y \equiv [y'_1, y_2', \ldots, y'_n]'$, $X \equiv [X'_1, X'_2, \ldots, X'_n]'$, $\delta \equiv [\delta'_1, \delta'_2, \ldots, \delta'_n]'$, $u \equiv [u'_1, u'_2, \ldots, u'_n]'$.

To estimate $\bar{\beta}$, Aitken' generalized least square is applied. Thus the best linear unbiased estimators for $\bar{\beta}$ is

$$\bar{b}(\theta) = (X'H(\theta)^{-1}X)^{-1}X'H(\theta)^{-1}y$$
$$= \left[\sum_{j=1}^{n} X_j^{'}\{X_j \Delta X'_j + \sigma_{jj} I_T\}^{-1} X_j\right]^{-1} \cdot \left[\sum_{i=1}^{n} X_i^{'}\{X_i \Delta X'_i + \sigma_{ii} I_T\}^{-1} y_i\right]^{-1} \qquad (2.9)$$
$$= \sum_{i=1}^{n} W_i(\theta) b_i$$

where

$$W_i(\theta) = \left[\sum_{j=1}^{n} \{\Delta + \sigma_{jj}(X'_j X_j)^{-1}\}^{-1}\right]^{-1} \cdot \left[\sum_{i=1}^{n} \{\Delta + \sigma_{ii}(X'_i X_i)^{-1}\}^{-1}\right]^{-1}, bi = (X'_i X'_i)^{-1}.X'_i y_i$$

(2.10)

For the panel data, the variance of estimated parameters (b_i) and the variance of disturbance error are different among individual observations because X_i varies across the individuals. bi is the best predictor of $\bar{\beta}_i$ because bi provides n-varying linear unbiased and uncorrelated estimators (with unequal variances) for the same parametric vector.

In order to calculate the technical efficiency of each firm, the estimation of potential output is the first thing that should be generated. The estimation of the potential output is based on the estimated of β_0^*, β_1^*, β_2^*,..., β_k^*which are parameter estimates of each firm's production response. From among these parameters, the production responses that follow the best practice method are selected. The parameters are selected from among the firm production response coefficients, which are different across individuals at the specific time period, as follows:

$$\beta_j^* = \max_i \{\beta_{ij}\}, j = 0,1,2,...,K. \qquad (2.11)$$

There are two different arguments about best response parameters (β_j^*). First, it is reasonably assumed that not every firm applies all its inputs efficiently. Hence, production response parameters are not required to be from one firm. To illustrate, assuming there are 100 observations, the best response of labour input maybe from the fifth observation, but the best response for capital may come from the twentieth observation. Another argument about the best response parameters is that the possibility of getting the best response parameter from one observation cannot be totally ruled out. 'The human capital theory literature argues that a firm which uses some inputs efficiently may also use all inputs efficiently' (Kalirajan and Obwona, p. 90, 1994).

2.2.3 Total factor productivity growth measurement

Thus, drawing on the above discussions, it is rational to argue that three components determining output growth are input growth, technological progress, and technical efficiency change. Assume that a firm faces two periods, periods 1 and 2, and hence, the firm will operate on two production frontiers, F1 for period 1 and F2 for period 2. Technological progress shows the improvement of potential outputs from period 1 to period 2 at the certain level of inputs used. This improvement is measured by the distance from F2 to F1, that is, (y2*" - y2*) by utilising X2 input levels or (y1*" – y1*) by applying X1 input levels. Technological progress or technical change involves the development of technology that can be represented by shifting the production frontier. To illustrate, the installation of more developed equipment for coal-fired power plants extends a firm's potential productivity beyond previous limits. Another component of TFP is technical efficiency. A firm is identified as technically inefficient if it does not work on its frontier production function, such as operating in Y_1 or Y_2. Therefore, technical inefficiency (TI) can be calculated by measuring the vertical distance between the potential output reflected on frontier output (Y_1* or Y_2*'') and the actual output produced by the firm (Y_1 or Y_2) at a certain level of input (X_1 or X_2). It can be seen that technical inefficiency is TI_1 in period earlier technology and TI_2 in period later technology. Moreover, technical efficiency improvement can be measured by calculating the difference between TI_l and TI_2 (TI_1 - TI_2). If the difference is positive, it shows that there has been technical efficiency improvement in the production process. On the other hand, if the value is less than zero, it indicates that technical inefficiency increases over time (Kalirajan et al., 1996). From Figure 2.1, it can be seen that the decomposition of output growth is

Output growth = $Y_2 – Y_1$

$$D = A + B + C$$

$$= [Y_1^* - Y_1] + [Y_1^{*''} – Y_1^*] + [Y_2 – Y_1^{*''}]$$

$$= [Y_1^* - Y_1] + [Y_1^{*''} – Y_1^*] + [Y_2 – Y_1^{*''}] + [Y_2^{*''} – Y_2^{*''}]$$

$$= [Y_1^* - Y_1] + [Y_1^{*''} – Y_1^*] – [Y_2^{*'} – Y_2] + [Y_2^{*''} – Y_1^{*''}]$$

$$= \{[Y_1^* - Y_1] - [Y_2^{*'} – Y_2]\} + [Y_1^{*''} – Y_1^*] + [Y_2^{*''} – Y_1^{*''}]$$

$$= \{TI_1 – TI_2\} + TC + \Delta Y_x \qquad (2.12)$$

= Technical inefficiency change + Technological progress + Output growth from input growth.

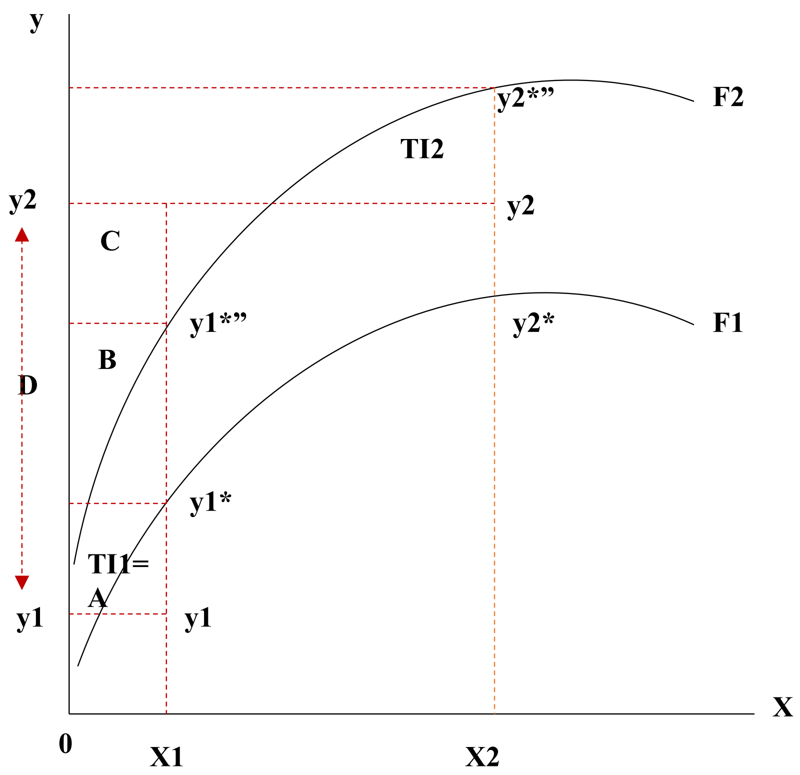

Figure 2.1 Output growth decomposition

Source: Kalirajan et al. (1996).

The measurements above improve the conventional Solow approach by considering input growth that shows the movement of output growth along a path or below the production frontier, a technical change that shows the movement of actual output converges or diverges toward the production frontier, and lastly technological progress that illustrates changes in the production frontier over time. Similar to the conventional approach to measuring total factor productivity, TFP growth can be determined as output growth that is not defined by input growth. Hence, Equation 2.12 can be modified into components, technical efficiency, and technical changes (Kalirajan et al., 1996) that is,

$$TFPG = (TI_1 - TI_2) + TC \qquad (2.13)$$

= Technical inefficiency change + Technological progress

Then, TFP growth in equation 2.13 between consecutive period (t-1) and t for *i*th firm can be estimated as:

$$\boldsymbol{\Delta TFP = ln\left(\frac{TFP_{i,t}}{TFP_{i,t-1}}\right)} \qquad (2.14)$$

2.3 Indonesia's context.

Pitt and Lee (1981) introduced variance component models to estimate the production frontier function in the Indonesian case. They used firm-level data from the Indonesian weaving industry. By implementing a time-invariant efficiency component with the Cobb-Douglas functional form, it was found that the weaving industry gained between 60 and 70 per cent in average technical efficiency. In this research, a robustness test is conducted by estimating a different specification that relaxes the time-invariant efficiency assumption. The authors also argued that firm characteristics such as age, size and ownership status determine the level of a firm's efficiency. Moreover, the correlation between efficiency and capital intensity is less strong when the firm's characteristics are controlled. Another study about Indonesian manufacturing performance was conducted by Hill and Kalirajan (1993). They examined firms' technical efficiency using the Indonesian textile industry from the Indonesian Small Industry Census in 1986. From a sample size of 2250 firms, the authors concluded that inter-firm disparities in inefficiency are substantial. The authors also argued that export orientation, financial integration, and female labour participation increased a firm's efficiency. Furthermore, their findings also suggested that the level of labour -to- capital substitution was substantially high in the textile industry.

Unlike Hill and Kalirajan (1993), Timmer (1999) studied firm performance in large-and medium- scale manufacturing in Indonesia from 1975 to 1995. In his paper, he estimated the final capital stock by applying the perpetual inventory method. From this method, it was found that capital stock grew on average by 7.6 per cent from 1975 to 1988, then it increased dramatically to 13.6 per cent per annum during the period 1989 to 1995. To estimate total factor productivity growth, Timmer applied the growth accounting method and estimated that manufacturing output grew at the rate of 60 per cent per year over the years observed. He argued that this output growth was decomposed by 18 per cent due to labour input and 22 per cent due to TFP growth, whose annual growth was 3 per cent. Timmer also found that there was no significant evidence of factor input shifting from less efficient to more efficient firms. However, policy changes in the manufacturing sector were found to be beneficial in boosting industries' performance. From the perspective of global competitiveness, it has been argued that with the actual level of TFP achieved, the Indonesian manufacturing sector faces challenges to catch-up with the world frontier.

By utilising firm-level data in some sectors in manufacturing, Margono and Sharma (2006) investigated the level of technical efficiency and TFP growth in the food, textile, chemical and metal products industries from 1990 to 2003 by implementing the stochastic frontier model and decomposing TFP into three components: technological progress, a scale component, and efficiency growth. Their results showed that the metal product sector achieved the highest mean technical efficiency, 68.9 per cent. On the other hand, the food, garment, and chemical industries obtained 50.8 per cent, 47.9 per cent and 68.7 per cent technical efficiency respectively. Regarding factors that can boost technical efficiency, in food sector firms, ownership status had a significant impact on firm efficiency. Meanwhile, firm location and size affected firm efficiency in the garment sector; the chemical and metal sectors had similar factors contributing to efficiency, which are the firm' size, ownership, and age. In terms of TFP growth, only the chemical sector gained positive TFP growth at the level of 0.5 per cent, while other sectors faced negative levels of TFP growth. The authors argued that TFP growth was driven positively by technical efficiency change, but negatively by technological progress.

Mohamad Ikhsan (2007) applied a similar methodology as Margono and Sharma (2006) to analyse TFP growth in medium and large-scale manufacturing firms from 1988 to 2000. He estimated that average technical efficiency generally decreased by 1.47 per cent per year with significant inter-industry variation as some particular sub-sectors had improved their level of efficiency. Moreover, he also argued that the Asian financial crisis in 1998 impacted differently on a firm's performance in each subsector industry. Regarding TFP growth, Mohamd Ihksan calculated that TFP grew at the rate of 2.8 per cent annually, contributed mainly by technical efficiency with the share of TFP contribution being 3.98 per cent. On the other hand, technological progress and scale component contributed 1.47 per cent and 1.28 per cent respectively towards TFP growth. His study argued that arranging and retaining technological infrastructure is crucial to increasing productivity growth since the learning-by-doing effect in technology adoption was found to be highly significant in the estimation. Furthermore, since technological progress had been decreasing, the component that may help to increase TFP growth is technical efficiency. Therefore, an increase in firm efficiency is crucial in the Indonesian manufacturing sector.

Unlike others who applied individual firm-level data, Margono et al. (2011) analysed technical efficiency and TFP growth in Indonesia using provincial-level data between 1993 and 2000. The authors who implemented SFA and TFP decomposition in their research found that TFP decreased gradually by 7.5 per cent annually across provinces because of low levels of technical efficiency. They argued that output growth was determined by the accumulation of input growth. Using a different data set, the Indonesia Stock Exchange data set, Prabowo and Cabanda (2011) investigated firm technical efficiency during 2000-2005 in 121 firms. Based on their estimation, the mean technical efficiency of the sample was 71 per cent. They argued that a firm’s characteristics such as age, size, market size, manufacturing classification and time period had significant influence on their technical efficiency.

Particular focus on the effect of FDI on domestic firm performance has also been analysed by Suyanto and Bloch (2009). They examined the effect of foreign direct investment (FDI) on productivity growth in Indonesian chemical and pharmaceutical plants by implementing stochastic frontier analysis and the Malmquist output-oriented index to decompose productivity growth. From their estimation, they argued that FDI provided positive spillovers for productivity growth in particular, boosting only technological progress, not technical efficiency. Moreover, FDI spillovers that were gained more by firms with research and development programs than without research and development programs were more significant in a more competitive market. Still having a focus on the effects of FDI on firms' performance, Suyanto and Salim (2013) investigated the effects of FDI spillovers on the technical efficiency of Indonesian pharmaceutical firms from 1990-1995. The authors compared two approaches, SFA and data envelopment analysis (DEA), to estimate how FDI affects domestic firms' efficiency. From the estimation, they argued that the two approaches demonstrated similar results. It has been concluded that foreign-owned firms gained higher technical efficiency than domestically owned firms. Similarly, it had been found that firm productivity of foreign-owned firms was higher than that of locally owned firms. However, when the degree of foreign ownership increased, productivity would decrease, but technical efficiency would increase.

After focusing on only one sector in the industry, Suyanto and Bloch (2014) investigated the effects of FDI on firms' efficiency in all manufacturing sectors between 1988 and 2000. Their results show that FDI had positive effects on efficiency improvement. However, when the estimation is divided into two different samples; low and high efficiency, the results were different. In the low-efficiency group, FDI boosted efficiency. In contrast, FDI brought negative impacts on the firm's efficiency in high-efficiency firms. These outcomes support the argument that if the efficiency gap between foreign and domestic owned firms were large enough, the former firms would easily gain spillover benefits from the later firms. Moreover, when FDI was classified into different spillovers such as horizontal, backward, forward, the effects of spillovers varied. Horizontal spillovers were found to have positive effects on productivity and technical efficiency. Backward spillovers contributed positively to efficiency but negatively to productivity. On the other hand, forward spillovers have an opposite direction where they have positive effects on productivity but negative effects on efficiency. Another spillover that was captured in Suyanto and Bloch's research is technology spillovers from FDI. It has been found that technology spillovers decrease as labour quality in the industry increases. Regarding market classification, upstream and downstream markets behave differently. In the early stages market, a firm's capacity to absorb energy was negatively correlated with the firms' productivity but positively correlated with the firms' efficiency. On the contrary, in downstream markets, factors that can boost firms' productivity include buyer's ability to identify, integrate and exploit knowledge spillovers (Sari et al., 2016).

2.4 Data and methodology

This research utilises firm-level data of the Indonesian yearly large and medium manufacturing industries survey between 2002 and 2014. The survey is conducted by the Indonesian Central Bureau of Statistics. Moreover, this research uses balanced panel data to measure technical efficiency and TFP because balanced panel data enables us to observe all existing firms, and to minimise additional disturbance error from entering and exit conditions in an industry. All the firms[2] are classified under 5-digit International Standard Classification (ISIC) Rev 4. Moreover, Baltagi (2009) also argues that using balanced data will avoid the problem of inflating error terms resulting from unbalanced panel data estimation. Since there are more than one-year periods, to consider the monetary effect, all the monetary variables are deflated using the wholesale price index (WPI) at 2005 as a base year.

In this paper, first, there will be a comparison of technical efficiency between conventional SFA and varying parameter SFA. The comparison is needed to prove that conventional SFA will differ from varying SFA. Following that, the total factor productivity of the firm will be measured according to varying parameter SFA results.

To estimate technical efficiency terms based on conventional SFA, this paper follows the output orientation approach (Battese & Coelli, 1995; Kalirajan & Shand, 1994). According to the literature, the production frontier can be written as:

$$Y_{it} = f\,(x_{it}, t; \beta).\ \mathrm{Exp}(vi_{it} - u_{it}) \qquad (2.15)$$

$$TE = \exp\,(\hat{u}_{it})$$

Y_{it} is the actual output of *i'th* firm in t period, X_{it} is the vector of inputs used by the firm; capital, labour, energy and raw material, *t* is a time variable capturing time changes across the periods, β is the production responses of all firms respected to each input. Moreover, v_{it} is the disturbance factors that is assumed to have independent and identical distribution, N (0, σ_v^2). u_{it} represents technical inefficiency of the production function. The assumptions of u_{it} are firm-specific, non-negative, and independent distribution but zero-truncated of the normal distribution.

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[2] No information in the survey whether a firm is an incorporated entity or production entity as there is no information about the detailed goods produced by the firm.

Technical efficiency resulting from conventional SFA above will be compared to the results obtained from varying parameter SFA. This comparison will illustrate how firm heterogeneity reflected by varying production response parameters will affect technical efficiency results. According to Kalirajan and Obwona (1994), the varying coefficient stochastic frontier production function will be estimated as:

$$\ln y_{it} = \beta_{i0} + \sum_{k=1}^{K} \beta_{ik} \ln X_{ikt} + \alpha_{it} t + u_{it} \quad (2.16)$$

Y is the *i'th* firm's actual output in period *t*; *x* is the level of kth input used by the *i'th* firm in the period *t*, which are capital, labour, energy, and raw material; *t* is the time variable (1,2,…T) whose effect on output produced will be estimated by α_{it}; the intercept of *i'th* firm is represented by β_{i0}; the *i'th* firm's response to the method of utilising kth input is shown by β_{ik}. β_{ik} is assumed to be $\beta_{ik} = \overline{\beta_k} + u_{ik}$; k= 1,2,..K and i =1,2,…N where $E(\beta_{ik}) = \overline{\beta_k}$, $E(u_{ik}) = 0$ and $var(u_{ik}) = \sigma_{uik}$. Moreover, u_{ik} is the random variable term with the assumption of zero mean and variance σ_{uik}. After considering all the assumptions, based on Kalirajan et.al (1996) model (2.16) can be presented as:

$$ln\, y_{it} = \overline{\beta_0} + \sum_{k=1}^{K} \bar{\beta}_{kt}\, ln\, X_{ikt} + \alpha_{it} t + w_{it} \quad (2.17)$$

$where$:

$$w_{it} = \sum_{k=1}^{K} u_{it}\, ln\, X_{kit} + u_{it}$$

$$E(w_{it}) = 0; var(w_{it}) = \sigma_{u11} + \sum_{k=2}^{K} \sigma_{ukk} ln^2 X_{ikt}; cov(w_{ki}, w_{ji}) = 0$$

The frontier production function that shows potential output and as a benchmark for all firm (y_i^*) is estimated by:

$$\ln y_i^* = \beta *_0 + \sum_{k=1}^{K} \beta *_k \ln Xi_k + \alpha * t \quad (2.18)$$

Where $\beta *_k = \max_i (\beta_{ik})$ for k = 0,1,…,K, $\alpha^* = \max(\alpha_{it})$ at the specific time period.

Therefore, a firm's specific TE will be: $\frac{\text{actual output}}{\text{potential output}}$ (2.19)

Moreover, from equation 13, labour efficiency can be estimated by taking the ratio of $\beta_L^* / \beta l$ where β_L^* is the maximum coefficient of labour and βl is a firm's coefficient of labour.

Based on results on varying-parameter stochastic frontier analysis, Total Factor Productivity growth will be calculated by:

$TFPG = (TI_1 - TI_2) + TC$ (2.20)

Then, TFP growth in equation 2.20 between period (t-1) and t for *i*th firm can be estimated as:

$$\boldsymbol{\Delta TFP = ln\left(\frac{TFP_{i,t}}{TFP_{i,t-1}}\right)} \quad (2.21)$$

All the equations above are estimated by using Stata 16 (StataCorp, 2019).

The variables used in the production function can be seen in Table 2.1 below.

Table 2.1. Definition of variables

Variables	Definitions
Y	The total output produced by a firm (thousand IDR) that is deflated by the wholesale price index (WPI) for five-digit ISIC industries at a constant price of 2005
C	Total value of fixed asset owned by firms, such as buildings, machinery, transportation, livestock and other capital goods, which contribute to the continuity of a production process (thousand IDR) deflated by WPI at a constant price of 2005
L	Total number of workers (males and females) in one year (person)
E	Total expenditure on gasoline, diesel fuel, kerosene, public gas, lubricant and electricity deflated by WPI at a constant price of 2005
M	Total values of raw materials are (goods are processed into another form) and other items used in the processing of raw materials. It is in thousand IDR and deflated by WPI at a constant price of 2005
t	Time trend

Table 2.2. Descriptive statistics of the output and input in the analysis

Period		Mean	Min	Max	Number of firms	Observation
2002 - 2008	Output	4.94e+07	26,727.3	2.79e+09	390	2,730
	Capital	5,079,993	12,021.7	1.79e+08	390	2,730
	Labour	206.9	20	7,716	390	2,730
	Energy	1,341,638	104.2	2.90e+08	390	2,730
	Raw material	3.71e+07	14,472.6	4.34e+09	390	2,730
2009 - 2014	Output	6.17e+07	24,430	3.74e+09	390	2,340
	Capital	6,084,576	11,252.22	3.27e+08	390	2,340
	Labour	201.4	20	7,616	390	2,340
	Energy	1,089,352	111.9	1.39e+08	390	2,340
	Raw material	4.47e+07	13,266.2	2.54e+09	390	2,340

2.5. Results and discussion

2.5.1 Comparison of VSFA and SFA

Table 2.3 presents the estimates of the response coefficient of input for an individual firm t resulting from Stochastic Frontier Analysis (SFA) and Varying Stochastic Frontier Analysis (VSFA) for the periods 2002-2008 and 2009-2014. It can be seen that production responses are assumed to be constant across individual firms under the SFA approach. On the other hand, the variations in the input response coefficient are quite substantial under the VSFA approach. This suggests that the application methods to use different inputs vary among firms. This means that each input contributes to output differently across the individual sample. It is also interesting to see that the input coefficients of SFA are generally within the range of input coefficients estimated by VSFA. Therefore, it can be argued that applying varying-slope to estimate production frontiers is more appropriate than a constant-slope approach.

Table 2.1. Range of estimates resulting from VSFA and SFA

Period	Inputs	SFA	VSFA
2002-2008 (earlier period)	Constant	-0.17	-0.047 – 0.056
	Capital	-0.006	-1.035 – 1.2
	Labour	0.0012	-0.29 – 0.03
	Energy	0.028	-0.22 - 0.092
	Raw material	0.12	-0.095 – 0.28
	Time	0.0033	-0.16 – 0.016
2009-2014 (later period)	Constant	-0.99	-0.05 – 0.037
	Capital	-0.094	0.88 – 1.36
	Labour	0.011	-0.32 – 0.068
	Energy	0.16	-0.2 – 0.052
	Raw material	0.11	-0.23 – 0.13
	Time	-0.002	-0.016 – 0.039

Source: Author's estimations.

In this research, technical efficiency (TE) is obtained by VSFA and SFA, but with the same data set. These two techniques resulted in a significant difference in technical efficiency estimation. In the earlier period, which is the years 2000–2008, the mean of technical efficiency resulting from SFA is 65 per cent with a standard deviation of 0.18. With this value of TE, firms in the manufacturing sector in this period were not fully technically efficient since with the same value of input combinations, they could increase their output by 35 per cent. Regarding the distribution of TE, this value is spread from 28 per cent to 100 per cent with the peak of the data occurring at about 76 per cent of 15 per cent of the sample. From the chart, it can be seen that the data is approximately symmetric but not normally distributed. However, the picture is different in TE resulting from VSFA. In terms of the mean of TE, TE under VSFA is lower than TE under SFA, which is 51 per cent. This means that firms could increase their output by about 50 per cent with the same set of inputs. The range of TE is between 27 per cent and 100 per cent with a standard deviation of 0.17. In terms of distribution, TE under VSFA is moderately skewed right with a peak of 42 per cent, which is gained by more than 20 per cent of the sample. Therefore it can be concluded that in the earlier period, TE resulting from SFA is higher compared to TE resulting from VSFA, but neither TE is normally distributed.

In the later period, between 2009 and 2014, there is a different pattern of technical efficiency. In this period, the mean of TE under VSFA estimation is far below the TE under SFA estimation, which are 49 per cent and 72 per cent respectively. If this value is compared to the result of the earlier period, it can be seen that TE under VSFA is quite stable, which shows that firms can increase their capacity by more or less 50 per cent with the same amounts of inputs. On the other hand, TE, under SFA estimation, indicates that there is an increase of TE on average. Regarding the distribution of the data, the period 2009-2014 has a similar pattern compared to 2002-2008. TE under SFA is symmetrically distributed with a standard deviation of 0.18 and the peak of data at 62 per cent during 2009-2014. Furthermore, VSFA resulted in a positively skewed distribution of TE with similar standard deviation as in the earlier period, 0.18, but with a lower mode of TE, which is 0.3. Technical efficiency resulting by VSFA and SFA is presented in Figure 2.2.

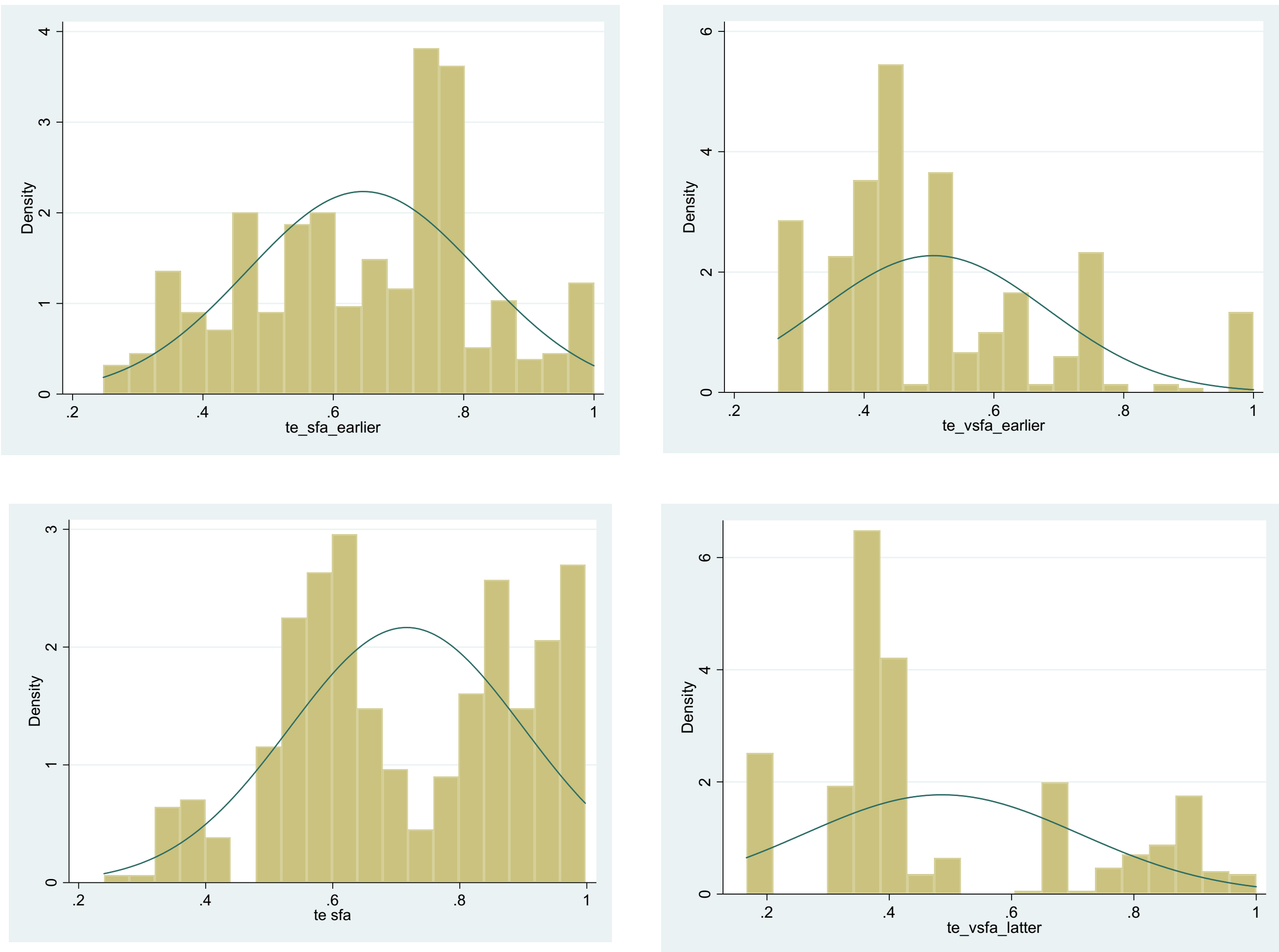


Figure 2.2 Technical efficiency under VSFA vs SFA

Source: Author's estimations.

Analysing technical efficiency scattering among firms is also important. The scatter plot of technical efficiency of firms in the period 2002-2008 is presented in Figure 2.3. From this chart, it can also be seen that the mean of TE under SFA is higher than VSFA. While the mean of TE is 65 per cent, 54 per cent of the total sample had TE that was higher than the average of whole sample. The figure is relatively different in TE resulting from VSFA. The mean TE in this approach is 51 per cent. With this mean, the number of firms with TE greater than the mean TE is lower than TE resulting from SFA, which is 36 per cent of the total sample. In contrast, there are a higher proportion of firms that perform worse than the average sample, which is 64 per cent of total firms.

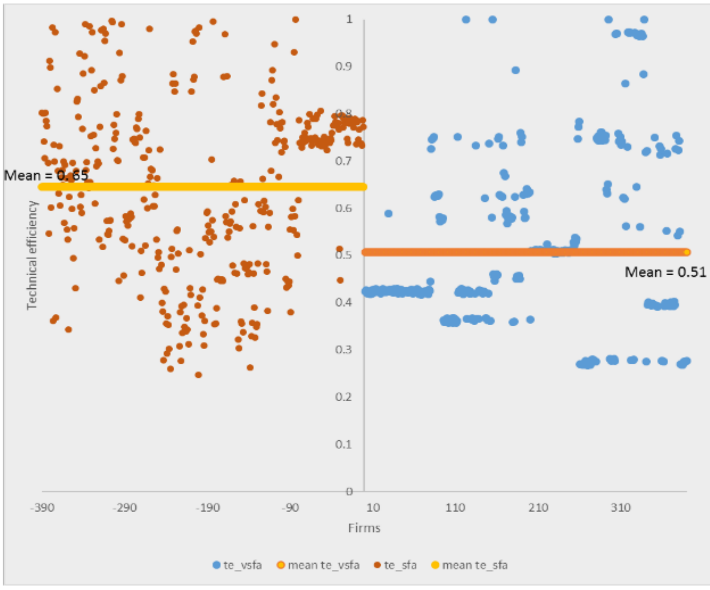


Figure 2.3. Figure Distribution of technical efficiency by firms, 2002-2008
Source: Author's estimations.

The number of firms performing better than the average sample was also found to be higher under the SFA approach during the period 2009-2014. Under SFA, the proportion of firms gaining higher than average TE is 46 per cent. This number is higher than that from the VSFA scheme, which revealed that only 29 per cent of total firms performed better than average. If the two periods are compared, we can see that the number of firms that perform better than the sample average decreased significantly. Moreover, from the figure, it can be inferred that VSFA results in a smaller number of firms performing well because under this approach it is assumed that the best practice method varies from input to input and thus not every firm would be applying all inputs efficiently.

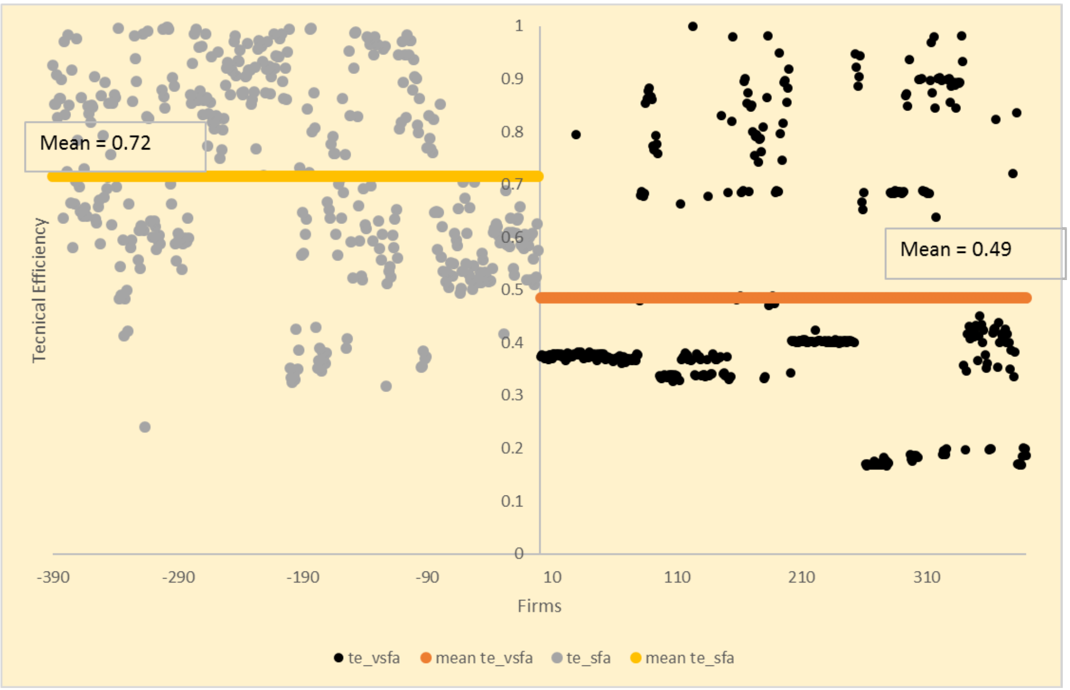


Figure 2.4. Distribution of technical efficiency by firms, 2009-2014

Source: Author's estimations.

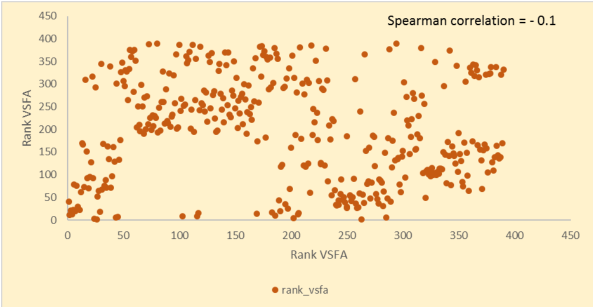
Another measurement of firm performance according to technical efficiency, is its position compared to others that can be seen through TE ranks. From Table 2.4, it can be seen that ranking based on TE under SFA is quite different from the ranking of TE under the VSFA approach. The top 10 best performers in the sample during the period 2002-2008 based on the SFA estimation are different compared to the 10 best firms based on the TE under VSFA estimation. The same situation also occurred for the lowest TE in both estimation techniques. In the later period, the best and worst performers among the sample are also different in each group of estimations. The only consistent result concerns the 3rd rank of the sample, which showed that in both techniques this position is held by firm ID 183, particularly during the later period. According to this condition, it can be inferred that since the assumption of SFA is different from VSFA, the ranking of TE resulting from in these techniques could be inconsistent.

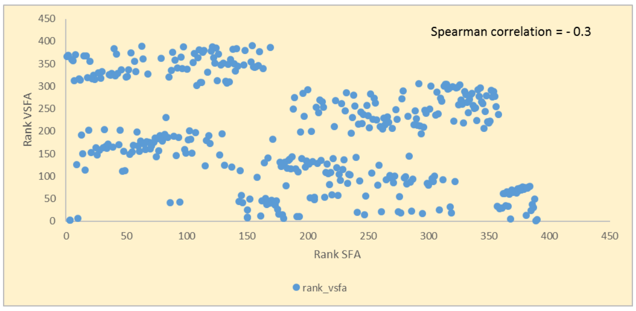
Table 2.2. Technical efficiency rank by firm ID

Rank	Firm ID			
	VSFA earlier	SFA earlier	VSFA later	SFA later
1	155	83	123	298
2	339	306	338	299
3	296	183	183	183
4	123	305	316	338
5	321	338	155	302
6	319	294	314	297
7	327	333	192	201
8	320	200	253	275
9	328	378	257	184
10	322	260	296	314
381	262	194	267	200
382	261	224	265	178
383	272	152	271	194
384	266	236	270	175
385	267	239	264	197
386	264	243	266	199
387	384	222	274	196
388	274	138	272	198
389	385	235	278	123
390	270	201	262	316

Source: Author's estimations.

The different results of TE rank based on SFA and VSFA can be supported by looking at their rank correlation. From Figure 2.5, it can be illustrated that in the earlier period (2002-2008), there was no clear pattern between rank based on VSFA and SFA. It is supported by the low value of Spearman's correlation coefficient, which is -0.11. This value indicates that the correlation of TE ranks of two techniques is very weak. With respect to the later period (2009-2014), the rank correlation between the two techniques is a little bit clearer and negatively correlated. However, the value of the Spearman correlation is still low, that is, -0.3. This rate still indicates a weak correlation between the ranks of TE. Therefore, it is still rational to argue that, due to the different assumptions of the two techniques, the rank of TE is less correlated so that the ranking is inconsistent.





Panel A, Year 2002-2008

Panel B, Year 2009-2014

Figure 2.5. Rank Correlation

Source: Author's estimations.

To provide policy recommendation to boost the manufacturing sector's performance, it is important to analyse technical efficiency performance by industry sub-sector. In this paper, firms are collapsed into 2-digits ISIC- the description of ISIC is presented in Appendix 1. From Table 2.5, it is illustrated that technical efficiency performance is different between the VSFA and SFA approaches. If a sub-sector's performance is compared to the mean of TE in each approach, it can be inferred that measurement under SFA is less consistent from the earlier period to the later period. This is because, under SFA, the best and worst sub-sector's performance is less stable. To illustrate, in the earlier period, the sub-sectors that needed to increase their technical efficiency were sectors 20 and 21. However, in the period 2009-2014, these two sectors jumped into the position where their TE was higher than the average TE. On the other hand, the lowest performing sub-sectors in this period were sectors 13 and 11. This inconsistency makes policy recommendations difficult to make. Therefore, to provide more robust policy recommendations, the performance of sub-sectors is taken from the VSFA estimation.

Table 2.3. Technical efficiency by 2-digits ISIC

ISIC	TE_VSFA_earlier	TE_SFA_earlier	TE_VSFA_later	TE_SFA_later
10	0.42	0.71	0.37	0.58
11	0.95	0.59	0.94	0.35
12	0.27	0.70	0.18	0.89
13	0.97	0.78	0.90	0.54
14	0.40	0.68	0.42	0.71
15	0.45	0.58	0.48	0.75
16	0.74	0.59	0.68	0.61
17	0.63	0.96	0.90	0.89
18	0.66	0.96	0.85	0.66
19	0.75	0.98	0.49	0.58
20	0.58	0.44	0.78	0.99
21	0.63	0.51	0.89	0.84
22	0.36	0.58	0.34	0.92
23	0.51	0.52	0.40	0.91
24	0.55	0.58	0.81	0.64
25	**NA**	**NA**	**NA**	**NA**
26	0.70	0.99	0.47	0.996
27	0.71	0.99	0.50	0.996
28	**NA**	**NA**	**NA**	**NA**
29	0.53	0.61	0.92	0.79
30	0.76	0.79	0.66	0.90
31	0.63	0.58	0.88	0.78
32	0.73	0.67	0.36	0.88
33	0.99	0.69	0.95	0.70
Mean TE by ISIC	**0.63**	**0.70**	**0.67**	**0.77**

NA: No firms belong to the indicated 2-digits ISIC

Source: Author's estimations.

Under the VSFA approach, analysing the best and worst preforming sub-sectors is easier since the results between the two periods are consistent. In both periods, sub-sector that achieved the highest technical efficiency was sector 33, which is sub-sector repair and installation of machinery and equipment. Another sub-sector that continually performed well in both periods is the sub-sector manufacturer of beverages. On the other hand, the sub-sectors that gained the lowest technical efficiency are sectors 22 (manufacture of rubber and plastics products) and 12 (manufacture of tobacco products).

The performance of sub-sectors in the manufacturing sector also can be seen by their technical efficiency ranking among all sub-sectors (Table 2.6). From the TE rank, four sub-sectors consistently were in the ten best ranking, which are sub-sectors 11 (manufacture of beverages), 13 (manufacture of textiles), 18 (printing and reproduction of recorded media), and 33 (repair and installation of machinery and equipment). Manufacture of beverages sub-sector is one of the champion sub-sectors in the Indonesian manufacturing sector. This sector is dominated by foreign-owned companies like Coca-Cola Amatil. These companies have a high degree of competitiveness because of a high level of investment and production capacity. Furthermore, the sub-sector of the manufacture of beverages survives well in the market because of high demand in domestic and international markets. Another well-performing sub-sector is the manufacture of textiles, which is mostly export-oriented firms in Indonesia. This sub-sector contributed on average 11.43 per cent of total exports from 2002 to 2014. Regarding the condition of export-oriented firms, this sub-sector should work efficiently to achieve a high degree of competitiveness to survive in the international market. Unlike sub-sector 13, sub-sector 18, which is printing and reproduction of recorded media, highly depends on the domestic market. This sector may produce merely to satisfy the domestic market, especially the market for packaging, media printing, and book printing.

Table 2.4. Technical efficiency rank by 2-digits ISIC

isic2	te_vsfa earlier	te_vsfa later
10	19	19
11	3	2
12	22	22
13	2	4
14	20	17
15	18	15
16	6	11
17	12	5
18	10	8
19	5	14
20	14	10
21	11	6
22	21	21
23	17	18
24	15	9
25	**NA**	**NA**
26	9	16
27	8	13
28	**NA**	**NA**
29	16	3
30	4	12
31	13	7
32	7	20
33	1	1

NA: No firms belong to indicated 2-digits ISIC

Source: Author's estimations.

2.5.2 Total factor productivity (TFP) based on VSFA[3]

In this study, technical efficiency, one of the components of Total Factor Productivity, is argued to be better estimated by varying stochastic frontier analysis to capture firms' heterogeneity. Hence, TFP, which is measured in the next step, is estimated based on the

[3] Explanation for variations in technological progress estimable from this specification is emerging from the levels and combination of inputs. The sectoral variations examined subsequently in the thesis (section 2.5.2) arise from variations in input level and input combination used by firms.

results of VSFA. The first component of decomposing TFP is technical inefficiency change. This is measured by changes in the years 2009-2014 compared to 2002-2008. The mean of technical inefficiency change is –0.023, which means that there is 2.3 per cent of the average increase in firm's technical efficiency in the later period compared to the earlier period. The inefficiency changes range from -3.8 per cent to 4.2 per cent. From all observations, 75 per cent of the total sample performed well relative to others. These firms gained higher technical efficiency improvement than the sample average. On the other hand, 23 per cent of the samples experienced a decrease in technical efficiency in the later period. Technical inefficiency change is presented in Figure 2.6.

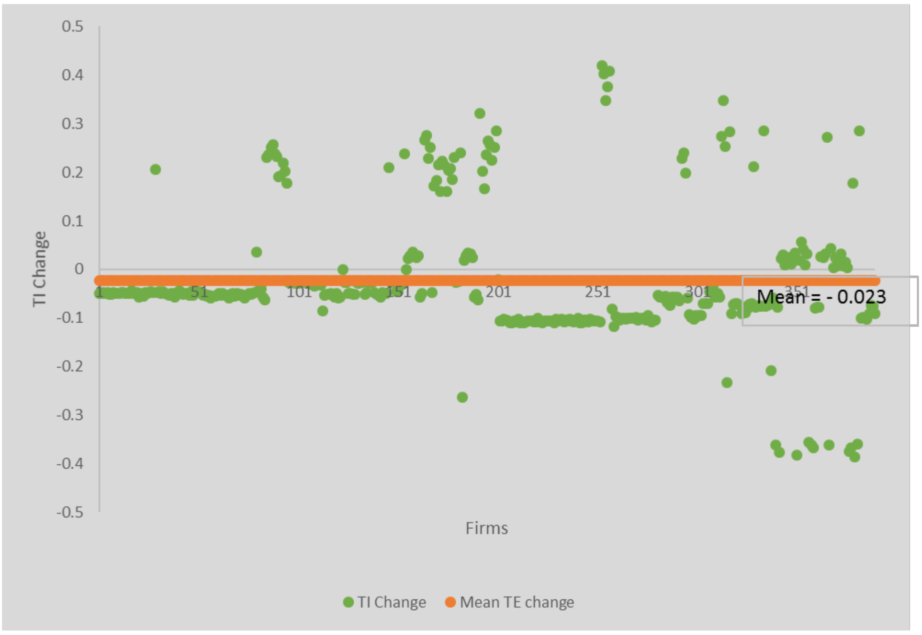


Figure 2.6. Technical inefficiency change by firms
Source: Author's estimations.

Another determinant of the decomposition of TFP is technical change or technological progress that measures how frontier production shift due to technological improvement. The average technological progress in the years 2009-2014 relative to 2002-2008 was 4.3 per cent with a range from -18.9 to 31.2 per cent. This condition reflects that technological progress in the manufacturing sector varies among individual firms. This is due to the fact that the degree of technological upgrading among sub-sectors in Indonesian manufacture is disparate. There are many factors contributing to the divergent pattern of technological development among the sub-sectors. For example, FDI, as the main source of technological progress, has remained heavily dominated by capital and resource-intensive sub-sectors (Frankema & Linblad, 2006). Another reason is that research and development expenditure in the manufacturing sector is still relatively low compared to other countries such as South Korea and Taiwan. The highest

R&D expenditure in Indonesia is dominated by the pharmaceuticals industry. The value of technological change is presented in Figure 2.7.

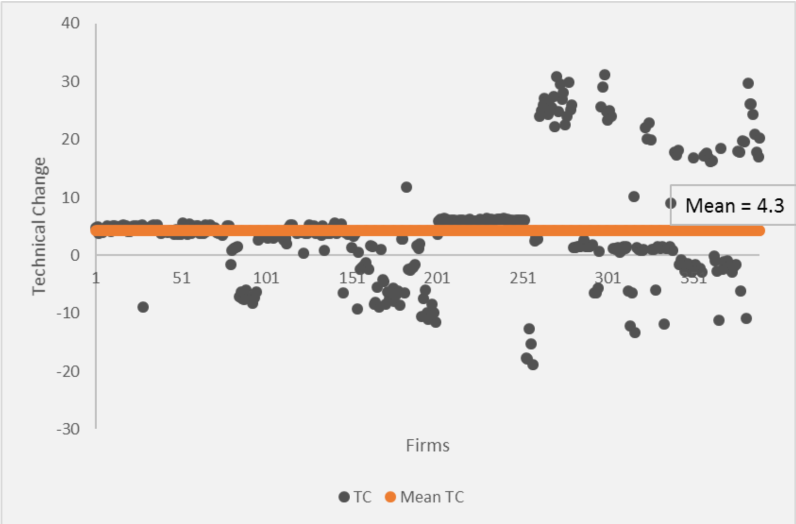


Figure 2.7. Technological change by firms

Source: Author's estimations.

After estimating values of technical inefficiency and technological change, TFP growth of each firm can be decomposed. From Figure 2.8, it can be seen that the average TFP growth in Indonesian manufacturing during the period 2002-2014 was 4.3 per cent. This result is relatively consistent with previous studies. Timmer (1999) found that the food industry's TFP grew at a rate of 5.7 per cent between 1991 and 1995. Meanwhile, the textile industry experienced TFP growth at a rate of 3.6 per cent. Besides, the chemicals and metals industries obtained 0.3 per cent and 6.9 per cent respectively for TFP growth in the same period. Aswicahyono and Hill (2002), using data on 28 industries, found that Indonesian manufacturing's TFP growth from 1981 to 1993 was 4.9 per cent on average. The findings of my study are not directly comparable with those previous studies due to the fact that the methodological approach taken is different. The previous studies assume a neutral shift in the production frontier instead of a non-neutral shift, as assumed in this study.

Considering the variance in TFP growth and the mean, it can be inferred that TFP growth in the sample is dominated by the value of technological progress. Regarding the general performance of the firms, 42 per cent of the sample gained higher TFP growth than the sample average. On the other hand, only 24 per cent of the sample experienced negative TFP growth. From this result, it can be said that generally in Indonesian manufacturing, output growth is contributed by TFP growth due to technological progress.

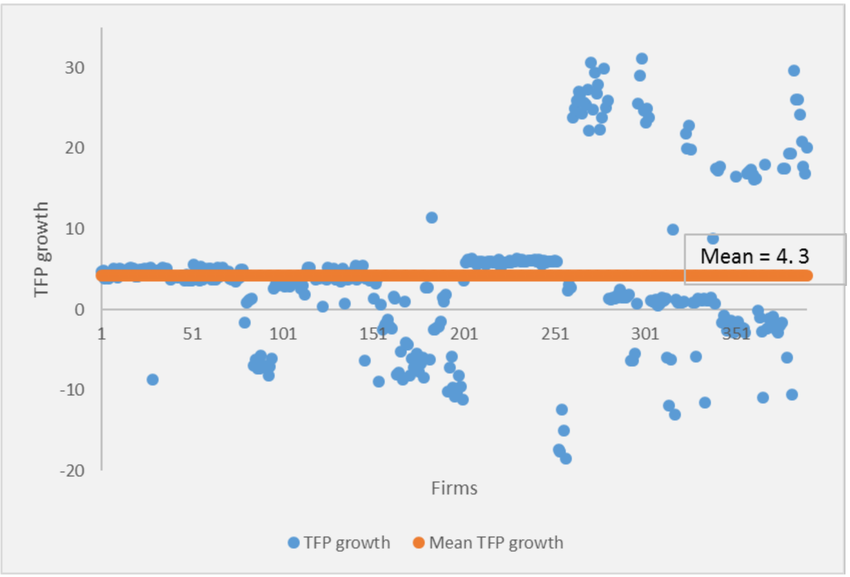


Figure 2.8. Total Factor Productivity (TFP) by firms

Source: Author's estimations.

It is interesting to note from Figure 2.9 that technical inefficiency has a negative correlation with TFP growth. This means that if firms could increase their technical efficiency, they would gain higher TFP growth. The declining inefficiency reflects that in the later period, firms gained higher technical efficiency that contributed positively to TFP growth.

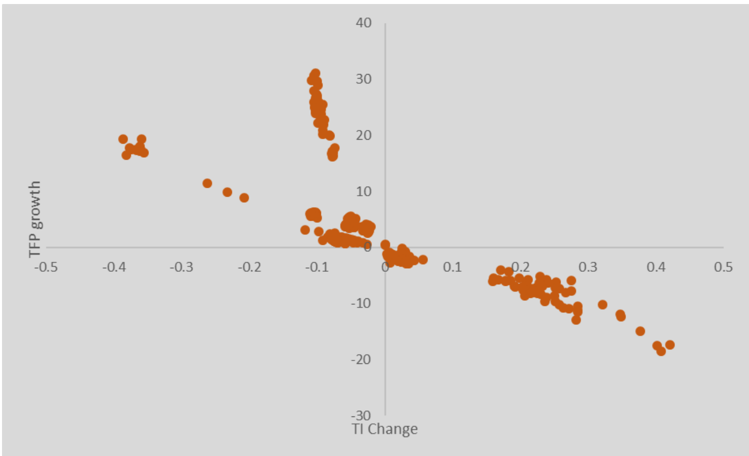


Figure 2.9. Technical inefficiency vs TFP

Source: Author's estimations.

Unlike technical inefficiency, as is expected, technological progress has contributed more positively to TFP growth. A higher rate of technological progress means a higher value of TFP growth. The relationship between these two variables is more linear than the relationship between technical inefficiency and TFP growth, as presented in Figure 2.10. From this graph, it is easily seen that firms in quadrant 1 are the best performers among the sample as their TFP grew positively due to a high rate of technological development.

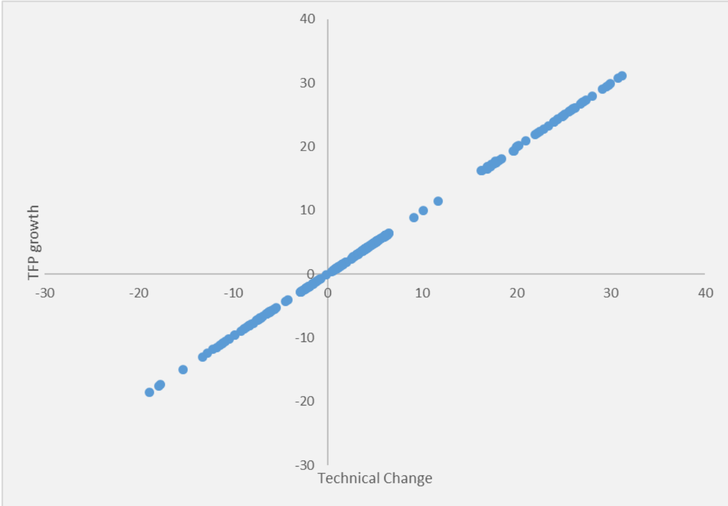


Figure 2.10. Technological change vs TFP

Source: Author's estimations.

A different pattern of sub-sectors performance can be drawn from the estimation of TFP growth by sub-sectors illustrated in Figure 2.11. Since the biggest contribution to TFP growth is technological progress, the best performer in TFP growth is completely different from the best performance based on TE. On average, sector 12 (manufacture of tobacco products) experienced the highest TFP growth among the sample, at 24 per cent. This sector performed very well in terms of TFP due to certain factors. For example, in this sector there was a huge and significant mechanisation program that boosted productivity. There had been a jump in investment with respect to machinery, sophisticated packaging, and product innovation in the tobacco industry since the 1980s. Another factor is that the tobacco industry is dominated by three big firms, Gudang Garam, Djarum, and Sampoerna/Philip Morris, which have an advantage in the export market with their ability to absorb new technology to boost productivity (Barber et al., 2008). Moreover,

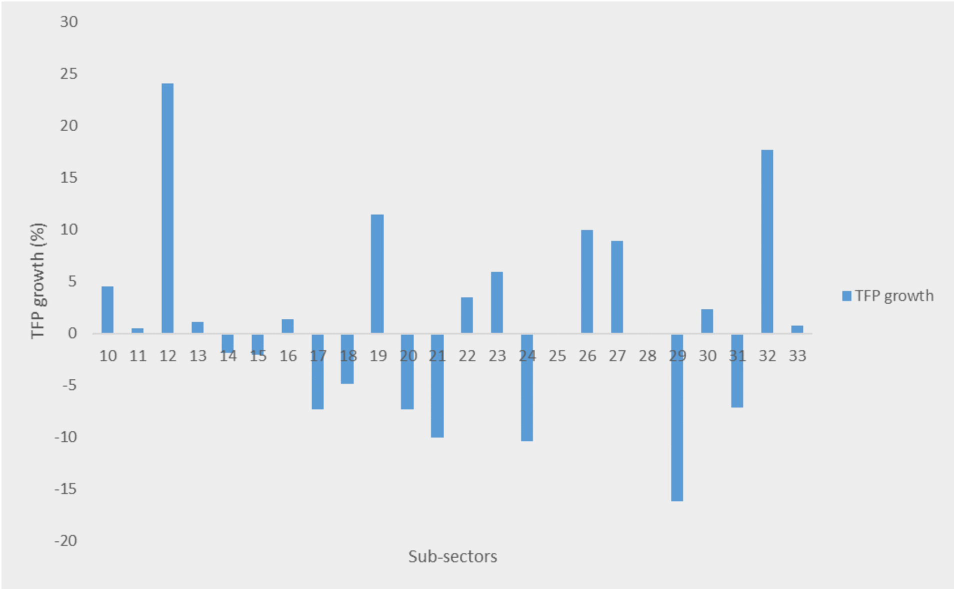


Figure 2.11. TFP growth by 2-digits ISIC

Source: Author's estimations.

2.5.3 Labour efficiency based on VSFA

After analysing what factors decomposed TFP in Indonesia's manufacturing sector, observing labour as one of the essential components in the production process is arguably crucial. Labour quantity and quality are important factors in determining the level of production in the manufacturing sector. In this paper, the labour condition is analysed by estimating labour efficiency. Labour efficiency is an essential factor affecting productivity because it represents how much time is spent by a worker to work productively. It consists of three critical elements: willingness or manageability, the amount of physical effort used and skills. By knowing the efficiency of labour, it can be seen whether labour is well equipped with technology and skills or merely dependent on physical effort (Wiles, 1951). Based on TFP decomposition results, it can be inferred that productivity is increased mostly by technological progress. The degree of technological progress absorption by labour could be reflected by labour efficiency indicators.

Labour efficiency in Indonesia's manufacturing sector both in the earlier and later periods, is relatively lower than the average technical efficiency. Figures 2.12 and 2.13 present the value of labour efficiency at the firm level in the earlier and later periods, respectively. In the earlier period, the average level of labour efficiency was 0.47, which means that in all samples, on average firm could still increase their output by 53 per cent using the current level of labour. This shows that the utilisation of labour is not fully optimised. In this period, 43 per cent of the sample generated labour efficiency that was higher than the average. Similar conditions are also captured in the later period. In this period, on average firms were still not fully labour efficient. The average level was 0.56. Despite a 14 per cent increase in labour efficiency, firms in Indonesia's manufacturing sector still failed to utilise their labour in optimal condition. They still have plenty of room to increase their output without changing the number of workers engaged at the current level of technology. The improvement of labour efficiency is also represented by the higher number of firms achieving efficiency higher than the sample average, which is 51 per cent of the total sample. The low level of labour efficiency appears to contradict the high level of technological progress condition. It implies that the high level of technological development in Indonesia's manufacturing sector is mostly absorbed by other inputs such as capital, raw material and energy. This condition shows that Indonesia's manufacturing sector, in general, continues to have a low level of human capital, causing problems in technological absorption and innovation. Hence implementing direct policies to overcome these problems is crucial. Kalirajan and Bhide (2004) emphasised that R&D investment, technical training programs for workers, and providing more high technology based system in operation and decision-making process are essential.

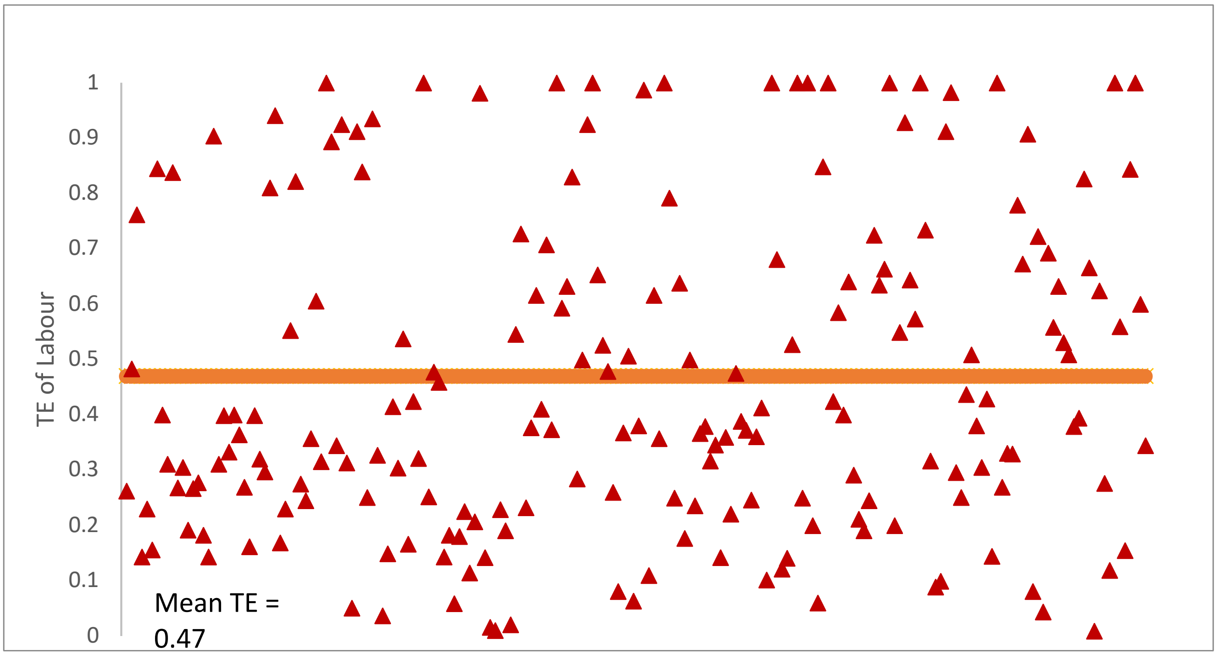


Figure 2.12. Firms' labour efficiency in the earlier period

Source: Author's estimations

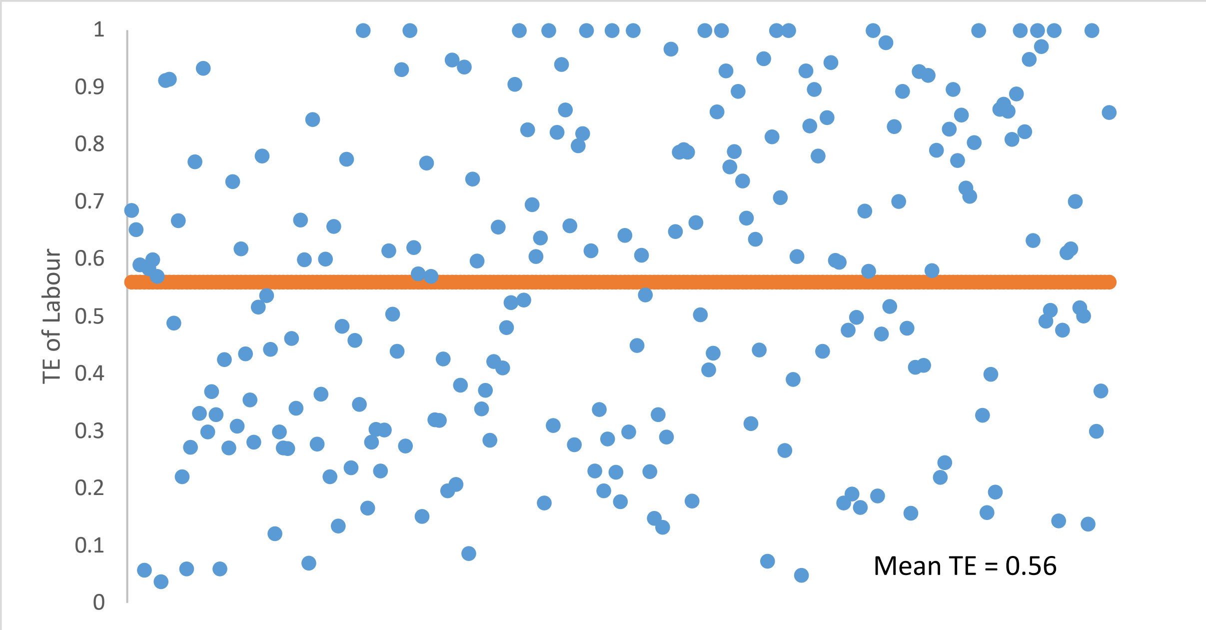


Figure 2.13. Firms' labour efficiency in the later period

Source: Author's estimations.

The level of labour efficiency in the division of industry is essential from a policy perspective. The level of labour efficiency in every division level (2 digits ISIC) is presented in Figure 2.14. The divisions of the industry that worked relatively more efficiently than others in both periods of study are the manufacture of beverages (ISIC 11), manufacture of paper and paper products (ISIC 17) and repair and installation of machinery and equipment (ISIC 33). These conditions are relatively similar, as reflected in the performance of technical efficiency in the earlier estimation. From the figure, it is also can be seen that there are some industries that made remarkable improvements in how they utilised their labour. These industries are manufacture of printing and reproduction of recorded media (ISIC 18), manufacture of chemicals and chemical products (ISIC 20), manufacture of basic metals (ISIC 24) and manufacture of motor vehicles, trailers and semi-trailers (ISIC 29). On the other hand, manufacture of coke and refined petroleum products (ISIC 19) and manufacture of computers, electronic and optical products (ISIC 26) experienced significant declines in the level of labour efficiency. Moreover, it is important to analyse that industry 23, manufacture of other non-metallic mineral products, has relatively low labour efficiency. According to Statistics Indonesia (2019), sector 23 has faced some challenges that contribute to the low labour efficiency condition. He argued that this division has some problems such as, there has been low foreign investment inflow into this sector that may bring new technology to enhance labour efficiency and productivity. Another problem that is still related to investment is that in this sector, most firms are small-scale and have limited access to financial institutions. Consequently, most firms find it difficult to enlarge their economies of scale. Another crucial problem in this sector is the low level of human capital. This condition leads to other problems such as difficulties in innovation and product diversification. All the challenges mentioned before obviously contribute to the ways the firms utilise their labour. Those challenges make it challenging to optimise labour inputs.

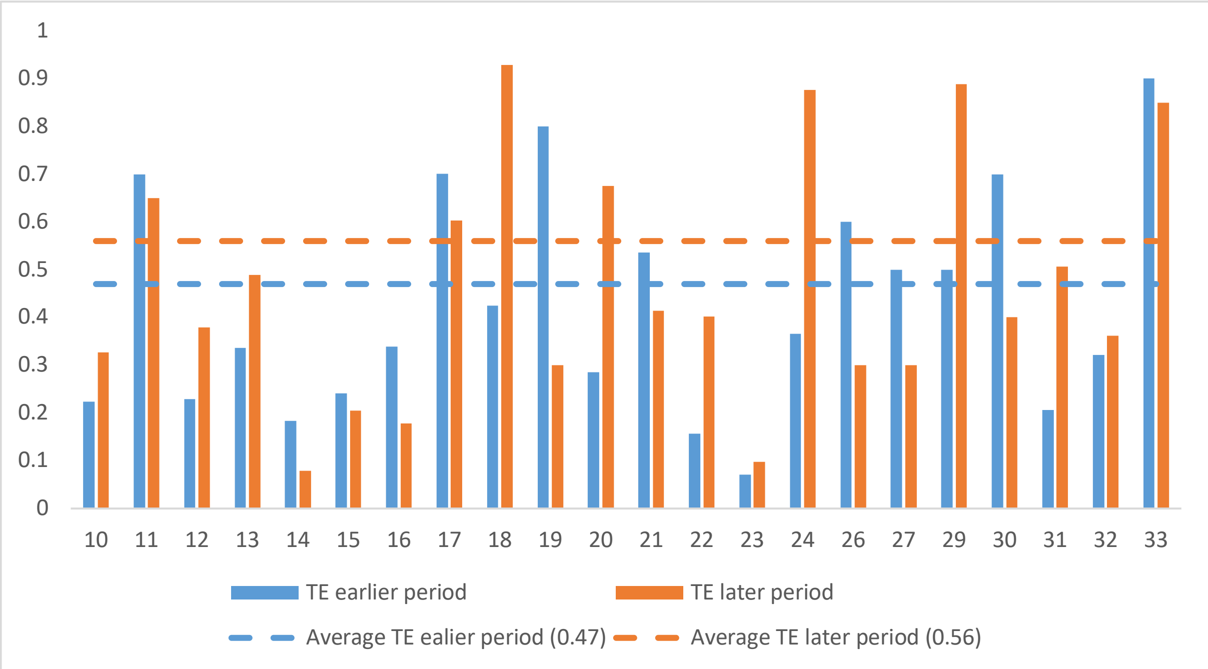


Figure 2.14. Labour efficiency by 2 digits ISIC

Source: Author's estimations.

2.6 Conclusion

This study measured total factor productivity (TFP) by decomposing into technical efficiency and technological progress. The analysis is demonstrated using the Indonesian manufacturing sector-large and medium scale firm-level dataset over the period from 2002 to 2014. Varying parameter stochastic frontier analysis (VSFA) is applied to consider firms' heterogeneity by assuming a non-neutral shift in the frontier production function. The results indicate that mean technical efficiency (TE) resulting from constant parameter stochastic frontier analysis (SFA) is overestimated. On the other hand, under the assumption that each firm has different production function responses, the TE is lower. Due to the different assumptions across approaches, the ranking of TE is less correlated between VSFA and SFA. However, the TE rank of sub-sectors is more consistent from the earlier to the later periods under VSFA with the best performer being the sub-sector of repair and installation of machinery and equipment (ISIC 33).

By arguing that it is logical to assume that firms should not have a constant production function response, the TFP is measured based on the VSFA results. It is estimated that the mean of TFP growth during the period 2002-2014 is 4.3 per cent mostly contributed by technological progress experienced by firms. Considering sub-sector performance, the sub-sector that gained the highest TFP growth is the sub-sector of the manufacture of tobacco products. The value of TFP growth is widely divergent among sub-sectors that shows, which shows that the degree of technological development among industries is very diverse. Therefore, to increase TFP growth in the Indonesian manufacturing sector, increasing opportunities among sub-sectors to develop their technology is crucial.

Another appealing result from the study is that labour efficiency in Indonesia's manufacturing sector is relatively low. Firms merely utilised their labour at the level of 47 per cent in earlier period and 56 per cent in the later period. This condition may reflect the fact that technological progress has been less absorbed by most labourers. The low level of technological absorption is mainly caused by the low level of human capital in this sector, which appears to be one of the challenges faced by some divisions of industry. Technology development is vital to enhance productivity. However, the development should be distributed to all divisions of industry. Moreover, an increase in the level of human capital used in the sector is crucial to guarantee that technology absorption by labour is also optimal.

2.A. Appendix 2

Table 2A.1. 2-Digits ISIC descriptions

ISIC Rev 4	Description
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparels
15	Manufacture of leather and related products and footwear
16	Manufacture of wood and products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials, bamboo, rattan and the like
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of pharmaceuticals, medicinal chemical and botanical products
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products excepts machinery and equipment
26	Manufacture of computers, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment

Chapter 3 Wage dispersion and productivity

Abstract

Does the degree of dispersion of wages across employees reduce firm productivity? According to the 'fairness' theory, it does; but according to the 'tournament theory' it does not have to. This research employs two different survey datasets, Indonesia's Labour Survey and Indonesia's Yearly Large and Medium Manufacturing Industries Survey over the period 2000 – 2015 to explore this question considering two competing theories. Our panel data-fixed effect models, dynamic panel data-system-Generalised Method of Moments (GMM) and two-stage least squares regression (2SLS) reveal a non-linear relationship: a positive relationship between wage dispersion and firm productivity up to a certain level, and a negative relationship thereafter. The findings imply that some wage dispersion might encourage productivity, but excessive dispersion can harm productivity.

3.1 Introduction

Wage levels is one of the key features in a labour market that determines how workers contribute effort to produce an output, which later on becomes an indicator of the firm's performance. Relative wages will strongly affect workers' effort since workers will compare their wages to others internally (within the same firm), or externally (with workers in other firms or industries) (Lallemand et al., 2004).

Two leading theories explain how relative wages can affect firm productivity, the 'fairness' theory developed by Akerlof and Yellen (1988) and the 'tournament' model established by Lazear and Rosen (1981) and Lazear (1989). These two theories analyse two different effects of wage inequality on firm performance. In the fairness model, it is argued that more compressed wages will generate more productivity. This is due to the fact that if workers receive less than a 'fair' wage, they become demotivated and reduce their efforts. Consequently, this will reduce firm productivity. On the other hand, according to the 'tournament' model, a certain level of wage disparity is required to boost workers' efforts to work more productively. However, further development of the tournament theory, Lazear (1989) emphasised that in the working environment, a more divergent wage structure will produce 'hawks' and 'doves' types of workers. Therefore, he argued that establishing a wage structure based on the personality of workers is needed to reduce adverse effects of wage inequality such as 'sabotage' behaviour. [4]

[4] Sabotage refers to a worker' deliberate behaviour or action that has adverse effects on other workers' output. Creating barriers in order to prevent co-workers from obtaining useful information is included in this definition (Lazear, 1989).

Empirical studies so far have found mixed results. Heyman (2002) and Grund and Westergaard-Nielsen (2008) found evidence in support of ‘fairness’ theory, based on their observations of the manufacturing sector in Sweden and Danish private firms, respectively. These studies discovered that wage dispersion has negative impacts on manufacturing firm performance due to perception of ‘unfairness’ among workers that reduces workers’ productivity. On the other hand, a positive correlation between wage inequality and firm productivity was discovered by some studies such as Hibbs and Locking (2000), Lallemand, et.al (2004), Winter-Ebmer and Zweimüller (1999), Mahy et al. (2011), and Franck and Nüesch (2011). In most of these studies, it is argued that the relationship between wage inequality and firm performance is non-linear. This implies that, at a low level, wage inequality has positive effects on productivity to motivate workers, but if wage inequality is too high, wage dispersion will bring adverse effects on firms. Other studies found that the relationship between wage compression and firm performance highly depends on certain environmental conditions. Hence, the results are reasonably ambiguous (Leonard, 1990; Frick et al., 2003; Pfeffer and Langton, 1993; Beaumont and Harris, 2003; Belfield and Marsden, 2003; Jirjahn and Kraft, 2000; Braakmann, 2008).

This paper aims to analyse the relationship between wage disparity and firm productivity, using datasets on large and medium scale firms in Indonesia’s manufacturing sector. Indonesia is an interesting case study for examining how wage dispersion affects firm productivity. Firstly, Indonesia, a developing country, managed to recover speedily from the Asian financial crisis that, as reflected by higher economic growth after 2000. However, higher economic growth seemingly has negative consequences for income distribution. Income inequality, as shown by the Gini Index, has increased during the past decade. Secondly, in terms of sectoral contributions, Indonesia’s economy has relied heavily on the manufacturing sector, particularly medium and large firms. This sector contributes significantly to Indonesia’s GDP, with labour productivity more than twice that of other sectors. However, this sector has also experienced relatively high wage inequality. It is important, from a policy perspective, to link wages and productivity so that gains from labour productivity are shared between employees and employers to increase the general standard of living in Indonesia. Finally, in the context of developing countries, and in Indonesia’s case particularly, empirical studies focusing on how wage disparity affects productivity are limited. Hence, this study contributes to the existing literature on wage dispersion analysis in developing countries, particularly Indonesia, by implementing rigorous econometric techniques to analyse the impact of wage dispersion on firm productivity using microeconomic indicators at a more detailed level.

To measure wage disparity, we use conditional and unconditional wage dispersion indicators that are estimated using data from Indonesia's Labour Force Survey – *Sakernas*. The firm productivity indicator used in this research is value added per worker, which is collected from the Indonesian Yearly Large and Medium Manufacturing Industries Survey. The analysis utilises data from 2000 to 2015. The methodology used in this paper is consistent with the study done by Winter-Ebmer and Zweimüller (1999). The estimations are divided into two stages. The first stage is to estimate conditional wage dispersion by estimating the standard error of wage regression. The second stage uses this standard error as an explanatory variable in the firm performance regression. For sensitivity purposes, I also use the Gini index and maximum-minimum wage ratio to explain the determinants of firm productivity. To ensure robust estimations, we apply different techniques: panel data-fixed effects model and dynamic panel data-system (Generalised Method of Moments – GMM). Two-stage least squares (2SLS) with the standard deviation of income tax as an instrumental variable is also applied as one of the robustness checks. I also estimate the regression with a different data set, which is data from the manufacturing survey without labour force survey synchronisation.

The results from the various techniques confirm that there are positive effects of wage dispersion on firm productivity, but the relationship is non-linear in Indonesia's manufacturing sector. This implies that when wage dispersion is relatively low, it increases firm performance , which is value added that includes both worker payments and firm profits. However, if wage inequality goes beyond the optimum level, there are adverse effects on productivity. It can be concluded that this paper supports the argument of the 'tournament' model rather than the 'fairness' model. These findings imply that relatively low wage dispersion is needed to motivate workers in Indonesian large and medium scale manufacturing firms. However, the existence of the 'hawks'- type of worker calls for caution in attempts to increase firm productivity. Hence, maintaining relatively low wage dispersion is beneficial. This can be done by increasing the quality of workers through equal access to good quality education. For future studies, if there is a possibility of using employer-employee data matching, this would be beneficial for more rigorous analysis. Furthermore, exploration of the gender wage gap and other environmental characteristics of workers causing wage dispersion will result in interesting studies.

The rest of the paper is organised as follows. Section 2 summarises the theory and literature review on relative wage analysis. After describing the data and methodology used in the study in Section 3, empirical results and discussion are presented in Section 4. Section 5 provides the robustness check estimations. Finally, Section 6 concludes the paper with acknowledgement of the limitations of this study.

3.2 Theory and literature review

3.2.1 Theory

One of the leading theories about wage dispersion and productivity was built by Akerlof and Yellen (1988,) who argued that low wage disparities would increase a firm's output, this is known as the 'fairness' argument. Their theory is based on the model of efficiency wages by Solow (1979), showing that output per unit of capital depends on labour efficiency. The labour efficiency model can be translated into the equation:

$$q = f(e(w/l)) \qquad (3.1)$$

where q is output per unit of capital, e is the efforts of workers, w is real wages, and l is working hours. Based on this equation, Akerlof and Yellen (1988) argued that efforts of workers are highly correlated with variance in wages, as shown in the equation below,

$$e = e\ (\sigma^2(w)) \qquad (3.2)$$

This is because firms with lower wage variance tend to have more cooperative worker relations, and thus firms can achieve higher output per worker. Based on this assumption, the profit function of the firm is:

$$\pi = e\ (\sigma^2(w))\ f\ (l_1, l_2) - w_1 l_1 - w_2 l_2 \qquad (3.3)$$

where l_1 is the worker with a higher wage and l_2 is the worker with a lower wage. From the profit equation, it can be seen that, as w_1 decreases, efforts will increase as the consequence of the decline in wage dispersion. The rationale behind firm behaviour is choosing l_2 and w_2 in maximising profit behaviour and the combination of l_1 and w_1 at market-clearing levels. With these two settings, the solution is $N_2 > Kl_2$ meaning that there is no unemployment for type 2 workers. The wage disparities between l_1 and l_2 will be compressed in comparison with the perfectly competitive equilibrium.

Akerlof and Yellen (1990) extended their study to provide further explanation about the fair-wage effort hypothesis. They argued that there is evidence supporting the existence of the fair-wage argument in the economy. First, they argued that efforts depend on actual real wages and 'fair' wages (w^*) as $e = \min(w/w^*, 1)$. Based on the equity theory, labourers who are not paid a fair wage for the input of effort = 1, will decrease their actual effort. Consequently, output per worker also decreases. Second, the fair-wage hypothesis is argued to be supported by relative deprivation theory, which explains how the fair wage is identified. Akerlof and Yellen argued that there are three possibilities for comparison: workers can compare with others in the same occupation and firms, workers can compare with others in a different occupation in the same firm, and workers can compare with other workers in other firms. Third, evidence of the fair-wage argument came from the social exchange theory by Homans (1961). Based on this theory, Akerlof and Yellen (1990) argued that labourers who receive a lower wage than the fair-wage would become demotivated and then reduce their effective labour input below the level they would offer if they were satisfied, $e = w/w^*$ for $w < w^*$.

Another theory complementing the fairness argument was developed by Milgrom and Roberts (1990). Their theory was constructed from the utility function model of firms that maximise the expected total utility of their workers. They argue that in maximising worker utility, there is an 'equity' factor that should be considered to increase efficiency in the process of generating alternatives and information in the organisational decision-making process. The decision-making process may permit rent-seeking, which has negative impacts on the firm's profit. The absence of equity has effects on the firm's performance through some channels, for example, some parties (highly paid workers) may block the flow of valuable information to influence decision-making.

Moreover, without 'fairness', highly paid workers tend to have incentive for rent-seeking activities instead of productive activities. They also argue that 'fairness' can reduce the potential tendency of workers to take personal interest decisions [5] that may be hazardous for firms. Levine (1991) also provides supporting arguments for the 'fairness' theory. He argues that an increase in wages at the low-end of the distribution will increase the firm's efficiency because of a rise in total output, leaving profit constant.

In contrast to the 'fairness' argument, Lazear and Rosen (1981) constructed the 'tournament' model. In their first study, their objective was to analyse the relationship between compensation and incentives with the constraint of a high cost of monitoring labourers' efforts and output. In their study, they considered a rank-order payment scheme that paid prizes to the winners and losers of labour market contests. Performance incentives were set to stimulate workers to win the contest. Hence, they argue that a more divergent wage structure based on worker performance brings benefits to firm productivity. They also state that it is optimal to provide higher compensation for executives to give incentives to all hard-working workers in the firm to win the top positions. Their model is built on the assumption of risk-neutral workers and firms with two types of workers: higher productive workers (W_1) and lower productive workers (W_2). By applying the utility maximisation approach, subject to a zero-profit constraint of the firm, they argue that a worker's effort will increase as wage dispersion increases between W_1 and W_2. Each

[5] A worker as a decision-maker for the organisation who makes decisions about a project should not make a decision based on personal interest but rather organisational goals.

worker tends to increase the probability of getting a higher wage because the return to winning diverges with the spread. From firms' perspective, they tend to increase the wage spread to induce more investment and higher productivity as their output and revenue increase. This argument is supported by McLaughlin (1988), who argued that to encourage workers' effort, there should be a positive correlation between wage spread and the number of contestants competing. He showed that the probability of winning the competition, which is getting a higher wage, is lower when the number of contestants is higher.

In a more developed theory, Lazear (1989) established the 'hawks and doves' theory. He considered political interaction among workers to be a significant aspect of the working environment. He argued that the organisation of the firm and the structure of relative wages are important since workers are able to affect other workers' productivity. He claimed that there are two crucial aspects to relative wage structure. First, competition among workers has positive as well as negative effects on worker productivity. Competition can increase effort among workers, but it also can discourage cooperation among workers and lead to sabotage initiated by uncooperative workers, 'hawks'. The larger the wage difference among workers, the more likely it is that negative effects of competition will happen. This condition drives firms to apply an equal wage structure. Second, cooperation and competition among workers are defined by the reference group definition. To illustrate, pairing two 'doves' workers, i.e., less aggressive workers, together may decrease their incentive to increase effort. Hence, different policies are applicable for different levels of the hierarchy. Moreover, some significant arguments of Lazear (1989) are that an equal wage structure is applicable when labourers have the ability to affect others; predatory behaviour of 'hawks' will decrease the firm's output; personal considerations are rational when hiring workers since personality matters and wage disparity have a positive correlation with organisations based on products rather than by function.

In his book, Lazear (1995) discussed the 'tournament' theory more thoroughly. He explains that there are three essential features of the tournament theory. First, wages are fixed in advance and are independent of absolute performance, meaning that in firms, there are wage slots that are fixed in advance. To illustrate, there may be one vice president slot and four assistant vice president slots. A vice president receives a higher salary associated with the vice president slot. This implies that the vice president's wage does not depend on the amount by which he or she exceeds the performance of the assistant vice-president in winning the job. The second feature is that a worker receives the winner's or loser's wage not by being good or bad but by being better or worse than other workers. This indicates relative performance rather than absolute performance. The last feature is that the effort of workers to pursue promotion depends on the size of the salary increase coming with the promotion. This means that the higher the wage increase associated with the promotion, the higher the effort of workers to win the promotion.

Mathematically, the tournament model can be seen by assuming only two workers and setting up two jobs. Workers compete to be a winner to get W_1 wage; W_2 is a loser wage. The probability of winning the contest depends on the amount of effort that each individual employs. Let the two individuals be j and k, q_j is j's output, and q_k is k's output. The outputs they produce are:

$$q_j = \mu_j + \varepsilon_j \qquad (3.4a)$$

$$q_k = \mu_k + \varepsilon_k \qquad (3.4b)$$

where μ_j and μ_k are j's effort and k's effort, respectively; ε_j and ε_k are random luck components. Workers' behaviour is modelled by worker j's optimisation problem as:

$$\max_{\mu_j} W_1 P + W_2(1-P) - C(\mu_j) \qquad (3.5)$$

where P is the probability of winning a higher wage, conditional on the level of effort chosen; $C(\mu_j)$ is the monetary value of the pay associated with any given level of effort μ_j. The first-order condition is:

$$(W_1 - W_2)\frac{\partial P}{\partial \mu_j} - C'(\mu_j) = 0 \qquad (3.6)$$

There is a similar problem for worker k. The probability that j defeats k is given by

$$P = \text{Prob}\ (\mu_j + \varepsilon_j > \mu_k + \varepsilon_k) = \text{Prob}\ (\mu_j - \mu_k > \varepsilon_k - \varepsilon_j)$$

$$= G\ (\mu_j - \mu_k) \qquad (3.7)$$

where G is the distribution function on the random variable $\varepsilon_k - \varepsilon_j$. Taking the first derivative of P with respect to μ_j yields g (μ_j -μ_k). Since j and k are ex-ante identical, there should exist a symmetric equilibrium where j and k choose the same level of effort. Thus the at optimum $\mu_j = \mu_k$ 3.3 becomes:

$$(W_1 - W_2)\ g(0) = C'(\mu_j) \qquad (3.8)$$

The equation above implies that:

1. If $W_1 - W_2$ increases, the level of effort also increases since $C'(\mu_j)$ is monotonically increasing in μ. This is due to the fact that the solution to the first-order condition

represented by equation 3.8 is $\mu = \mu^*$. If the wage difference ($W_1 - W_2$) increases to ($W_1 - W_2$)', the optimum value of effort will be μ', not μ^* where $\mu' > \mu^*$ since marginal cost $C'(\mu_j)$ is necessarily increasing in μ. This condition shows that a higher wage increase will induce workers to compete harder for promotion.

2. The lower g (0), which is the measure of the importance of luck, the lower the level of effort is. When luck is significant (when the distribution of $\varepsilon_k - \varepsilon_j$ has fat tails), g(0) becomes very low. This means that when luck is the dominant factor determining the outcome of a promotion decision, workers will not put more effort to win the promotion.

Lazear (1995) proved how internal worker interaction is important to define workers' output which later became known as the 'hawk and doves' argument. This argument can be mathematically proven by changing equations 3.4a and 3.4b into:

$$q_j = \mu_j - \eta_k + \varepsilon_j \qquad (3.9a)$$

$$q_k = \mu_k - \eta_j + \varepsilon_k \qquad (3.9b)$$

where η_k is the harm k can inflict on j and η_j is the harm that j can inflict on k. In this environment, j does well not only by making her or himself look good but also by making k look bad. This environment shows that workers do not want to cooperate with one another because their compensation depends upon 'defeating' other workers within the firms. Firms that are able to recognise this 'sabotage' behaviour may adopt a payment compression approach to mitigate the negative effects of sabotage behaviour. However, this approach can be a double-edged sword. This is due to the fact that, if wage disparity decreases, workers will reduce their efforts, which is bad for the firm. In contrast, to reduce 'sabotage' behaviour, making wages more equal is favourable because of the decreasing value of winning the contest.

Lazear (1995) then argued that the optimal way to mitigate uncooperative behaviour resulting from competition is by considering personality and behaviour in hiring decisions. Since workers can be divided into 'hawks', who are good at attacking others, and 'doves', who may find it costly to engage in 'sabotage' behaviour, a firm has to apply different payment strategies for the different groups of workers. If 'hawks' and 'doves' are put together, the optimal strategy is applying a wage compression system. This system will reduce the efforts both of 'hawks' and 'doves'. However, if 'hawks' can be separated from 'doves', wage dispersion will induce more effort of the 'doves' without making them suffer. For a group of 'hawks', firms should provide a compensation system that accommodates more closely the direct interests of these type of workers. Hence, segregation is more optimal than the integration of worker types.

3.2.2 Earlier studies

The 'fairness' model has been empirically studied by some researchers. For instance, Heyman (2002) observed data on short-term wage statistics and short-term employment statistics collected by Statistics Sweden from 1991 to 1996 to test the hypothesis of a positive correlation between wage dispersion and job reallocation. He discovered that wage dispersion has a negative and significant effect on the manufacturing sector, particularly on job turnover. Furthermore, Grund and Westergaard-Nielsen (2009) used employer-employee data from the Danish private sector to analyse the relationship between wage dispersion and firm performance. They found that higher wage spread will have counterproductive effects on firm performance due to the danger of 'unfairness' perceptions among workers, particularly among white-collar workers. Moreover, they also argue that firms should be cautious when they deviate in wages distribution because immediate changes in the equilibrium will cause financial losses. An increase in existing wage inequality will decrease value added because the negative productivity effects from workers perceiving unfairness are larger than the positive incentive effects.

Some studies support the 'tournament argument'. For instance, a study by Hibbs and Locking (2000) discovered that the reduction of wage differentials brings positive contributions to aggregate output and productivity growth. By using Swedish private firms' data, the authors explored conditions under a regime of centralised 'solidarity' bargaining followed by substantial decompression of wages after central bargaining broke down. Finally, it is concluded that the argument of 'fairness' exists due to structural reasons emphasised by Swedish trade unions. The following year, research by Bingley and Eriksson (2001) that utilised 6,501 medium and large firms from the Danish private sector from 1992 - 1995 provided supporting evidence of tournament arguments. Their results are: the more divergent the pay and skewness, the more firm productivity will be gained. This effect was stronger when the sample was restricted to multi-plant firms. Similarly, the positive effects of wage differentials are stronger for white-collar workers than blue-collar workers. Moreover, there was no evidence of the counterproductive effects of wage dispersion on workers' efforts, which is in line with tournament arguments.

Another study supporting the 'tournament model' was done by Lallemand, et al. (2004). They used matched employer-employee data of large Belgian private firms in the year 1995. To analyse wage differentials, they used two different measurements, that is, conditional wage dispersion estimated by wage regressions, and conditional wage dispersion measured by standard deviation, coefficient variation and the maximum-minimum ratio of wages. By applying the 2SLS method with the standard deviation of income tax paid by the firm as an instrumental variable, they concluded that there was a positive relationship between wage dispersion and firm productivity. Furthermore, Plasman and Lallemand also found that the positive correlation between pay spread and firm performance was stronger for blue-collar workers and within firms with a high level of monitoring. Hence, these findings are more consistent with the 'tournament model' by Lazear and Rosen, (1981) than with the 'fairness' model by Akerlof and Yellen, (1988).

More development theory was argued by Lazear (1989), whose 'hawks and doves' theory has also been empirically investigated. Winter-Ebmer and Zweimüller (1999) evaluated how wage disparity affects firm productivity using panel data of Austrian firms in the period between 1975 and 1991. They found that the relationship between wage inequality and firm productivity among white-collar workers was non-monotonic. At the low level of wage spread, wage disparity has a positive impact on firm productivity. However, when wage dispersion grows very high, the firms' performance will decrease. In contrast, the impact of wage dispersion on firm performance is different for blue-collar workers. In this type of workers, for most observations, too little wage inequality is harmful to productivity due to the lack of incentives. Hence, wage dispersion has a positive correlation with standardised wages as a proxy of firm performance.

Mahy et al. (2011) have similar ideas in supporting the argument that wage dispersion has nonlinear effects on firm performance. In their research, employer-employee data of Belgian firms are estimated by considering simultaneous problems, time-constant workplace characteristics and changes in the productivity adjustment process. From the results, they concluded that there is an existence of a positive relationship between conditional wage dispersion and firm productivity. However, the positive effects decrease when pay spread increases. Furthermore, they also argue that firms dominated by more highly skilled workers benefit more from the positive effects of wage disparity on their productivity. However, these effects do not depend on how wages are collectively renegotiated at the firm level.

Using more specific data which is German soccer league data from 1995 to 2006, Franck and Nüesch (2011) analysed the impact of wage dispersion on team productivity with a non-linear model. Utilising this data, they discovered a U-shaped relationship between wage dispersion and team success. They argue that teams having very low or very high wage dispersion are more successful than teams with a medium level of wage disparity. Moreover, they also discussed that wage structure affected the playing style of the teams.

Ambiguous correlation between wage disparity and performance has also been discovered in some studies. To illustrate, a study by Leonard (1990) found that firms' performance does not depend on the level of wage equity across workers, but it has a positive and strong relationship with the hierarchical structure, which is considered an important mechanism for sorting individuals based on human capital endowment. He also argued that firms with long-term incentive plans gain more return on equity (ROE) than firms with short-term incentive mechanisms. In this research, Leonard (1990) used data for 439 large firms in the United States from 1981 to 1985. Moreover, Frick et al. (2003) analysed the impact of wage disparity on performance across different sports leagues. They found that 'fairness' arguments exist for some leagues, but 'tournament' theory also occurred for others.

Correlation between wage dispersion and performance also depends on other factors, as revealed in some studies. In terms of academic departments' performance, it has been found that a positive correlation between wage compression and performance highly depends on individual's position in the wage structure and other factors such as access to information, commitment, consensus and degree of certainty in the evaluation process (Pfeffer and Langton, 1993). Beaumont and Harris (2003) concluded that firms' size and ownership status are important factors affecting the correlation between wage equality and firm performance in the UK. Using the same country data set as Beaumont and Harris (2003), Belfield and Marsden (2003) revealed that how wage dispersion affects the firm's performance depends on the firm's monitoring environment. Jirjahn and Kraft (2007) demonstrated that the positive impact of wage inequality on German firms' performance is statistically significant only if the interaction variable that represents incentives and industrial relations schemes is taken into account. Braakmann (2008) claimed that there is a non-linear relationship between wage dispersion and firm productivity, although it is very weak. Finally, Martins (2008) discovered that wage inequality had positive impacts on Portuguese firms' performance only if fixed effects were considered. On the other hand, if control of fixed effects is released, wage dispersion has counterproductive effects on firm performance.

In terms of the Indonesian case, Tadjoeddin (2016) observed real-wage earning, productivity and earning disparity, particularly the differentials among provinces and economic sector. By implementing the GMM approach, he found that there was no significant correlation between wages and productivity after the 1997 Asian financial crisis. He argued that productivity continued to increase while wages were constant or declining. This ambiguous relationship has some consequences such an increase in overall earnings inequality, as well as opening a new discussion on the broader issue of quality of growth and quality of employment since robust economic growth was not followed by improvement in human capital in the post-crisis period in Indonesia.

3.3 Indonesia's context

In general, Indonesia's Gini coefficient worsened over the period 2000-2015. It can be seen from Figure 3.1 that the Gini Index grew from 0.29 in 2000 to 0.40 in 2015. A relatively low level of inequality is still needed for the economy to grow rapidly. However, a high level of income disparity has adverse effects on overall economic performance in the long term (Stiglitz, 2016). Hence, from the perspective of macroeconomic policy, reducing income inequality is still a significant concern for the Indonesian government.

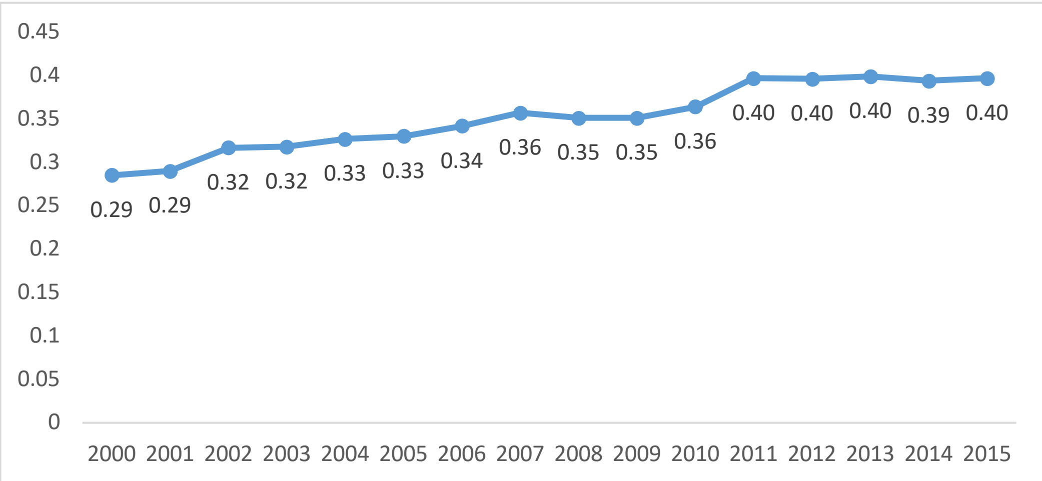


Figure 3.1. Indonesia's Gini Index, 2000-2015

Source: World Bank Data, 2000-2015

Indonesia's income inequality has been influenced by wage disparity among sectors. The manufacturing industry, which is dominated by medium and large firms, contributes highly to Indonesia's economy – more than 20 per cent of Indonesia's total value added. This sector has gained the highest labour productivity among the sectors. Figure 3.2 illustrates that among the biggest sectors providing job opportunities, labour productivity more than doubled in the manufacturing industry, making more than others, from 2000 to 2015. This high productivity should be distributed between employers and employees to result in less income inequality. On the other hand, the manufacturing sector is relatively high on the Gini Index. The Gini index of this sector grew from 0.27 in 2000 to 0.40 in 2015. This condition highlights the fact that an increase in labour productivity in the manufacturing sector has not been followed by wage equality. In fact, gains from labour productivity in this sector seemingly cannot be translated into the better wages and working conditions that are important to increase Indonesian living standards (ILO, 2015).

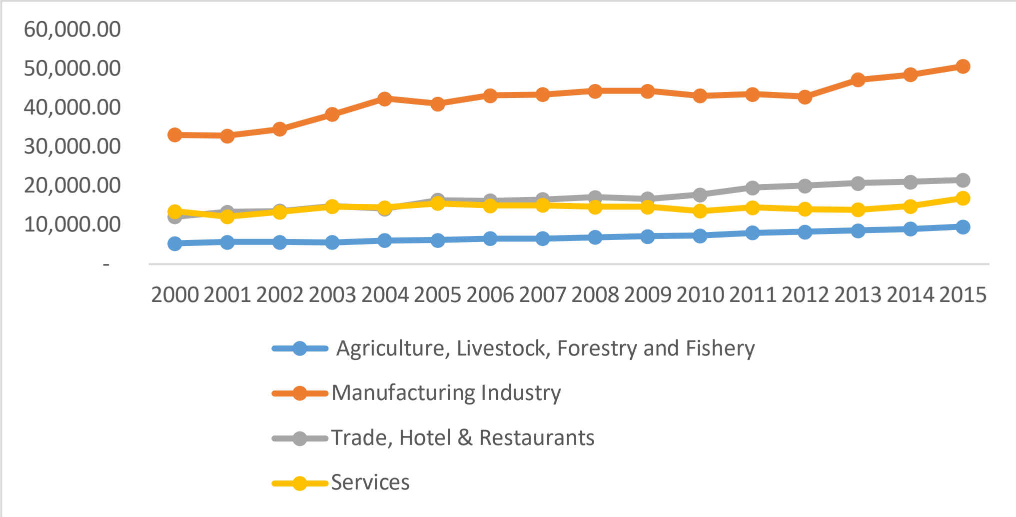


Figure 3.2. GDP per employed person, IDR millions, 2010 at constant market price

Source: BPS, 2000-2015

The inequality picture in Indonesia's manufacturing sector can be seen by looking at the Gini index in each sub-sector (2 digit – International Standard Classification – ISIC). Figure 3.3 shows that in overall sub-sectors, there was a significant increase in the Gini index from 2000 to 2015. The only sub-sector that experienced a decrease in the Gini index was sector 30, which is 'Office, Accounting, and Computing Equipment'. The possible reason for this is that there was a dramatic decline in the number employed and personal costs spent in this sector in 2015. Moreover, in this sector, 85.3 per cent of input costs are derived from raw materials. As may be expected, the electronics and appliance industry is more energy-intensive than manufacturing firms in general.

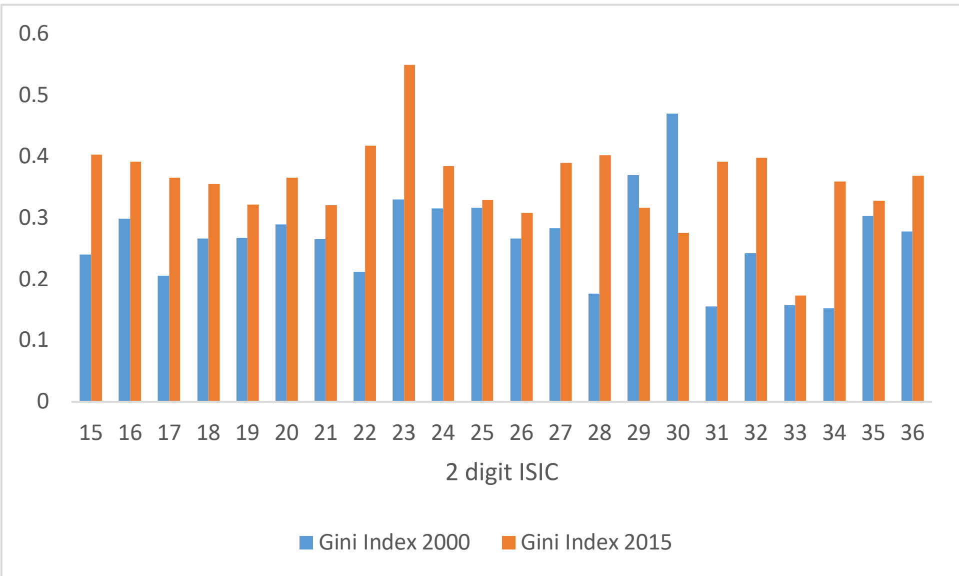


Figure 3.3. The Gini Index by 2-digits ISIC

Source: Calculated from Labour Survey data 2000–2015

In this research, however, I will not focus on the effects of wage inequality on development indicators, but rather on the microeconomic measurement of firm productivity. I will focus on how labour behaviour that is determined by inequality of payment affects firm productivity. Knowing how wage inequality affects worker's behaviour and consequently affects firm productivity is arguably important not only for firms' benefit but also for Indonesia's economic growth in general. This is because the manufacturing sector, especially large and medium scale manufacturing, contributes highly to the Indonesian economy, on average 27 per cent of Indonesia's GDP from 2000 to 2015.

In the context of developing countries, and in Indonesia's case particularly, empirical studies focusing on how wage disparity affects productivity are limited. One study done by Tadjoeddin (2016) found insignificant effects of wage inequality on productivity after the Asian Financial Crisis in 1997. However, in his research, Tadjoeddin (2016) applied macroeconomic indicators at the provincial level to measure productivity and wage disparity. Hence, my study contributes to the existing literature on wage dispersion analysis in developing countries, particularly Indonesia, by implementing some rigorous econometric techniques to analyse the impact of wage dispersion on firm productivity using microeconomic indicators at a more detailed level, which is a group of industry (3-digits ISIC).

3.4 Data and methodology

3.4.1 Data

Data used in this research are individual firm-level data obtained from Indonesia's Yearly Large and Medium Manufacturing Industries survey and data about workers 'characteristics from the Labour Force Survey from 2000 to 2015 conducted by the Indonesian Central Bureau of Statistics. This is a survey of large and medium manufacturing industries that includes only firms having more than 20 workers; it contains detailed information about firm-level characteristics at the 5 digits ISIC level (e.g. firm performance, firm expenditure, firm ownership status, production inputs). However, in this survey, there is no detailed information about workers' characteristics. Hence, to accommodate workers' characteristics, data is gathered from the labour force survey. This survey contains a wealth of details about workers' characteristics such as age, education, wages, and occupation. However, the information about workers can only be identified by industry grouping (3 digits ISIC). Hence to synchronise the data about workers characteristics that are needed to estimate conditional wage dispersion from the wage equation, in this research, the unit analysis is 3 digit ISIC by sub-sector in the manufacturing industry. Industrial classifications are based on ISIC Rev. 3. Table 3.1

presents the means and standard deviations of variables used in the estimations. Moreover, before running the estimations, correlation tests between explanatory variables were conducted to ensure no high multicollinearity between variables. From the test (Appendix 1), it confirms that the correlation between explanatory variables is relatively low. Hence, it shows that there are no multicollinearity problems among variables.

Table 3.1. Summary statistics

Variable (per group of industry – 3 digits ISIC)	Mean	Std. Dev	Min	Max
Average value added per labour (Rp)	1.77E+05	2.51E+05	3.58E+03	2.06E+06
Wage inequality indicators				
Conditional inequality (σ)	0.16	0.12	0.03	0.97
Gini ratio	0.29	0.1	0.10	0.76
Maximum-minimum wage ratio	1.29	0.51	1.00	13.58
Worker's characteristic				
Share of workers at age limit among total workers	0.32	0.14	0.00	1.00
Share of blue-collar workers among total workers	0.75	0.2	0.00	1.00
Share of female workers among total workers	0.26	0.21	0.00	1.00
Share of low educated workers among total workers	0.44	0.26	0.00	1.00
Industry's characteristic				
Share of low technology firms among a group of industry	0.34	0.45	0.00	1.00
Share of medium technology firms among a group of industry	0.35	0.45	0.00	1.00
Share of high technology firms among a group of industry	0.24	0.41	0.00	1.00
Capital-labour ratio (Rp)	1.24E+07	3.67E+08	89.47	1.18E+10
Capital-output ratio (Rp)	4.74	107.19	1.77E-04	3438.14
Share of domestic owned firms among a group of industry	0.84	0.17	0.00	1.00
Share of locally owned firms among a group of industry	0.05	0.14	0.00	1.00
Share of central government-owned firms among a group of industry	0.03	0.09	0.00	1.00
Share of foreign-owned firms among a group of industry	0.17	0.16	0.00	1.00
Share of joint-owned firms among a group of industry	0.84	0.18	0.00	1.00

Variable (per group of industry – 3 digits ISIC)	Mean	Std. Dev	Min	Max
Share of exporting firms among a group of industry	0.12	0.1	0.00	1.00
Share of firms located in Java Island among a group of industry	0.86	0.15	0.00	1.00
Number of observations		982		

3.4.2 Methodology

Two types of wage dispersion indicators can be found in the literature: unconditional indicators, where wage dispersion is measured between heterogeneous workers, and conditional indicators, where wage dispersion is measured between workers with similar observable characteristics. A conditional indicator appears more appropriate to examine theories such as 'tournaments' or 'fairness' since they refer to wage differentials between similar workers. I thus examine the impact of wage dispersion on firm productivity using a conditional indicator. However, to do sensitivity tests, I also run the regression of unconditional indicators for wage dispersion that are presented by the Gini Index and maximum-minimum ratio of wages. This sensitivity test is to compare the effects of conditional and unconditional wage dispersion on firm productivity.

To compute a conditional wage inequality indicator, Winter-Ebmer and Zweimüller's (1999) methodology, which rests upon a two-step estimation procedure, is applied. In the first step, wage dispersion is estimated by for each 3 digits ISIC separately:

$$\ln w_{ij} = \alpha_0 + y_{ij}\alpha_1 + \varepsilon_{ij} \qquad (3.11)$$

where w_{ij} is the wage of worker i in sub-sector j, y_{ij} is the vector of individual characteristics including age, age squared, sex, education and occupation, and εij is the error term. The standard error of these regressions, σ_j, is then used as a conditional measurement of wage dispersion. This measurement is taken as an explanatory variable in the second step to analyse the effect of wage dispersion on sub-sector performance. In this first step estimation, I used data from the labour force survey from 2000 to 2015. There are some limitations of using this data, such as that firm-level data, is unavailable. Worker characteristics can only be identified by groups of the manufacturing industry (3 digits ISIC). Hence, the unconditional wage dispersion can be estimated for 3 digit ISIC only. Another limitation is that there is no information about the scale of the manufacturing firm where the worker is engaged. To overcome this problem, following Osterreich (2013) I only used paid workers that worked over 35 hours a week as an indicator of decent work in the manufacturing sector to eliminate the effects of small and micro firm workers. This inclusion will be matched with the firm's performance data gathered from Indonesian yearly large and medium manufacturing survey.

The second step of regression is to estimate the effects of wage inequality on firm performance as below:

$$ln\, va\_worker_{jt} = \beta_0 + \beta_1 wage\ inequality_{jt} + \alpha Z_{jt} + \partial X_{jt} + \varepsilon_{jt} \quad (3.12)$$

$$ln\, va_{worker jt} = \beta_0 + \beta_1 wage\ inequality_{jt} + \beta_2 (wage\ ineequality)^2{}_{jt} + \alpha Z_{jt} + \partial X_{jt} + \varepsilon_{jt}$$

(3.13)

where:

va_work$_{it}$:	the performance of a group of industry (3 digits ISIC) j, measured by the average value added per worker
Wage inequality$_{it}$:	1: the conditional wage dispersion indicator = standard error of wage regression 2: unconditional wage dispersion indicators = maximum-minimum wage ratio; Gini ratio
Zjt:	Aggregated characteristics of workers in a group of industry such as share of workers having at most a degree of lower secondary education; share of workers who are aged less than 25 and more than 49 (age limit); the share of blue-collar workers; share of female workers
Xjt:	Aggregated characteristics of firm characteristics in a group of industry (3 digit ISIC) such as capital-labour ration; capital-output ratio; share of firms based on the category of technology adaption; share of firms based on investment ownership; share of exporting firms; share of firms located in Java
εjt:	The error term

To regress the second step estimations, it is argued that using standard panel data regression will create endogeneity problems. This is due to the potential simultaneity problem between firm productivity and wages inequality. It could be argued that the more productive firms, the higher the wage dispersion. Hence, to address this problem, I apply the dynamic system – GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). The advantages of using this method are: being able to control time-invariant heterogeneity of the firms as well as addressing the potential simultaneity problem between firm productivity and wage inequality. One-year lagged productivity is thus used as an additional explanatory variable. Equations (3.12) and (3.13) are translated into the following:

$$ln\, va\_worker_{jt} = \beta_0 \;\; ln\, va\_worker_{jt-1} + \beta_1 wage\ inequality_{jt-1} + \alpha Z_{jt} \; + \partial X_{jt} \; + \varepsilon_{jt} \quad (3.14)$$

$$ln\, va_{worker\, jt} = \beta_0 \;\; ln\, va_{worker\, jt-1} + \beta_1 wage\ inequality_{jt-1} + \beta_2\, (wage\ inequality)^2{}_{jt-1} + \alpha Z_{jt} \; + \partial X_{jt} \; + \varepsilon_{jt} \quad (3.15)$$

Bond et. al. (2001) argue that a dynamic structure model estimated by pooled OLS and within groups estimates should be considered respectively as the upper and lower bounds. The dynamic equations in models (3.14) and (3.15) make the OLS estimator upward biased and inconsistent. This is because the lagged level of firm productivity is correlated with the error term. On the other hand, dynamic panels estimated by fixed-effects estimators are downward biased and even inconsistent because of the Hurwicz bias (Nickell, 1981). Main analysis in this paper is based on system GMM estimations. It is because system GMM fits better for a small number of individuals panel data (Soto, 2009), which is the case in this paper. Furthermore, Rodman (2009) also argued that system GMM works better than difference GMM in dealing with the problem of weak instrumentation. Consistent system-GMM estimates should lie between OLS and fixed effects. In this research, there is evidence that using system-GMM is valid because the system-GMM estimates lie between OLS and fixed effects and the instrument set is also valid.

To provide more sensitivity analysis, this paper also implements other robustness checks. First robustness check is using a similar dataset to before but with a different technique. Two-stage least squares (2SLS) with the standard deviation of income taxes paid by firms as an instrumental variable is applied. Of course, it is very difficult to find an appropriate instrument for intra-firm wage inequality. However, I believe that my instrument is able to break the simultaneity problem since it is less affected by the value added of the firm. Also, the tax rate is exogenous for workers and firms since it is decided by the government. In other words, we expect the intra-firm standard deviation of income taxes to be uncorrelated (or at least less correlated) with the error term and highly correlated with the endogenous variable (i.e. wage dispersion) (Lallemand et al., 2004).

The second robustness check in this study involved estimating the effect of wage disparity on firm performance using different datasets, which is only using data collected from the Yearly Large and Medium Manufacturing Industries survey from 2000 to 2015. This is applied due to the fact that in this survey, wage information is also available. The advantage of using this data is an increase in the number of observations since the unit of analysis is 5 digit ISIC, which is a more detailed classification of the manufacturing sector. In fact, using this data, we have now more than 3900 observations. However, there is a disadvantage of using this survey. Only using manufacturing survey data, wages regression cannot be estimated since there is no information about workers' characteristics such as education, age, and occupation. Hence, the conditional wage dispersion measurement cannot be used to estimate its effect on firm productivity. The possible estimation is made by predicting the effects of unconditional wage dispersion measured by the Gini index and max-min wage ratio on firm performance. This condition is the reason why, in this study, the primary uses the synchronised data from the labour survey and manufacturing survey to analyse how wage dispersions under both measurements, unconditional and conditional dispersion, affects firm productivity.

The last robustness check that is done in this paper is limiting the observations (workers and firms) to only those located on Java Island. This is due to the fact that on average across the group of industries, the majority of firms are located on Java Island. Another reason is that the fundamental of 'fairness' or 'tournament' theory are closely related to the theory of labour mobility. Lazear and Oyer (2003) argued that the personnel economics approach related to how workers' efforts is affected by wages are closely related to the ability of labour mobility either in 'internal' or 'external' labour markets. In a fluid labour environment, labourers have the opportunity to move between firms. Hence, I argue that labour mobility may be easier if labourers are located in the same area. Furthermore, the information about wage disparity among firms may be easily spread out if workers are also in the same area. Therefore, the effect of wage dispersion could be stronger. All identification strategies are estimated by using Stata 16 (StatataCorp, 2019).

3.5 Results and discussion

3.5.1 Regression results: Linear relationship

Table 3.2 presents the estimation of the effects of wage inequality in manufacturing performance in a linear form. The Hausman test confirms that the fixed-effects model is preferable to the random effects model. These regressions are estimated by applying both non-dynamic structure and dynamic structure models. The dynamic structure model is estimated by OLS, fixed-effects model, and system-GMM with robust standard errors presented in the brackets. From the fixed-effects model estimation, without considering dynamic terms, it shows the existence of a positive and significant relationship between both conditional and unconditional wages and manufacturing performance. The intensity of this relationship is relatively similar among different indicators. Overall, the point estimates are from 0.15 to 0.18, which worked out to be elasticity between 0.03 and 0.19. The elasticity confirms that on average, an increase of 10% in wage dispersion will increase manufacturing performance by between 0.3% and 1.9% depending on the indicators used.

In order to deal with the simultaneity problem, a dynamic structure model is applied in this paper. This model is estimated by OLS, fixed effects and system-GMM. From Table 3.2, it can be seen that system-GMM estimates for lagged firm productivity lie between OLS and fixed effects in all wage inequality measurements. Additionally, the Sargan t-statistic for overidentifying restrictions and Arellano-Bond's test for second-order autocorrelation in the first-differenced error are applied in the estimation to examine the system-GMM reliability. From the p-value, it can be seen that both tests do not reject the null hypothesis of valid instruments and of no autocorrelation. According to the above evidence, the linear relationship between wage inequality and firm productivity are analysed based on a system-GMM approach. The point estimates of GMM for all wage inequality measurements are between 0.16 and 0.40. These estimates support the results of the non-dynamic model, which is positive and significant effects of wage dispersion (one year lagged) on manufacturing performance but with bigger magnitude. The point estimates can then be translated into the elasticity of wage dispersion (one year lagged) on value added per worker within the range 0.03 – 0.21. These values suggest that on average if wage dispersion (one year lagged) rises by 10 per cent, the value added per worker will increase by 0.3 to 2.1 per cent depending on the inequality indicators.

The positive relationship between wage inequality and manufacturing performance indicates that the 'tournament' model (Lazear and Rosen, 1981) is likely to exist in Indonesian large and medium scale manufacturing industry. This model suggests that if workers are relatively homogenous, wage dispersion will encourage workers to put more effort into their working activities. Lallemand et al. (2004) argue that the existence of the tournament model suggests that employers should distribute prizes differently among workers depending on their productivity. Higher prizes would be awarded to more productive workers. Moreover, according to all regression results, in this research, the sample is essentially composed of 'doves' based on the 'hawks' and 'doves' model (Lazear, 1989 and 1995). 'Doves' indicate that, generally, workers support the policy of industry that implements a more differentiated wage structure.

Table 3.2. Linear relationship regression results

Dependent variable : Value added per worker (ln)												
	FE-no dynamic term			OLS			FIXED EFFECTS			GMM		
One year lagged value added per worker (ln)				0.66 ***	0.66 ***	0.65 ***	0.11 ***	0.21 ***	0.13 ***	0.14 ***	0.30 **	0.14 **
				(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)	(0.05)	(0.15)	(0.07)
Conditional wage inequality (σ)	0.16 *											
	(0.09)											
One year lagged conditional wage inequality (σ)				0.12 *			0.05 **			0.16 ***		
				(0.07)			(0.03)			(0.06)		
Maximum-minimum ratio of wages		0.15 ***			0.03 *							
		(0.04)			(0.16)							
One year lagged maximum-minimum ratio of wages								0.02 *			1.19 *	
								(0.01)			(0.68)	
Gini ratio			0.18 *									
			(0.10)									
One year lagged Gini ratio						0.60 ***			0.10 **			0.40 **
						(0.2)			(0.05)			(0.18)
Intercept	9.33 ***	9.20 ***	9.37 ***	1.10 **	1.14 ***	1.13 ***	6.77 ***	6.76 ***	6.78 ***	6.38 ***	6.18 *	6.21 ***
	(0.59)	(0.53)	(0.59)	(0.43)	(0.43)	(0.43)	(1.19)	(1.16)	(1.15)	(2.27)	(3.57)	(3.45)
Workers characteristic	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firms characteristic	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
ISIC dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R squarred	0.48	0.49	0.48	0.71	0.71		0.55	0.66	0.66			
F stat	32.03 ***	33.74 ***		118.9 ***	118.9 ***	***	76.94 ***	78.90 ***	75.80 ***			
Hausman test	100.65 ***	125.29 ***										
Number of instruments										58	58	58
Hansen statistic--P value > z										0.32	0.50	0.70
Diff Hansen test										0.28	0.45	0.56
Arellano BPm statistic (AR2)-P value > z										0.59	0.41	0.42
Weak instrument test (K-p-value)										0.35	0.26	0.33
Number of groups										66	66	66
Number of observations	982	982	982	900	900	900	900	900	900	900	900	900

Source: Author's estimations.

Notes: ***/**/* significant at the 1, 5 and 10 per cent levels respectively. Robust standard errors are shown in brackets. Full regressions are presented in Appendix 3.4-3.10.

3.5.2 Regression results: A quadratic relationship

The positive correlation between wage inequality and manufacturing performance generated from the linear relationship suggests that there the tournament model exists in Indonesian large and medium scale manufacturing industries. However, it can be argued too that the relationship between wage dispersion and manufacturing performance is not linear but a qudratic-shaped relationship. In fact, a low level of wage differential may boost firm performance, but too high wage dispersion will affect the firm negatively because of 'fairness' or 'sabotage' issues.

To analyse a quadratic relationship, I add the wage inequality indicators in a quadratic form to Equation (3.12), which is translated into Equation (3.13), and Equation (3.14) becomes (3.15). This quadratic-shaped relationship is also estimated by non-dynamic and dynamic structures. The results of these estimations are presented in Table 3.3. Based on the fixed-effects estimation with no dynamic components, the coefficients of wages inequality indicators are again positive and statistically significant. Then, this is followed by negative and statistically significant point estimates of wages inequality indicators in the quadratic term. This finding confirms an inverted U-shaped relationship between wage inequality and manufacturing performance. Hence, in this type of relationship, we can estimate the maximum point of value added per worker generated by a certain value of wage dispersion. By ignoring the possible simultaneity problem, it can be inferred that firm productivity will be maximal when conditional wage inequality is Rp 0.10 and unconditional equality, i.e., maximum-minimum ratio and Gini Index are 1.27 and 0.36 respectively.

As mentioned earlier, the non-dynamic structure model will suffer from endogeneity problems since firm productivity may affect wage inequality. Hence, the application of panel dynamic estimation is argued to be a better approach in explaining the phenomena. The quadratic-shaped relationship in dynamic structure is observed based on system-GMM estimation. This is due to the fact that there is valid evidence such as autoregressive parameters that all wage inequality measurement estimations are between the upper bound and lower bound estimations; the instruments used are valid, and there is no autocorrelation. It can be seen from the relatively large p-value of the Sargan test and Arellano Bonds test conducted from the sample. Hence, the system-GMM is statistically proven to be a valid approach in this research.

The findings also suggest that the relationship between wage dispersion and value added per worker is not linear, but an inverted U-shaped relationship. From this type of relationship, the maximum value of firm performance can be estimated. Resulting from three different measurements, if the conditional wage dispersion is 0.41, Gini index is 0.44 or min-max ratio is 3.11 (all one year lagged), value added per worker will reach the peak point. Beyond this range, wage dispersion will reduce manufacturing performance. However, the value of these maximum points should be interpreted with care given a big multicollinearity problem between wage dispersion variables in level and squared.

The existence of an inverted U-shaped relationship between wage inequality and manufacturing performance indicates that with relatively ‘low’ wage dispersion, workers in Indonesian large and medium scale manufacturing industry tend to support the wage differential to boost their performance. Hence, in this phase, a different wage system among workers has a positive impact on firm performance. However, if the level of wage dispersion is relatively high or increasing, the issue of ‘fairness’ and or ‘sabotage’ becomes more critical and concerning. A considerable difference in wages among workers will demotivate them and decrease their efforts. Consequently, it harms firms’ value added. This phenomenon can be a warning for some groups of industries that during the study period, on average, had higher wage inequality indicators than the threshold point as mentioned above. Since there are different indicators, it is more precise to analyse based on each indicator. For conditional wage inequality, the groups of industries that have a high risk of decreasing productivity due to high levels of inequality are electric and battery accumulator industry (ISIC 314); manufacture of goods from asbestos (ISIC 266); petroleum refining industry, natural gas processing, and manufacture of petroleum refineries (ISIC 232); office and accounting equipment industry; accounting, and data processing industry (ISIC 300); and manufacture of electric motors and generators (ISIC 311). The Gini indicator shows a different group of industries which their wage inequality went beyond the maximum level during the study period. These industries are petroleum refining industry, natural gas processing, and manufacture of petroleum refineries (ISIC 232) and chemical industry (ISIC 241). On the other hand, according to the maximum-minimum ratio indicator, other food industries (ISIC 154) have a higher likelihood of experiencing negative impacts of wage inequality on firm performance due to excessive levels of wage inequality.

Table 3.3. Quadratic relationship regression results

Dependent variable : Value added per worker (ln)												
	FE-no dynamic term			OLS			FIXED EFFECTS			GMM		
One year lagged value added per worker (ln)				0.66 ***	0.66 ***	0.65 ***	0.11 ***	0.31 ***	0.13 ***	0.13 **	0.43 **	0.14 **
				(0.02)	(0.23)	(0.02)	(0.02)	(0.06)	(0.02)	(0.06)	(0.17)	(0.07)
Conditional wage inequality (σ)	0.06 *											
	(0.039)											
One year lagged conditional wage inequality (σ)				1.03 **			0.36 **			2.01 *		
				(0.43)			(0.16)			(1.10)		
Conditional wage inequality (σ)^2	-0.30 **											
	(0.15)											
One year lagged (conditional wage inequality (σ)^2)				-1.35 **			-0.55 **			-2.44 *		
				(0.58)			(0.26)			(1.30)		
Maximum-minimum ratio of wages		0.14 *										
		(0.08)										
One year lagged maximum-minimum ratio of wages					0.08 *			0.05 *			1.74 *	
					(0.05)			(0.02)			(1.04)	
Maximum-minimum ratio of wages^2		-0.055 *										
		(0.003)										
One year lagged (maximum-minimum ratio of wages^2)					-0.01 *			-0.002 *			-0.28 *	
					(0.005)			(0.001)			(0.15)	
Gini ratio			1.23 **									
			(0.61)									
One year lagged Gini ratio						0.91			0.18 **			1.40 **
						(0.66)			(0.08)			(0.70)
Gini ratio^2			-1.69 *									
			(1.02)									
One year lagged (Gini ratio^2)						-0.53			-0.13 **			-1.60 **
						(1.1)			(0.06)			(0.80)
Intercept	9.35 ***	9.24 ***	9.51 ***	1.04 **	1.06 **	1.10 **	6.75 ***	6.80 ***	6.78 ***	6.95 **	6.74 ***	6.07 *
	(0.6)	(0.61)	(0.59)	(0.43)	(0.44)	(0.43)	(1.18)	(1.14)	(1.15)	(3.18)	(1.17)	(3.52)
Workers characteristic	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firms characteristic	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
ISIC dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R squarred	0.48	0.49	0.48	0.72	0.71	0.72	0.55	0.55	0.68			
F stat	34.58 ***	32.87 ***	32.94 ***	113.76 ***	112.91 ***	114.33 ***	74.07 ***	79.05 ***	74.03 ***			
Hausman test	206.56 ***	122.40 ***	151.55 ***									
Number of instruments										59	59	59
Hansen statistic--P value > z										0.29	0.25	0.89
Diff Hansen test										0.18	0.23	0.68
Arellano BPm statistic (AR2)-P value > z										0.53	0.55	0.36
Weak instrument test (K-p-value)										0.58	0.47	0.28
Number of groups										66	66	66
Number of observations	982	982	982	900	900		900	900		900	900	900

Source: Author’s estimations.

Notes: ***/**/* significant at the 1, 5 and 10 per cent levels respectively. Robust standard errors are shown in brackets. Full regressions are presented in Appendix 3.4-3.10.

3.5.3 Robustness check

3.5.3.1 Application of External Instrumental Variables – Two-stage least squares (2SLS)

From the results (Table 3.4), it can also be inferred that wage inequality has positive and significant effects on firm performance. The point estimates resulting from 2SLS are even larger than in the fixed-effect model. This finding is similar to the results found by Heyman (2002) and Lallemand et al. (2004). The elasticity of wage dispersion worked out to be 0.6 to 1.6 per cent. This means that a 10 per cent rise in wage inequality will lead to an increase of value added per worker on average by 2 to 16 per cent. To validate that 2SLS is a robust approach, under-identification and weak identification tests are used. It can be seen from all wage dispersion measurements that the values of the test are statistically significant at the 1 per cent alpha. This indicates that the equations are identified and strongly support the identification of the instrument. Moreover, it also can be seen from the first-stage regression (Appendix 3A.3) that the standard deviation of income tax has a significant positive effect on wage dispersion. Hence, using income tax as an instrumental variable is arguably valid.

Table 3.4. Two-stage least squares (2SLS) estimation

Dependent variable : Value added per worker (ln)						
	1			2		
Conditional wage inequality (σ)	4.16 **			6.43 **		
	(1.92)			(2.93)		
Conditional wage inequality (σ)^2				-7.11 **		
				(3.41)		
Maximum-minimum ratio of wages		0.29 *			0.82 *	
		(0.16)			(0.50)	
Maximum-minimum ratio of wages^2					-0.05 **	
					(0.028)	
Gini ratio			5.38 **			2.31 *
			(2.75)			(1.44)
Gini ratio^2						-3.40 *
						(2.15)
Intercept	0.97 **	1.32 ***	1.83 ***	1.14 ***	1.30 ***	1.34 ****
	(0.35)	(0.25)	(0.44)	(0.29)	(0.34)	(0.41)
Workers characteristic	YES	YES	YES	YES	YES	YES
Firms characteristic	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
ISIC dummies	YES	YES	YES	YES	YES	YES
Adjusted R squared	0.21	0.39	0.12	0.37	0.44	0.32
F stat	18.95 ***	30.93 ***	15.22 ***	25.26 ***	26.48 ***	11.33 ***
Underidentification test- Chi sq	12.77 ***	14.97 ***	9.96 ***	34.89 ***	61.81 ***	15.99 ***
Weak identification test - F test	12.31 ***	14.43 ***	9.60 ***	26.85 ***	65.94 ***	15.84 ***
Number of observations	982	982	982	982	982	982

Source: Author’s estimations.

Notes: ***/**/* significant at the 1, 5 and 10 per cent levels respectively. Robust standard errors are shown in brackets. 1 is the linear relationship estimations. 2 is the quadratic relationship estimation.

The findings of the 2SLS estimations also support the evidence of an inverted U-shaped relationship between wage dispersion and firm performance in the Indonesian large and medium scale manufacturing industries. In this estimation, I used the same instrument variable, which is the standard deviation of income tax paid by the firms. The instrument variable is statistically proven as a valid instrument for wage dispersion. Moreover, based on the under-identification and weak identification tests it can be concluded that the equation regressed by 2SLS is identified and rejects the weak identification assumption in alpha at the 1 per cent level. Based on the 2SLS regression, the maximum value added per worker can be achieved when the conditional wage indicators is 0.45 Rupiah, the Gini index is 0.34 and the max-min ratio of wages is 8.2. If wage inequality indicator rise beyond this point, firm performance may decrease. However, the value of these maximum points should be interpreted with care given the high multicolinearity problem between wage dispersion variables in level and squared. The results of the quadratic-shaped relationship are also presented in Table 3.4.

3.5.3.2 Robustness analysis using the manufacturing survey data

In order to estimate the linear relationship between firms' values added and wage dispersion, I also apply three techniques, which are panel regression-fixed effect model, system-GMM, and 2SLS with the standard deviation of income taxes paid by firms as the instrumental variables. The results for the linear relationship from the three methods are similar to the main results provided before as shown in Table 3.5. It shows that wage inequality impacts positively on firm productivity, and is statistically significant. Using the Gini Index, it is found that point estimations vary between 0.31 and 2.44 from three different approaches with the parameters resulting from the 2SLS the largest. From the point estimates, it can be implied that for every 10 per cent increase in Gini index, firm value added per worker will increase between 1 per cent and 7 per cent. On the other hand, using the max-min ratio, the elasticities lie between 0.08 and 2.05. This means that if the max-min ratio increases by 1 per cent, value added per worker will increase in a range of 0.08-2.05 per cent.

Similarly, the quadratic relationship regressions from the manufacturing survey data also support the main findings. This shows that, in the manufacturing sector in Indonesia, a certain level of wage dispersion is needed to push workers' effort and firm productivity. However, too high a level of wage inequality will negatively affect firm performance. The quadratic-shaped relationship regressions are presented in Table 3.6.

Table 3.5. Linear relationship regression for manufacturing survey data

Dependent variable: Value added per worker (ln)						
	Fixed Effects		2SLS		GMM	
One year lagged value added per worker (ln)					0.08 *	-0.10 *
					(0.04)	(0.052)
Maximum-minimum ratio of wages (ln)	0.08 **		2.05 *			
	(0.027)		(1.49)			
One year lagged maximum-minimum ratio of wages					0.13 *	
					(0.09)	
Gini ratio		1.35 ***		2.44 *		
		(0.17)		(1.35)		
One year lagged Gini ratio						0.31 *
						(0.18)
Intercept	-257.04 ***	-277.62 ***	9.72	-11.01 ***	14.85	58.18
	(13.26)	(13.5)	(6.29)	(1.017)	(25.87)	(98.57)
Workers characteristic	YES	YES	YES	YES	YES	YES
Firms characteristic	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
ISIC dummies	YES	YES	YES	YES	YES	YES
Adjusted R squared	0.35	0.38	0.16	0.29		
F stat	13.25 ***	5.67 ***	20.01 ***	2.33 ***		
Underidentification test- Chi sq			13.0 ***	13.10 ***		
Weak identification test - F test			13.57 ***	17.90 ***		
Hansen statistics p-value					0.51	0.81
Weak instrument test (K-p-value)					0.48	0.66
Arellano BP statistic (AR2)-P value > z					0.99	0.70
Number of observations	3942	3942	3942	3942	3451	3451

Source: Author's estimations.

Notes: ***/**/* significant at the 1, 5 and 10 per cent levels respectively. Robust standard errors are shown in brackets.

[1] Workers characteristics can only be measured by the share of production workers and share of female worker

Table 3.6. Quadratic relationship regressions for manufacturing survey data

Dependent variable: Value added per worker (ln)												
	Fixed Effects				2SLS				GMM			
One year lagged value added per worker (ln)									0.08 (0.038)	**	0.03 (0.019)	*
Maximum-minimum ratio of wages	0.2 (0.01)	*			4.69 (3.33)	*						
One year lagged maximum-minimum ratio of wages									1.69 (1.25)	*		
Maximum-minimum ratio of wages^2	-0.01 (0.006)	*			-0.35 (0.21)	*						
One year lagged (maximum-minimum ratio of wages^2)									-0.12 (0.09)	*		
Gini ratio			0.44 (0.26)	*			4.94 (3.06)	*				
One year lagged Gini ratio											0.27 (0.15)	*
Gini ratio^2			-0.87 (0.52)	*			-4.48 (2.6)	*				
One year lagged (Gini ratio^2)											-0.04 (0.019)	**
Intercept	-256.61 (13.23)	***	-283.90 (13.99)	***	7.12 (12.18)		22.40 (13.75)	*	19.20 (28.1)		33.03 (28.05)	
Workers characteristic	YES		YES		YES		YES		YES		YES	
Firms characteristic	YES		YES		YES		YES		YES		YES	
Year dummies	YES		YES		YES		YES		YES		YES	
ISIC dummies	YES		YES		YES		YES		YES		YES	
Adjusted R squared	0.35		0.38		0.24		0.29					
F stat	16.50	***	16.50	***	24.05	***	6.89	***				
Underidentification test- Chi sq					15.98	***	15.90	***				
Weak identification test - F test					33.48	***	15.80	***				
Hansen statistic-P value > z									0.99		0.98	
Weak instrument test (K-p-value)									0.79		0.85	
Arellano BP statistic (AR2)									0.99		0.62	
Number of observations	3942		3942		3942		3942		3451		3451	

Source: Author’s estimations.

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets.

[1] Workers characteristics can only be measured by the share of production workers and the share of female workers

3.5.3.3 Robustness analysis using Java data only

In estimating the linear and quadratic-shaped relationships for observations from Java Island, I used two methods, fixed effect panel regression and system-GMM. I am unable to run the 2SLS technique due to the unavailability of data for income tax paid by firms on Java Island only. From the results presented in Table 3.7, it can be seen that the positive impacts of wage inequality on firm productivity are statistically significant only for the conditional wage dispersion measurement and Gini index measurement. If these two indicators increase by 10 per cent, value added per worker will rise by 0.4 and 0.7 per cent respectively. Moreover, if the previous year of unconditional wage inequality and Gini index rise by 10 per cent, the current year of firm productivity will increase by 0.5 and 1 per cent.

It is also proven that an inverted U-shaped correlation between wage dispersion and manufacturing performance exists in the manufacturing sector on Java Island, even though it is only statistically significant for the measurement of conditional wage inequality and the Gini index. Using point estimates presented in Table 3.8, I can estimate that when conditional wage dispersion is 0.36 and the Gini index is 0.37, the value added per worker will be maximised. In fact, when one year lagged of sigma is 0.35 and one year lagged of Gini ratio is 0.3, current firm productivity will reach the maximum point.

Table 3.7. Linear relationship regression for Java only

Dependent variable: Value added per worker (ln)						
	Fixed Effects			GMM		
One year lagged value added per worker (ln)				0.11 * (0.06)	0.20 * (0.11)	0.11 (0.085)
Conditional wage inequality	0.25 * (0.15)					
One year lagged conditional wage inequality				0.31 * (0.19)		
Maximum-minimum ratio of wages		0.04 (0.044)				
One year lagged maximum-minimum ratio of wages					0.02 (0.07)	
Gini ratio			0.25 ** (0.11)			
One year lagged Gini ratio						0.40 * (0.22)
Intercept	22.96 *** (1.37)	22.80 *** (1.46)	22.97 *** (1.37)			
Workers characteristic	YES	YES	YES	YES	YES	YES
Firms characteristic	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
ISIC dummies	YES	YES	YES	YES	YES	YES
Adjusted R squared	0.1709	0.16	0.18			
F stat	16.39 ***	15.85 ***	18.01 ***			
Hansen statistic-P value > z				0.69	0.68	0.16
Weak instrument test (K-P-value)				0.55	0.46	0.23
Arellano BP statistic (AR2)-P value > z				0.83	0.94	0.27
Number of observations	982	982	982	900	900	900

Source: Author's estimations.

Notes: ***/**/* significant at the 1, 5 and 10 per cent levels respectively. Robust standard errors are shown in brackets.

Table 3.8. Quadratic relationship regressions for Java only

Dependent variable : Value added per worker (ln)						
	Fixed Effects			GMM		
One year lagged value added per worker (ln)				0.40 ***	0.68 ***	0.56 ***
				(0.07)	(0.08)	(0.06)
Conditional wage inequality	1.24 *					
	(0.75)					
One year lagged Conditional wage inequality				0.59 *		
				(0.35)		
Conditional wage inequality ^2	-1.69 **					
	(0.79)					
One year lagged Conditional wage inequality a ^2				-0.85 *		
				(0.51)		
Maximum-minimum ratio of wages		0.14 *				
		(0.08)				
One year lagged maximum-minimum ratio of wages					0.44 *	
					(0.26)	
Maximum-minimum ratio of wages^2		-0.01 *				
		(0.004)				
One year lagged (maximum-minimum ratio of wages^2)					-0.03	
					0.02	
Gini ratio			2.19 *			
			(1.25)			
One year lagged Gini ratio						2.04 *
						(1.22)
Gini ratio^2			-2.97 *			
			(1.78)			
One year lagged (Gini ratio^2)						-3.65 *
						(2.19)
Intercept	23.08 ***	22.46 ***	23.10 ***			
	(1.39)	(1.4)	(1.46)			
Workers characteristic	YES	YES	YES	YES	YES	YES
Firms characteristic	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
ISIC dummies	YES	YES	YES	YES	YES	YES
Adjusted R squared	0.1734	0.15	0.17			
F stat	17.56 ***	15.20 ***	17.79 ***			
Hansen statistic-P value > z				0.73	0.98	0.90
Weak instrument test (K-P-value)				0.55	0.78	0.65
Arellano BP statistic (AR2)				0.35	0.99	0.64
Number of observations	982	982	982	900	900	900

Source: Author’s estimations.

Notes: ***/**/* significant at the 1, 5 and 10 per cent levels respectively. Robust standard errors are shown in brackets.

3.6 Conclusion

This study aimed to observe how wage disparity affected firm productivity in large and medium scale firms in Indonesia's manufacturing sector from 2000 to 2015. To answer the research question of this study, two different datasets are used, which are Indonesia's Labour Force Survey and Indonesian Yearly Large and Medium Manufacturing Industries survey. The advantage of using these two sources is that the ability to use conditional wage dispersion estimated by wage regression from workers' characteristics data, unconditional wage dispersion measured by the Gini index, and the maximum-minimum ratio of wages as explanatory variables in the firms' performance regression.

According to various techniques: panel data – fixed effects model, dynamic panel data – system-GMM and two-stage least squares (2SLS) with standard deviation of income tax as the instrumental variable, it is found that this paper supports the 'tournament' argument in explaining the effects of wage inequality on firm productivity. The results of the estimation show that wage dispersion has positive and significant impacts on firm performance but in a non-linear relationship framework. This means that relatively low wage inequality increases firm productivity, but when it goes too high, firm productivity decreases.

The implications of this study are that in Indonesian large and medium scale manufacturing firms, relatively low wage dispersion is needed to motivate workers. However, when wage inequality is too big, it will harm the firms. This condition may occur due to the existence of 'hawks' type workers among the firms concerned. Hence, maintaining relatively low wage inequality is essential. Policy may directly address the problem of different quality of workers due to different access to good quality education among citizens.

For future research, if data on employer-employee matching is available for Indonesia or other developing countries, it could be used to explore the effects of wage dispersion on firm productivity at the firm level more deeply. Moreover, gender gap issues in wages are still a problem, including in Indonesia, and exploring this issue as well as other environmental characteristics that may cause wage disparity will be beneficial to contributing to knowledge.

3.A Appendix 3.

Table 3A.1 Group of Industries Description

ISIC Rev 3	Group of industries
15	Food products and beverages
16	Tobacco
17	Textiles
18	Garment industry
19	Leather industry and products
20	Industry and products from timber (excluding furniture) and twine
21	Paper and paper products
22	Publishing, printing and reproduction of recorded media
23	Coal, refined petroleum products and nuclear fuel
24	Chemicals and chemical products
25	Rubber and rubber products
26	Other non-metallic mineral products
27	Basic metals
28	Metal industries, except machinery and equipment
29	Machinery and equipment n.e.c
30	Office, accounting, and computing machinery
31	Electrical machinery and apparatus n.e.c
32	Radio, television and communication equipment and apparatus
33	Medical, precision and optical instruments, watches and clocks
34	Motor vehicles, trailers and semi-trailers
35	Other transport equipment
36	Furniture and related industries.

Table 3A.2. Multicollinearity tests

Variables	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15	-16	-17	-18	-19	-20
(1) l_va	1.0																			
(2) sigma	0.2	1.0																		
(3) gini	0.2	0.2	1.0																	
(4) mm-ratio	0.0	-0.1	0.2	1.0																
(5) sh_age_limit	0.0	0.0	0.0	0.0	1.0															
(6) sh_woman	-0.2	-0.2	-0.1	0.0	0.3	1.0														
(7) sh_low_edu	-0.4	-0.1	0.0	0.1	0.0	0.2	1.0													
(8) sh_blue	-0.1	-0.2	0.1	0.1	0.1	0.1	0.5	1.0												
(9) lcl	0.4	0.0	0.1	0.1	0.0	-0.1	-0.2	0.0	1.0											
(10) co	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	1.0										
(11) share_low	-0.2	-0.2	0.1	0.2	0.0	0.2	0.3	0.2	0.1	0.0	1.0									
(12) share_med	-0.1	0.1	-0.2	-0.1	-0.1	-0.2	0.0	0.0	-0.1	0.0	-0.6	1.0								
(13) share_high	0.4	0.2	0.1	-0.1	0.0	-0.1	-0.3	-0.2	0.1	0.1	-0.4	-0.4	1.0							
(14) share_com	0.0	0.0	0.1	0.1	-0.1	0.0	0.1	0.3	0.1	0.0	0.2	0.0	-0.1	1.0						
(15) share_dom	-0.1	-0.1	0.1	0.0	-0.2	0.0	0.1	0.3	0.1	0.0	0.2	0.0	-0.2	0.7	1.0					
(16) share_localgov	-0.1	0.0	-0.1	0.0	0.1	0.0	0.1	-0.2	-0.1	0.0	0.0	0.0	-0.1	-0.7	-0.7	1.0				
(17) share_central~v	0.0	0.0	0.0	0.0	-0.1	-0.2	-0.1	-0.1	0.0	0.0	0.0	-0.1	0.1	-0.2	-0.2	0.0	1.0			

Variables	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15	-16	-17	-18	-19	-20
(18) share_foreign	0.4	0.2	-0.1	-0.1	0.1	0.0	-0.4	-0.1	0.1	0.0	-0.5	0.1	0.4	-0.4	-0.4	-0.1	0.0	1.0		
(19) share_ekspor	0.1	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.2	0.0	-0.2	-0.2	0.0	0.1	0.3	1.0	
(20) share_java	-0.1	0.0	-0.1	0.0	0.1	0.1	-0.1	0.0	-0.1	0.0	-0.1	-0.1	0.2	0.0	0.1	0.0	-0.1	0.0	-0.2	1.0

Table 3A.3. First Stage Estimation for 2SLS

Dependent variable:	**Conditional wage inequality (σ)**	**Maximum-minimum ratio of wages**	**Gini ratio**
Tax	8.04E-14 ***	9.93216E-14 ***	5.53E-14 ***
	(0.0000000000000218)	(0.0000000000000248652)	(0.000000000000019)
Workers characteristic	YES	YES	YES
Firms characteristic	YES	YES	YES
Year dummies	YES	YES	YES
ISIC dummies	YES	YES	YES
Underidentification test- Chi sq	15.36 ***	16.89 ***	9.20 ***
Weak identification test - F test	13.66 ***	15.96 ***	8.45 ***

Table 3A.4. Full regression of linear estimation-Sigma

Dependent variable : Value added per worker (ln)			
	OLS	FE	GMM
One year lagged value added per worker (ln)	0.66 ***	0.11 ***	0.14 ***
	(0.02)	-0.02	(0.049)
One year lagged conditional wage inequality (σ)	0.12 *	0.05 **	0.16 ***
	(0.07)	(0.03)	(0.06)
sh_age_limit	-0.069	0.107	0.308
	(0.17)	(0.11)	0.36
sh_woman	-0.05	0.24	-0.03
	(0.11)	(0.15)	0.37
sh_low_edu	-0.25 **	-0.18	-0.05
	(0.11)	(0.14)	0.34
sh_blue	0.03	-0.06	-0.13
	(0.13)	(0.19)	0.41
lcl	0.09 ***	0.06 ***	0.04
	(0.01)	(0.01)	0.03
co	-3.07E-05	-4.96E-05	8.28E-04
	(0.0002)	(0.00004)	(0.00)
share_low	0.96 ***	0.66 **	1.55
	(0.2)	(0.26)	0.94
share_med	0.90 ***	0.66 ***	0.16
	(0.2)	(0.24)	0.62
share_high	1.13	0.99 ***	0.47
	(0.2)	(0.25)	0.57
share_com	0.41	0.58	1.67
	(0.48)	(0.62)	1.41
share_dom	0.99 *	0.48	2.47
	(0.54)	(0.79)	2.16
share_localgov	-0.26	3.53 ***	-4.11
	(0.53)	(1.27)	3.13
share_centralgov	1.10 ***	0.89	-1.98
	(0.4)	(1.0)	2.45
share_foreign	1.60 ***	1.01	1.22
	(0.25)	(0.68)	1.42
share_ekspor	0.15	0.84	0.57
	(0.23)	(0.51)	0.94
share_java	-0.48 ***	-0.93 **	0.47
	(0.15)	(0.43)	1.27
share_less than median	-0.002	-0.001	-0.001
	(0.002)	(0.002)	0.005
_cons	1.10 **	6.77 ***	6.38 ***
	(0.43)	(1.19)	(2.27)
Year dummies	YES	YES	YES
ISIC dummies		YES	YES
Adjusted R squared	0.71	0.55	
F stat	118.86 ***	76.94 ***	
Hansen statistic--P value > z			0.32
Diff Hansen test			0.28
Arellano Bond statistic (AR2)-P value > z			0.59
Weak instrument test (K-P-value)			0.35
Number of observations	900	900	900

Table 3A.6. Full regression of a quadratic relationship - Sigma

	OLS	FE with dynamiceffects	GMM
One year lagged value added per worker (ln)	0.66 ***	0.11 ***	0.13 **
	(0.02)	(0.02)	(0.06)
Conditional wage inequality (σ)			
Conditional wage inequality (σ)^2			
One year lagged conditional wage inequality (σ)	1.03 **	0.36 **	2.01 *
	(0.43)	(0.16)	(1.10)
One year lagged (conditional wage inequality (σ)^2)	-1.35 **	-0.55 **	-2.44 *
	(0.58)	(0.26)	(1.30)
sh_age_limit	-0.10	0.09	0.20
	(0.16)	(0.12)	(0.32)
sh_woman	-0.02	0.24	-0.07
	(0.12)	(0.15)	(0.36)
sh_low_edu	-0.24 **	-0.18	-0.11
	(0.11)	(0.14)	(0.27)
sh_blue	0.04	-0.06	-0.03
	(0.13)	(0.19)	(0.30)
lcl	0.09 ***	0.06 ***	0.04
	(0.01)	(0.013)	(0.03)
co	-3.84E-05	-5.24E-05	7.77E-04
	(0.0002)	(0.00004)	(0.0009)
share_low	0.98 ***	0.66 **	1.56
	(0.20)	(0.26)	(1.16)
share_med	0.91 ***	0.67 ***	0.44
	(0.20)	(0.24)	(0.70)
share_high	1.13 ***	0.98 ***	0.61
	(0.20)	(0.25)	(0.70)
share_com	0.36	0.54	0.97
	(0.48)	(0.62)	(1.17)
share_dom	0.99 *	0.48	2.06
	(0.54)	(0.78)	(3.13)
share_localgov	-0.30	3.50 ***	-4.31
	(0.52)	(1.27)	(4.52)
share_centralgov	1.09 ***	0.89	-1.94
	(0.4)	(0.99)	(3.09)
share_foreign	1.55 ***	0.99	0.84
	(0.25)	(0.68)	(1.66)
share_ekspor	0.20	0.85 *	0.36
	(0.23)	(0.51)	(0.99)
share_java	-0.49 ***	-0.92 **	0.44
	(0.15)	(0.43)	(1.57)
share_less than median	-0.002	0.00	-0.002
	(0.002)	(0.002)	(0.006)
_cons	1.04 **	6.75 ***	6.95 **
	(0.43)	(1.18)	(3.18)
Year dummies	YES	YES	YES
ISIC dummies		YES	YES
Adjusted R squared	0.72	0.55	
F stat	113.76 ***	74.07 ***	
Hansen statistic--P value > z			0.29 ***
Diff Hansen test			0.18
Arellano Bond statistic (AR2)-P value > z			0.53
Weak instrument test (K-P-value)			0.58
Number of observations	900	900	900

Table 3A.7. Full regression of linear estimation-Gini Index

Dependent variable : Value added per worker (ln)			
	OLS	FE	GMM
One year lagged value added per worker (ln)	0.65***	0.13***	0.14**
	(0.02)	(0.02)	(0.07)
One year lagged Gini ratio	0.60***	0.10**	0.40**
	(0.2)	(0.05)	(0.18)
sh_age_limit	-0.05	0.10	0.38
	(0.15)	(0.12)	(0.37)
sh_woman	-0.04	0.24	-0.05
	(0.11)	(0.15)	(0.38)
sh_low_edu	-0.26**	-0.18	-0.04
	(0.11)	(0.14)	(0.25)
sh_blue	0.02	-0.06	-0.15
	(0.13)	(0.19)	(0.3)
lcl	0.09***	0.06***	0.04
	(0.01)	(0.01)	(0.04)
co	-3.27E-05	-5.06E-05	8.34E-04
	(0.0002)	(0.00004)	(0.0009)
share_low	0.95***	0.66**	1.48
	(0.2)	(0.26)	(1.17)
share_med	0.91***	0.66***	0.17
	(0.2)	(0.24)	(0.71)
share_high	1.13***	0.99***	0.46
	(0.2)	(0.24)	(0.71)
share_com	0.36	0.57	1.65
	(0.48)	(0.62)	(1.25)
share_dom	0.98*	0.50	2.46
	(0.54)	(0.79)	(3.0)
share_localgov	-0.32	3.53***	-3.99
	(0.52)	(1.27)	(4.66)
share_centralgov	1.07***	0.91	-2.14
	(0.4)	(1.0)	(3.1)
share_foreign	1.57***	1.02	1.08
	(0.25)	(0.69)	(1.6)
share_ekspor	0.19	0.85	0.58
	(0.23)	(0.52)	(0.9)
share_java	-0.43***	-0.93**	0.54
	(0.15)	(0.43)	(1.47)
share_less than median	-0.002	-0.001	0.0002
	(0.002)	(0.002)	(0.006)
_cons	1.13***	6.78***	6.21***
	(0.43)	(1.15)	(3.45)
Year dummies	YES	YES	YES
ISIC dummies	YES	YES	YES
Adjusted R squared	0.72	0.66	
F stat	120.44***	75.80***	
Hansen statistic--P value > z			0.70
Diff Hansen test			0.56
Arellano BPm statistic (AR2)-P value > z			0.42
Weak instrument test (K-P-value)			0.33
Number of observations	900	900	900

Table 3A.8. Full regression of a quadratic relationship – Gini Index

Dependent variable : Value added per worker (ln)	OLS		FE with dynamic effects		GMM	
One year lagged value added per worker (ln)	0.65	***	0.13	***	0.14	**
	(0.02)		(0.02)		(0.07)	
Gini ratio						
Gini ratio^2						
One year lagged Gini ratio	0.91		0.18	**	1.40	**
	(0.66)		(0.08)		(0.70)	
One year lagged (Gini ratio^2)	-0.53		-0.13	**	-1.60	**
	(1.1)		(0.06)		(0.80)	
sh_age_limit	-0.05		0.10		0.41	
	(0.16)		(0.11)		(0.38)	
sh_woman	-0.05		0.24		-0.07	
	(0.11)		(0.15)		(0.39)	
sh_low_edu	-0.26	**	-0.18		-0.002	
	(0.11)		(0.14)		(0.27)	
sh_blue	0.01		-0.06		-0.16	
	(0.14)		(0.2)		(0.29)	
lcl	0.09	***	0.06	***	0.04	
	(0.01)		(0.01)		(0.04)	
co	-3.34E-05		-5.02E-05		8.24E-04	
	(0.0002)		(0.00004)		(0.001)	
share_low	0.94	***	0.66	**	1.45	
	(0.2)		(0.26)		(1.14)	
share_med	0.91	***	0.66	***	0.10	
	(0.2)		(0.24)		(0.72)	
share_high	1.13	***	0.99	***	0.38	
	(0.2)		(0.24)		(0.72)	
share_com	0.33		0.58		1.52	
	(0.49)		(0.6)		(1.2)	
share_dom	1.00	*	0.50		2.51	
	(0.54)		(0.78)		(3.0)	
share_localgov	-0.33		3.53	***	-3.80	
	(0.52)		(1.27)		(4.72)	
share_centralgov	1.07	***	0.92		-2.20	
	(0.4)		(1.0)		(3.11)	
share_foreign	1.56	***	1.02		0.91	
	(0.25)		(0.69)		(1.56)	
share_ekspor	0.19		0.85		0.61	
	(0.23)		(0.52)		(0.89)	
share_java	-0.43	***	-0.93	**	0.66	
	(0.15)		(0.43)		(1.5)	
share_less than median	-0.002		-0.001		0.000	
	(0.002)		(0.002)		(0.006)	
_cons	1.10	**	6.78	***	6.07	*
	(0.43)		(1.15)		(3.52)	
Year dummies	YES		YES		YES	
ISIC dummies	YES		YES		YES	
Adjusted R squared	0.72		0.68			
F stat	114.33	***	74.03	***		
Hausman test						
Hansen statistic--P value > z					0.89	
Diff Hansen test					0.68	
Arellano BPm statistic (AR2)-P value > z					0.36	
Weak instrument test (K-P-value)					0.28	
Number of observations	900		900		900	

Table 3A.9. Full regression of linear estimation – Maximum-minimum ratio

Dependent variable : Value added per worker (ln)						
	OLS		FE		GMM	
One year lagged value added per worker (ln)	0.66	***	0.21	***	0.30	**
	(0.02)		(0.04)		(0.15)	
One year lagged maximum-minimum ratio of wages	0.03	*	0.02	*	1.19	*
	(0.02)		(0.01)		(0.68)	
sh_age_limit	-0.06		0.11		-0.06	
	(0.16)		(0.11)		(0.29)	
sh_woman	-0.06		0.24		0.08	
	(0.11)		(0.15)		(0.34)	
sh_low_edu	-0.25	**	-0.18		-0.14	
	(0.11)		(0.14)		(0.27)	
sh_blue	0.02		-0.05		0.06	
	(0.13)		(0.19)		(0.42)	
lcl	0.09	***	0.06	***	0.04	
	(0.01)		(0.01)		(0.03)	
co	-2.95E-05		-5.06E-05		8.98E-04	
	(0.0002)		(0.00004)		(0.001)	
share_low	0.95	***	0.65	**	1.51	
	(0.2)		(0.26)		(1.06)	
share_med	0.89	***	0.66	***	0.09	
	(0.2)		(0.24)		(0.68)	
share_high	1.12	***	0.99	***	0.41	
	(0.2)		(0.25)		(0.65)	
share_com	0.42		0.57		1.29	
	(0.48)		(0.62)		(1.38)	
share_dom	1.00	*	0.48		3.44	
	(0.54)		(0.79)		(3.33)	
share_localgov	-0.26		3.53	***	-2.41	
	(0.53)		(1.28)		(3.67)	
share_centralgov	1.08	***	0.89		-1.28	
	(0.4)		(1)		(3.47)	
share_foreign	1.61	***	1.00		2.22	
	(0.25)		(0.68)		(1.93)	
share_ekspor	0.16		0.85	*	0.18	
	(0.23)		(0.51)		(0.81)	
share_java	-0.48	***	-0.93	**	-0.10	
	(0.15)		(0.42)		(1.63)	
share_less than median	-0.002		-0.001		-0.002	
	(0.002)		(0.002)		(0.006)	
_cons	1.14		6.76	***	6.18	*
	(0.43)		(1.16)		(3.57)	
Year dummies	YES		YES		YES	
ISIC dummies	YES		YES		YES	
Adjusted R squared	0.71		0.66			
F stat	118.86	***	78.90	***		
Hansen statistic--P value > z					0.50	
Diff Hansen test					0.45	
Arellano BPm statistic (AR2)-P value > z					0.41	
Weak instrument test (K-P-value)					0.26	
Number of observations	900		900		900	

Table 3A.10. Full regression of a quadratic relationship – Maximum minimum ratio

Dependent variable : Value added per worker (ln)						
	OLS		FE with dynamic effects		GMM	
One year lagged value added per worker (ln)	0.66	***	0.31	***	0.43	**
	(0.02)		(0.06)		(0.17)	
One year lagged maximum-minimum ratio of wages	0.08	*	0.05	*	1.77	*
	(0.05)		(0.03)		(1.02)	
One year lagged (maximum-minimum ratio of wages^2)	-0.01	*	-0.002	*	-0.29	*
	(0.005)		(0.001)		(0.15)	
sh_age_limit	-0.06		0.11		0.04	
	(0.16)		(0.11)		(0.31)	
sh_woman	-0.06		0.24		0.07	
	(0.11)		(0.15)		(0.37)	
sh_low_edu	-0.25	**	-0.18		0.10	
	(0.11)		(0.14)		(0.26)	
sh_blue	0.01		-0.05		-0.20	
	(0.13)		(0.19)		(0.48)	
lcl	0.09	***	0.06	***	0.04	
	(0.01)		(0.01)		(0.03)	
co	-2.79E-05		-5.10E-05		6.80E-04	
	(0.0002)		(0.00004)		(0.0008)	
share_low	0.95	***	0.66	**	0.89	
	(0.2)		(0.26)		(1.01)	
share_med	0.90	***	0.66	***	0.32	
	(0.2)		(0.24)		(0.74)	
share_high	1.13	***	0.98	***	0.43	
	(0.2)		(0.25)		(0.69)	
share_com	0.41		0.57		1.43	
	(0.48)		(0.62)		(1.32)	
share_dom	1.01	*	0.48		4.24	
	(0.54)		(0.79)		(3.03)	
share_localgov	-0.27		3.53	***	-0.06	
	(0.53)		(1.28)		(3.47)	
share_centralgov	1.09	***	0.90		-1.16	
	(0.4)		(1.00)		(3.54)	
share_foreign	1.61	***	1.00		3.25	*
	(0.25)		(0.68)		(1.92)	
share_ekspor	0.17		0.85	*	-0.22	
	(0.23)		(0.51)		(0.87)	
share_java	-0.47	***	-0.93	**	-0.39	
	(0.15)		(0.42)		(1.88)	
share_less than median	-0.002		-0.001		0.001	
	(0.002)		(0.002)		(0.006)	
_cons	1.06	***	6.80	***	6.74	***
	(0.44)		(1.14)		(1.17)	
Year dummies	YES		YES		YES	
ISIC dummies	YES		YES		YES	
Adjusted R squared	0.71		0.55			
F stat	112.91	***	79.05	***		
Hausman test						
Underidentification test- Chi sq						
Weak identification test - F test						
Hansen statistic--P value > z					0.25	
Diff Hansen test					0.23	
Arellano BPm statistic (AR2)-P value > z					0.55	
Weak instrument test (K-P-value)					0.47	
Number of observations	900		900		900	

Chapter 4 How do manufacturing jobs and labour mobility affect wage inequality?

Abstract

This paper investigates how employment and labour mobility, measured by geographical and occupational mobility, determine wage inequality in the form of linear and quadratic relationships. This research employs two different survey datasets, Indonesia's Labour Survey and Indonesia's Yearly Large and Medium Manufacturing Industries Survey, over 2007–2015. The findings reveal that manufacturing jobs and occupational mobility have an inverted - U shaped relationship with wage inequality. On the other hand, geographical labour mobility significantly affects wage distribution in a U-shaped pattern. These findings are robust across many dimensions: a different type of wage inequality measurement; conditional and unconditional wage disparity, and various estimation techniques; OLS, GMM panel data and instrumental variable (IV) techniques. The most critical implication of these findings is that the low level of human capital could explain the problem of wage inequality and labour market restrictions in the Indonesian manufacturing sector.

4.1 Introduction

It has been argued that wage inequality in the industry affects productivity significantly (Akerlof and Yellen, 1988; Lazear and Rosen, 1981; Lazear, 1989). Hence, analysing the factors that can determine wage inequality in the industry is crucial as the steady growth in wage inequality has been evident in many countries. There have been alternative theories about wage determination, such as the efficiency wage theories (Stiglitz, 1984, Yallen, 1984) or the union model by Dickens and Katz (1986). These theories can be linked to the phenomenon of size-wage effects that explains how labour absorption that is represented by firm size in an industry will create different wage schemes (Brown and Medoff, 1989; Groshen, 1991; Oi and Idson, 1999), and other labour market conditions such as labour mobility that can result in variance in wages across or within industries (Stijepic, 20176). This paper focuses on these two aspects, which can affect wage inequality through job absorption and labour mobility in the manufacturing sector.

Numerous studies have observed specifically how job absorption can affect wage inequality. This is because job absorption that can be measured by firm size plays an important role in determining wage offerings. Firms with different numbers of workers will pay wages differently (Martin and Esteves, 2008, Arcidiacono and Ahn, 2004; Fox, 2009; Winter-Ebmer and Zweimüller, 1999; Romanguera, 1991; Brown and Medoff, 1989; Haber and Lamas, 1988; Barth et al., 2014). Consequently, wage disparity exists either inter- or intra-industries. It is argued that the more labour is employed, the worse wage inequality will be, mainly due to labour heterogeneity (Oi, 1983; Dickens and Katz, 1986; Fox, 2009; Song, et al., 2019). On the other hand, job absorption can also reduce wage inequality because as firms grow, firms' attributes will move toward wage compression (Lambson, 1991; Kremer, 1993; Davis and Haltiwanger, 1995; Lallemand and Ryck, 2006; Sun, 2014; Barth et al., 2014).

Further, how labour mobility, spatial and occupational (job) mobility affects wage inequality has also been an interesting topic in labour market research. There has been no agreement about how labour mobility affects wage inequality. Some researchers have found that spatial mobility in the labour market worsens wage inequality, mainly because of asymmetrical effects coming from heterogeneous worker's characteristics (Burda and Wyplosz, 1992; Feser and Sweeney, 2003; Elhorst, 2003; Südekum, 2005; Epifani and Gancia, 2005; Partridge and Rickman, 2006; Østbye and Westerlund, 2007; Francis, 2009). On the other hand, it is also argued that geographical labour mobility will reduce wage inequality due to downward pressure on wages in destination areas or sectors (Pissarides and McMaster, 1990; Kanbur and Rapoport, 2005). Similarly, there have been mixed results in research about job mobility and wage disparity. Dorantes and Padial (2007) and Belley et al., (2012) argue that job mobility reduces wage inequality. However, some also argue that job mobility will widen the wage gap (Kambourov and Manovskii, 2009; Hoffmann and Shi, 2011; Soria et al., 2015; Stijepic, 2017; Park, 2019).

This paper draws from the above literature that conceptualises how manufacturing jobs and labour mobility affect wage inequality in industry. However, the above-cited papers mostly used data from developed countries such as the US or OECD countries. In contrast, this paper provides empirical evidence in the context of a developing country, Indonesia. Indonesia is an interesting case study. Despite the fact that labour productivity has more than doubled in the Indonesian manufacturing industry, and is higher than in other sectors, this sector has experienced a relatively stagnant and low rate of labour absorption (Indonesian Ministry of Industry, 2019). The low level of labour engaged in the manufacturing sector may reflect the condition that a relatively high rate of productivity cannot be distributed among workers. Hence, wage inequality exists in this sector. In fact, gains from labour productivity in this sector seemingly cannot be translated into better wages and working conditions, which are important to increase Indonesian living standards (ILO, 2015). Furthermore, this paper also explores possible reasons behind the relationship between manufacturing jobs, labour mobility and wage inequality.

In terms of labour market conditions, Indonesian workers engaged in the manufacturing sector experience relatively unique labour mobility condition, geographical mobility and job mobility. Regarding geographical mobility, the manufacturing sector was the third highest sector having commuting workers, which is 21 per cent of total workers. Moreover, in terms of job mobility, as can be seen from Table 4.1, the number of people moving out of the manufacturing sector (19.45%) is higher than the influx of workers into the manufacturing sector (16.75%). In fact, from 19.45 per cent of workers who went out of the manufacturing sector, 8.23 per cent were changing their job within the manufacturing sector. This figure indicates that the highest proportion of the inflow of the workers in the manufacturing sector was from the manufacturing sector itself. This situation implies that job mobility from other sectors to the manufacturing sector is relatively low. This shows that there is rigidity in the Indonesian labour market, particularly the manufacturing sector, which may be caused by the rigidity in Indonesia's labour regulations. In 2003, the rigidity of labour regulations was increased by the Manpower Law, which required a significant increase in severance rates and gratuity payments making Indonesia one of the most rigid countries in East Asia and the world (The World Bank, 2010). Medium and large-scale manufacturing firms, which are mostly in the formal sector, are affected by the law. Hence, this sector has become more rigid in terms of job creation.

Table 4.1. The proportion of workers who change the job, 2007-2015

		current primary work (the type of industry)									TOTAL
		1	2	3	4	5	6	7	8	9	
previous primary work (the type of industry)	1	16.5	1.11	2.38	0.02	3.01	3.09	0.89	0.1	1.36	28.46
	2	0.76	0.31	0.17	0	0.33	0.22	0.06	0.01	0.09	1.95
	3	2.72	0.25	8.23	0.05	1.23	3.94	1.2	0.29	1.54	19.45
	4	0.04	0.01	0.04	0.04	0.03	0.03	0.01	0.01	0.02	0.23
	5	3.82	0.23	0.89	0.1	2.51	1.57	0.59	0.14	0.64	10.49
	6	3.01	0.21	2.74	0.06	0.93	8.48	1.06	0.75	1.92	19.16
	7	1.05	0.12	0.6	0.02	0.59	1.24	1.08	0.23	0.59	5.52
	8	0.21	0.06	0.19	0.01	0.15	0.88	0.25	0.65	0.35	2.75
	9	2.35	0.13	1.51	0.04	0.57	2.58	0.57	0.32	4.28	12.35
TOTAL		30.46	2.43	16.75	0.34	9.35	22.03	5.71	2.5	10.79	100

Note: [1] Agriculture, livestock, forestry and fishery, [2] mining and quarrying, [3] manufacturing industry, [4] electricity, gas and water supply, [5] construction, [6] trade, hotel and restaurants, [7] transport and communication, [8] finance, real estate and business services, [9] services.

Source: Labour survey 2007-2015

Overall, this paper has the main objective to examine how manufacturing jobs and labour mobility affect wage inequality in the Indonesian manufacturing sector. The estimations show that manufacturing jobs and occupational mobility have an inverted-U-shaped relationship with wage inequality. This implies that a relatively low level of job absorption and occupational mobility among the labour will hamper wage distribution. However, when it is beyond the threshold, it will reduce wage disparity. On the other hand, spatial mobility in the labour supply will reduce inequality at a relatively low level. Once it is above the threshold, it will increase wage inequality. These findings are robust across many dimensions: different types of wage inequality measurement, conditional and unconditional wage disparity, using OLS, FE, dynamic panel models with and without lagged independent variables, instrumental variables (IV) techniques and the use of different levels of data-industrial group and regional level data. The various dimensions used in the estimation aim to address the limitations of previous studies, where only a few studies have considered both labour absorption and mobility in determining wage inequality. In fact, both factors can affect wage distribution simultaneously (Lewis, 1954). The use of different measurements, particularly wage inequality based on workers' characteristics, has not been explored in previous studies.

There are some implications based on the findings in this paper concerning the Indonesian manufacturing sector. First, Indonesian manufacturing jobs heavily depends on low-medium technology sectors[6], group such as garments except for apparel, food products, spinning, weaving and finishing of textiles products, etc., which generally experience negative relationships between job absorption and wage distribution. On the other hand, medium-high technology sectors, such as porcelain products, basic precious and non-ferrous metals, general-purpose machinery products, electricity distribution and control apparatus, etc., may need to increase their labour demand as their labour absorption is still below the limit when job absorption can reduce wage inequality. The bigger problem behind this is that it is not easy to increase labour demand in medium-high technology industry when human capital quality in Indonesia is still limited. Problems about human capital quality in the Indonesian manufacturing sector have been supported by findings about job mobility effects. Even though the relationship between occupational mobility and wage disparity is an inverted U-shape, most industrial groups fall into the area where job mobility hinders wage distribution. According to Park (2019), the vital reason why job mobility has a negative impact on wage distribution is because of the skill mismatch problem, which is evident in the Indonesian manufacturing sector. Lastly, geographical mobility also has a nonlinear relationship with income disparity, with most industrial groups falling into the negative area of the curve where geographical mobility can reduce inequality. However, there are some groups dominated by medium-high technology that need to limit their workers from outside the regions. This indicates that the most attractive sectors for mobile workers are medium-high technology sectors, which can be

[6] The classification of the manufacturing industry based on technology intensity by OECD, 2011.

caused by two factors, the supply factor, which is wage attraction, and the demand factor, which is lack of availability of required labour in the destination region, so this type of industry needs to absorb labour from different regions.

The remainder of this paper is organised as follows. Section 2 reviews the theoretical framework regarding the effects of manufacturing jobs and labour mobility on wage dispersion. The general picture of Indonesia's manufacturing conditions is described in Section 3, followed by the description of data and methodology in Section 4. The estimations about job absorption and worker mobility are analysed in Section 5. Finally, Section 6 concludes the paper.

4.2 Theoretical framework

4.2.1 Manufacturing jobs and inequality

Generating employment is argued to be one of the critical approaches to solving many problems in the development arena. Employment creation is claimed to be able to eradicate poverty by increasing income. By promoting more job opportunities, governments can improve both economic and political stability (ILO, 2009; World Bank, 2011). How employment creation can reduce poverty highly depends on distribution quality is. Distribution quality, which refers to job type, job location, duration, wage levels, spatial distribution, and allocation across the income distribution, is an essential factor in determining to what extent employment takes a role in poverty eradication (Holmes et al., 2013). Hence, employment arguably has a significant relationship with inequality as a part of its role in reducing poverty. Angeles-Carlo (2006), who investigated the effects of employment on inequality by utilising data from 93 countries between 1980 and 1998, found that employment has a statistically positive and significant effect on inequality. He argued that if unemployment reduces by 4.75 points, the inequality index will decrease by 1 point (Angeles-Carlo, 2006).

Employment can reduce poverty and wage inequality when workers are engaged in relatively high productivity sectors. This is because productivity is closely related to access to resource, assets and markets (Holmes et al., 2013). The manufacturing sector is theoretically and empirically argued to be one of the sectors that generate high productivity. A neo-Ricardian economist, Kaldor (1967), argues that the manufacturing sector plays an important role as an economic growth engine because of its high productivity, linkage effects and demand effects. Moreover, Lewis (1954) argues that manufacturing, as one of the potential capitalist sectors has an essential role in the economy because of its ability to reinvest profit more productively compared to other sectors by doing capital accumulation. This capital accumulation significantly affects labour productivity, which is translated to wages and later on affects total income in the economy. Furthermore, the ability of the manufacturing sector in generating technological progress and innovation is also one of the elements determining its role in productivity growth (Kaldor 1967; Rodrik, 2012; Marconi, Reis & Araujo, 2016).

The role of the manufacturing sector in employment creation has also been investigated. Haraguchi et al. (2017) claimed that, unlike developed economies that have already experienced deindustrialisation, developing countries have continued relying on the manufacturing sector to contribute to labour demand. He argued that since 1970, the aggregate share of manufacturing employment in total employment has changed only insignificantly. Following that, using some robustness techniques, it was found that employment absorption in developing countries has not declined yet. Furthermore, research indicates that one factor contributing to a high economic growth in China during the global financial crisis was a significant reduction in unemployment due to a significant increase in manufacturing jobs creation by the end of 2009 and in 2010 (Cook, 2020).

How job creation affects inequality in the manufacturing sector has been explored by some studies. It was discovered that an increase of 2.4 points in the ratio of manufacturing employment to total employment reduced the inequality index by one point in 93 countries during 1990-1998 (Angeles-Carlo, 2006). Moreover, with the aim of exploring the effects of manufacturing jobs creation on inequality in Latin America, FitzGerald (2006) concluded that industrialisation helps in inequality reduction by providing higher labour incomes as a result of increased productivity. Besides, higher labour incomes in this sector are also caused by significant human capital formation in manufacturing. Human capital development, as well as technological development, will narrow the gap of labour productivity across workers.

Regional studies have also been done to analyse how manufacturing jobs have significant effects on income distribution. By using 3,200 observations from different countries, it was found that over the period 196 -1999, a one per cent increase in manufacturing employment helped in reducing income inequality by 2 per cent (Galbraith and Kum, 2005). Furthermore, Jaumotte et al. (2008) found that in 51 countries (lower and higher-income economies) throughout 1981-2003, a one per cent decrease in manufacturing jobs was associated with an 11 per cent increase in the income inequality index. In the United States, it was found that a decrease in manufacturing jobs increased inequality in both levels, states and cities. By utilising US census data from 1970, 1980, 1990 and 2000, it was shown that deindustrialisation had a significant role in income distribution through job polarisation. Deindustrialisation has made workers shift to alternative and lower-wage jobs as well as putting downward wage pressure on lower-wage workers because of excess supply of unskilled workers (Gould, 2015). Mehic (2018) also argued that a drop in industrial employment brings negative impacts on income distribution. Using data from 1991 to 2014 for

27 developed economies, he claimed that a one per cent decline in manufacturing jobs increased the income inequality by 2.1 per cent in most of middle to high-income countries.

Besides the phenomenon of inequality at the macroeconomic level, wage inequality, whether it is within-firms or between-firms, has also been an important issue in microeconomic conditions concerning firm performance. In terms of within-firm inequality, there have been mixed results in research on how the number of workers affects wage inequality within the same firm. It has been claimed that firms with different numbers of workers will pay wages differently (Martin and Esteves, 2008, Arcidiacono and Ahn, 2004; Fox, 2009; Winter-Ebmer and Zweimüller, 1999; Romanguera, 1991; Brown and Medoff, 1989; Haber and Lamas, 1988; Barth et al., 2014). This is because different sizes of firms deal with different firm and worker characteristics, which affect the level of monitoring costs. Generally, firms with more workers or bigger sizes will pay a wage higher than market-clearing since the opportunity cost for monitoring worker productivity is higher than in smaller firms. Consequently, in order to maintain productivity, bigger firms must provide higher incentives for their workers (Oi, 1983). A similar finding was concluded in research investigating manufacturing sectors in the United States and Sweden that firm size has a positive relationship with wage distribution. This is because bigger firms need to compensate workers for negative assumptions about the working environment in bigger enterprises (Fox, 2004).

In contrast with the above research, many studies have found that large numbers of workers bring adverse effects of income equality (Belfield and Wei, 2004; Raposo and Menezes, 2011; Sun, 2014). Furthermore, some studies have found an ambiguous relationship between firm size and wage distribution. It has been found that firm size does not have significant effects on wage inequality due to the fact that size is merely the proxy of risk of firm failure (Mayo and Murray, 1991; Burdett and Mortensen, 1998). Furthermore, Du Caju et al. (2009) argued that size matters in determining wage inequality only for larger firms. If the size of the firm is small that is fewer than 50 workers, firm size insignificantly affects wage distribution.

Despite the interesting issues around within-firm inequality, between firms or intra-industry inequality is also an important topic as it determines the aggregate level of inequality. There has been no consensus on how firm size affects wage inequality intra-industry. Dickens and Katz (1986) claimed that wage inequality between firms would increase with the increased size of firms. This is due to factors such as the rate of quitting, labour productivity, workers characteristics, concentration ratio and profit of the firms. Likewise, in the US, it was found that between-firms inequality contributed significantly to a general increase in wage inequality. Two-thirds of the contribution of total increase had a positive relationship with the number of workers. The sources of this relationship are an increase in employee sorting and segregation. This means that high-wage workers are engaged in bigger firms with higher wages, and higher wages and bigger firms are clustered with other high-paid workers (Song et al., 2019).

The inverse relation between firm size and between-firm inequality has also been debated. Despite arguing that within-firm inequality will increase when a firm is larger, Davis and Haltiwanger (1995) argue that between-firm inequality reduces as the size of the firm rises. This is due to possible attributes such as that bigger firms are more likely to be unionised, to implement more standardised technology that requires more homogenous workers and a higher rate of standard wage rate compliance leads to greater wage compression. Kremer (1993) supports the argument that bigger firms implement more standardised technology with complements of homogenous and high skill labour, which generate lower dispersion of wages. Similar arguments were brought up by Lallemand and Ryck (2006). They claimed that wage inequality between firms would fall as employer size increased because smaller firms would be more diversified in terms of technology, and hence the result would be more diversity in average workforce skills in smaller firms. Their findings support the theory of life-cycle dynamics of plants (Lambson, 1991). Firm size will reduce between-firm inequality as in larger firms the availability of career training systems is higher than in smaller firms. This will help to develop intra-firm equality (Sun, 2014). A neutral relationship between the number of workers and inequality among firms has also been discovered. Despite that fact the wage inequality across firms increased in the 1970s to 2000s; it was found that the size of firms contributed insignificantly to wage inequality. The more critical factor was the type of industry (Barth et al., 2014).

Based on the above literature, manufacturing jobs have been proven empirically to have significant effects on wage distribution at the regional or sectoral level. However, there is no single conclusion on how this affects wage dispersion. More people engaged in the manufacturing sector can create better or worse wage distribution depending on which environmental factors dominate. A bigger workforce size may increase wage inequality because of factors such as a high rate of workers concentrated in high-paid jobs and worker heterogeneity. On the other hand, job creation may create better wage distribution because of positive industrial spillovers such as human capital formation and higher rate compensation, minimum wage compliance and unionisation. As the effects of manufacturing jobs may not be linear, in this research, their effects are estimated by linear and quadratic estimations to analyse whether the positive or negative effects of job creation on wage inequality dominate or are dominated.

4.2.2. Labour mobility and inequality

4.2.2.1 Spatial mobility and inequality

Earlier theory about labour mobility was developed by Harris and Todaro (1970). Their theory originally discussed rural-urban migration in developing countries. They demonstrated that despite a high unemployment rate in an urban area, rural-urban migration would persist as long as individual workers act to achieve higher incomes and better jobs based on rationality. Based on this study, many subsequent studies have explored how migration affects economic development outcomes, particularly income distribution.

There has been no consensus on whether the geographical mobility of labour brings positive or negative impacts on income distribution. Some studies have found that labour migration helps in reducing income inequality. Pissarides and McMaster (1990), using data from nine regions in Great Britain from 1961 to 1982, found that interregional migration had a significant relationship with regional disparity. In the long run, through a market mechanism in labour migration, the regional disparity could be removed, although it took a long time about 20 years. Based on traditional neoclassical models, labour migration has a positive relationship with income distribution. This is because the number of mobile workers will increase the labour supply and put downward pressure on wage levels in the destination, with the assumption that a labour moves from low wage regions to high wage regions (Kanbur and Rapoport, 2005).

On the other hand, many studies have argued that labour migration would increase income disparity. The implications are that a high rate of labour mobility would worsen income distribution among regions. This is because externalities resulting from labour movement will lead to a process of cumulative causation where the destination region will grow faster due to agglomeration brought by the inflow of workers (Südekum, 2005; Epifani and Gancia, 2005; Francis, 2009). Further, cumulative causation is also caused by selective migration. This means that labour migration may be dominated by high skilled workers that induce productivity and wages in the destination areas (Burda and Wyplosz, 1992; Feser and Sweeney, 2003). Selective migration also brings other negative effects on income distribution through asymmetric mobility effects. These asymmetrical effects come from heterogeneous characteristics of workers. The more the diverse worker characteristics are, the more difficult the impacts of labour mobility are to justify (Østbye and Westerlund, 2007). Workers heterogeneity may cause human capital redistribution because mobile workers may have different skills from the general workforce in the destination place (Elhorst, 2003). Moreover, there are also externality effects on consumption and investment resulting from the heterogeneity effects of labour mobility (Partridge and Rickman, 2006).

On the other hand, some studies have also concluded an ambiguous relationship between labour mobility and wage inequality. In the United States over the 1960-1970 period, it was discovered that the effects of labour mobility on inequality depended on changes in the labour supply and demand curves (Chalmers and Greenwood, 1985). Moreover, it was concluded that in Germany over the period 1989-1992, labour migration had a different relationship with wage distribution depending on the type of workers. Labour migration tended to increase when wage inequality of skilled workers increased. On the other hand, migration has a negative relationship with wage differentials of unskilled workers (Parikh and Van Leuvenseijn, 2003). Moreover, by utilising data from 1995 to 2005, it was found that labour migration had a weak relationship in reducing regional income disparity in Germany. This is because Germany has a collective wage bargaining system as the institutional setting in the labour market (Niebuhr et al., 2012).

A unique pattern of geographical labour mobility, which is commuting, is also interesting to explore since the majority of workers in Indonesia's manufacturing sector are commuters. Some studies, conducted mostly in developed countries, have arrived at diverse conclusions about commuting behaviour and wage disparity relationships. The discussion about commuting issues have become prominent since the discovery of the spatial mismatch hypothesis that discusses high rural poverty and unemployment in Afro-American residents due to job decentralisation in the US (Kain 1968, 1992). This hypothesis has been supported by some empirical studies such as Arnott (1998), who argued that commuting could help Blacks to get a job in suburbia with living downtown as their primary constraint. Furthermore, Zenou (2000) also provides evidence of the spatial mismatch hypothesis by implementing the urban employment equilibrium model. He argues that if workers live further away from their jobs, their wages are higher, and the level of unemployment in their residential area is also higher. Hence, providing subsidies for commuting costs is essential to reduce inequality between areas. Using data from Baltic countries, Hazans (2014) argued that commuting has a negative relationship with wage inequality. He pointed out that the magnitude effects of commuting depend on spatial patterns of commuting, workers educational background, types of occupations and labour market policy.

The debate on how commuting will benefit income distribution exists because there is no general conclusion on how commuting behaviour affects wage inequality. By using a firm-level framework, it was found that commuting had a significant effect on wage equilibrium. Workers living in farther areas will receive lower net wages because of commuting costs. Hence, commuting will worsen income distribution because commuting workers living in remote areas are generally low on two conditions, physical space and skill match (Brueckner, Thisse, and Zenou, 2002). Furthermore, Gutierrez (2018) argued that commuting also increased wage inequality between men and women as well as across industries. He observed that women incurred higher commuting costs as a result of job type and location gap. Women tend to choose to find jobs in industries that are closer to home and offer relatively low wages. Unlike those studies, using data from the National Longitudinal Surveys-Youth Cohort in the US, it was found that the effects of commuting on income distribution are ambiguous. It highly depends on worker characteristics. Commuting can affect income distribution either positively or negatively depending on demographic characteristics like gender and marital status as well as the place of residence (Howell and Bronson, 1996). Elhorst (2003) also argued that commuting has an essential effect on income distribution. However, the effects resulting from commuting might be lower than migration because of the impact of local job applicants and a spatial mismatch with vacancies. This means commuting workers do not compete with local employees. Hence, inward commuting workers may not affect wages, unlike inward immigrant workers.

As explained above, how geographical labour mobility affects wage disparity has not been concluded in a single consensus. Geographical mobility may reduce wage inequality because of downward pressure effects. On the other hand, spatial movement among labour may also worsen wage disparity as it will induce asymmetric mobility problems resulting from the high level of worker heterogeneity. Hence, it is arguably important to estimate not only linear forms but also quadratic estimations to observe whether at some points the positive (negative) effects of geographical labour mobility are taken over by the negative (positive) effects.

4.2.2.2 Job mobility and inequality

It is also important to discuss how labour movement between sectors or jobs affects income distribution in industries. Some studies discovered that job mobility helped in reducing wage disparity among workers. Dorantes and Padial (2007), utilising Spanish data from the European Community Household Panel, found that job mobility reduced the wage gap among workers, particularly between indefinite and fixed contract workers. Job mobility helped in raising the wage for both indefinite-term and fixed contract workers, even though wage growth rates enjoyed by workers varied depending on the workers' efforts in keeping their jobs. Moreover, according to the US National Longitudinal Survey of Youth in 1979, it was discovered that job mobility had a negative relationship with wage disparity. This is because even though job changers received lower wage in the beginning, they had much higher wage growth rates than job stayers due to the quality of signalling at the new jobs and the revelation mechanism (Belley et al., 2012).

On the other hand, it is also argued that job mobility widens the wage gap among workers. Kambourov and Manovskii (2009) discovered that occupational mobility accounted for more than 90 per cent of the increase in wage disparity over the period 1970-1990 in the United States. By implementing a dynamic equilibrium model, they concluded that labour mobility between sectors in the US widened wage inequality in all sectors. This is because to increase competition in the market, the upper end of wages distribution in all sectors thickened making the inequality worse (Hoffmann and Shi, 2011). Soria et al. (2015) discovered that labour mobility increased wage inequality in hospitality industries located in Andalusia. This is because of educational mismatch and labour policy discriminations.

Furthermore, Stijepic (2017) claimed that inter-firm labour mobility increased the skill wage premium as a result of factor input reallocation from international trade. A similar pattern was also found in the US from 2000 to 2015. It was observed that labour mobility increased wage inequality in industries because of the existence of labour mobility frictions. The friction was mainly due to three factors: training cost, job search and moving cost and skill mismatch resulting from the rapid growth of technology (Park, 2019). Moreover, Mukhopadhaya (2003) argued that an increase in wage inequality, particularly interoccupational inequality, is due to a relative wages stagnation for unskilled workers.

Unlike the above studies, some studies have argued that the relationship between job mobility and wage inequality is unclear. Labour mobility is highly dependent on tenure in affecting wage distribution. Tenure affects human capital formation first. Then it will affect wage distribution. For young workers, labour mobility will accumulate their human capital, and later it will increase their wages. On the other hand, for more mature workers, frequent movers will earn lower wages than stayers regardless of their demographic characteristics (Mincer and Jovanovic, 1981). Garnero et al. (2016) argued that a positive relationship between labour mobility and wage disparity in 24 OECD countries was statistically significant only for the bottom of the distribution where there was a movement from employment to unemployment.

By reviewing some studies above, it can be argued that the effects of changing jobs among workers on wage dispersion are not linear. Job mobility may have positive or negative relationships with wage inequality depending on unique sample characteristics. When incentives work well, wage disparity will be lowered as job mobility increases. On the other hand, along with job mobility, some labour market disturbance, such as educational mismatch and labour policy, will worsen wage inequality. Hence, to see which form of the relationship exists, in this paper, a quadratic relationship has been applied in the estimations.

4.3 Indonesia's context.

The distribution of workers engaged in large and medium scale manufacturing firms isspread out across a group of industries. The champion within the manufacturing sector for labour absorption in the period over 2007-2015 was the food products and beverages industry. Almost 16 per cent of workers were engaged in this sector. Many factors contributed to the performance of the food and beverages industry. The first is due to the relatively high supply and demand in this sector. The number of firms playing in this sector was more than 5000 on average or around 23 per cent of total firms from 2007 to 2015. In terms of the demand side, the food and beverages industry contributed about 20 per cent of the total GDP of large and medium scale manufacture in the same period (Statistics Indonesia, 2020). Another factor supporting this sector is relatively high competitiveness because of a high degree of foreign direct investment (Asian Development Bank, 2019). Moreover, the three other most significant contributors in providing jobs for Indonesians were the garment industry with 13.73 per cent contribution, furniture and related industries with 12 per cent contribution and lastly the textiles industry, contributing 11 per cent of total labour. The average worker distribution across a group of industries is presented in Figure 4.1.

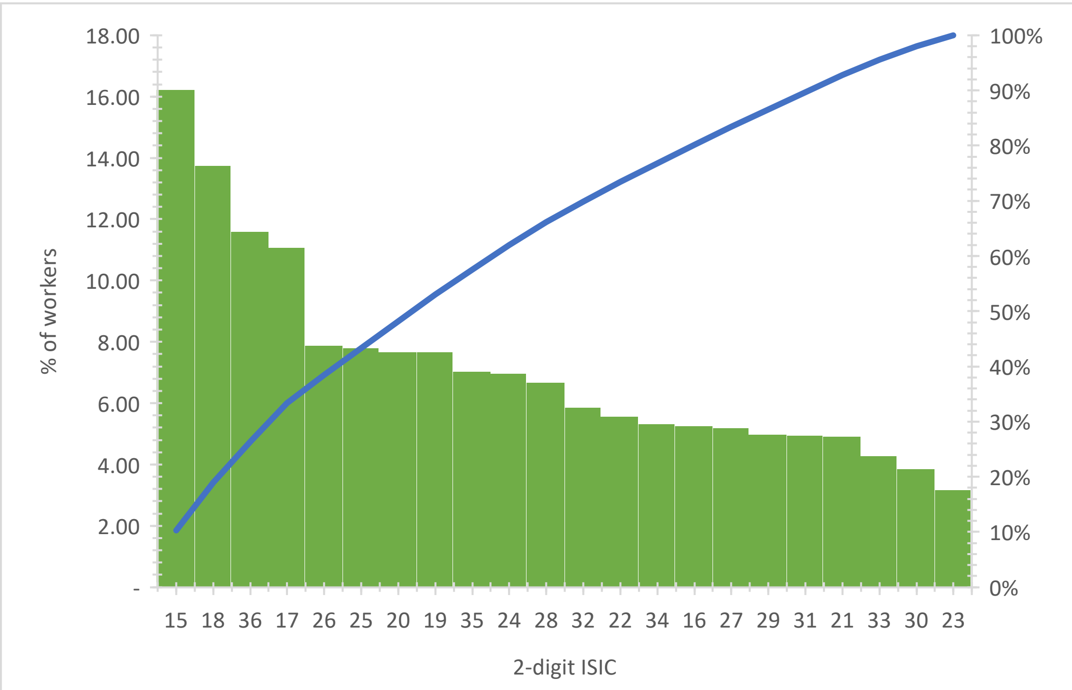


Figure 4.1. Average distribution of workers from 2007-2015 by a group of industries

Source: Author's calculation based on Indonesia's large and medium manufacturing survey 2007-2015

In terms of geographical dispersion, manufacturing workers are concentrated in Java and Sumatera. On average, more than 80 per cent of large and medium manufacturing establishments are located in Java. Java is an economic engine for the Indonesian economy with on average 60 per cent contribution to the total Indonesian GDP in the period of 2007 - 2015. In terms of manufacturing sector development, the Indonesian government has established Java as an economic corridor, focusing on manufacturing and services development to achieve the Indonesian vision in 2025 (Indonesia, 2011). Java is the centre for development in specific industries, namely food and beverages, textile, transportation, shipping, information and telecommunications, and the defence equipment industry. Despite the rapid economic growth in Java, this corridor still has faced some challenges such as relatively high income disparity among provinces and sectors, relatively low domestic and foreign investment as well as low quality supporting infrastructures. Geographical distribution regarding labour absorption is captured in Figure 4.2.

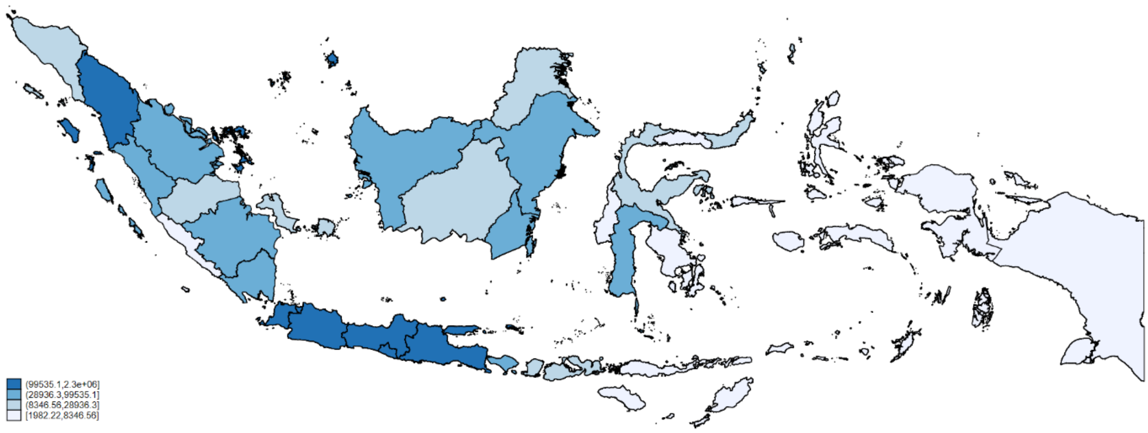


Figure 4.2. Manufacturing workers based on geographical distribution period 2007 - 2015

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

Human capital is an essential factor determining sectoral performance, including in the manufacturing sector. The quality of workers that as represented by their educational attainment, has an important role in determining manufacturing productivity. On average, more than 40 per cent of workers engaged in the manufacturing sector have completed senior secondary education. However, only about 6 per cent had a higher education degree in the period 2007-2015. Sector 30 (office, accounting and computing machinery) is the sector with better human capital conditions compared to others as this sector has more than 30 per cent of workers with degree-level education.

On the other hand, sector 19 (the leather industry) has only 3 per cent of workers with a minimum undergraduate degree. Data presented in Table 4.2 show that the Indonesian manufacturing sector continues to have low education levels in its workforces. Relatively low human capital quality is the main reason why labour efficiency and technology adoption in Indonesian manufacturing have been relatively low, and will affect overall production performance. To deal with this problem, the Indonesian government has promoted many programs to improve human capital, such as: increasing investment in education services in industrial areas where workforces are concentrated, decreasing gaps in skills and education by providing more training programs for workers as well as increasing access to education in relatively less educated rural areas to develop local economy (Indonesia Development Forum, 2019).

Table 4.2. Manufacturing workers based on education (in the human capital quality percentage of total workers) period 2007- 2015

	Sectoral divisions	Unfinished or never	Primary School	Lower Secondary	Upper Secondary	Higher Education
15	Food products and beverages	7.75	23.21	22.82	40.44	5.79
16	Tobacco	9.9	29.46	26.82	29.43	4.39
17	Textiles	4.8	20.4	28.7	41.93	4.17
18	Wearing apparel	3.68	23.87	35.15	34.29	3.02
19	Tanning and dressing of leather	3.35	19.91	30.41	43.32	3
20	Wood and products of wood except furniture and plating materials	7.86	24.88	27.28	36.98	3.01
21	Paper and paper products	2.9	13.25	23.58	53.62	6.65
22	Publishing, printing and reproduction of recorded media	2.06	9.66	16.49	53.47	18.31
23	Coal, refined petroleum products and nuclear fuel	4.05	9.97	10.99	51.47	23.52
24	Chemicals and chemical products	3.02	11.49	18.51	51.63	15.35
25	Rubber and plastics products	3.8	14.57	24.25	51.06	6.33
26	Other non-metallic mineral products	14.45	30.65	19.32	31.35	4.23
27	Basic metals	3.01	12.49	17.23	57.95	9.32
28	Fabricated metal products, except machinery and equipment	5.39	20.23	25.42	44.65	4.31
29	Machinery and equipment n.e.c	2.27	8.58	16.24	61.63	11.29
30	Office, accounting, and computing machinery	0.09	1.65	6.3	57.35	34.62
31	Electrical machinery and apparatus n.e.c	1.85	8.69	15.48	65.18	8.79
32	Radio, television and communication equipment and apparatus	0.8	4.23	8.99	74.4	11.58
33	Medical, precision and optical instruments, watches and clocks	1.88	6.03	17.93	58.57	15.6
34	Motor vehicles, trailers and semi-trailers	1.49	7.6	10.34	68.48	12.08
35	Other transport equipment	2.69	9.9	12.8	65.61	8.99
36	Furniture and manufacturing n.e.c	6.07	25.89	28.86	35.59	3.6
	Whole sector:	**5.49**	**20.32**	**24.94**	**43.26**	**5.99**

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

Workers' ability to move spatially or occupationally is an essential aspect of the labour market. Labour mobility will help the workforce to adjust to any economic shocks or structural changes. Moreover, labour movement may also elevate productivity by raising the probability of job matching conditions in terms of workers' skills or preferences. Labour mobility, in terms of job mobility in this paper, can generally be classified into three categories: similar, related and unrelated sector mobility. Job mobility in a similar sector is defined as when workers move from and to jobs within a similar three-digit ISIC code. Related job mobility is defined as the movement of workers within similar two-digit ISIC, excluding similar mobility. Last, unrelated job mobility happens when workers move between different two-digit ISIC classifications. This classification has been modified based on Franken et al. (2007).

Indonesia's conditions of job mobility are presented in Figure 4.3. In this chart, overall job mobility in large and medium scale manufacturing was relatively low from 2007 to 2015. In the sample, on average, only 8.3 per cent of total workers moved from a different job before engaging in their current job within the one year survey period. Among these movers, the majority of workers moved from an unrelated sector. Around 72 per cent of total movers moved jobs from different divisions of industry, which is different 2-digit ISIC. Moreover, 4.2 per cent of movers moved jobs in a similar industry group (within a similar 3-digit ISIC), and only about 2 per cent of movers had a previous job in a related industry (similar 2-digit ISIC). The rest of the movers' component, unfortunately, was unidentified as there was no information filled in the survey about workers' previous job.

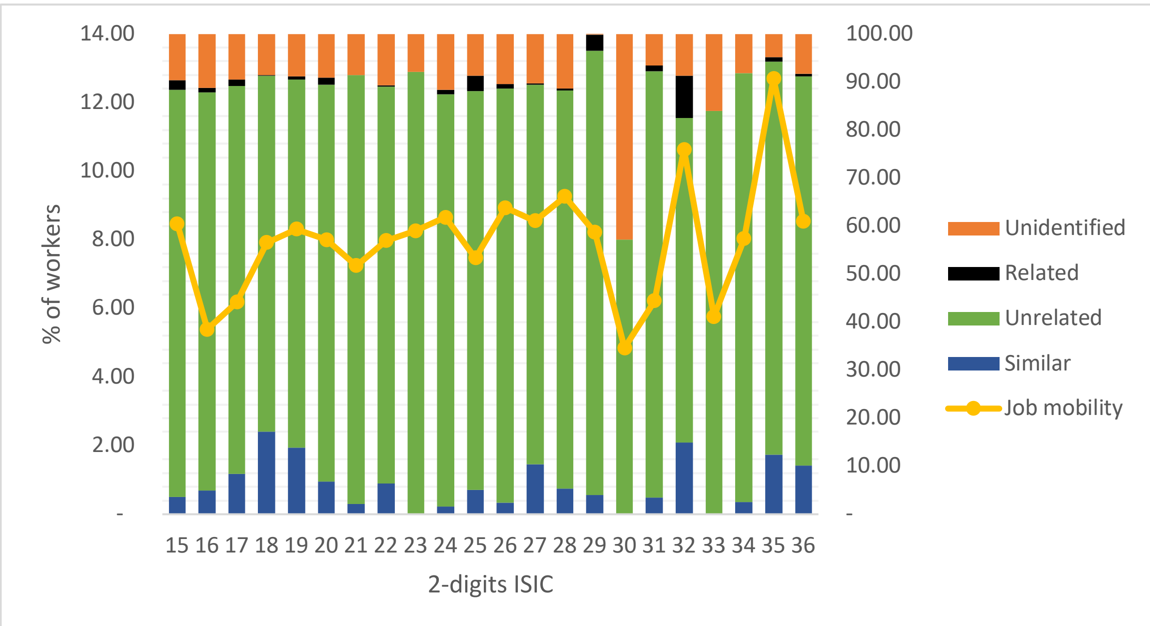


Figure 4.3. Job mobility period 2007-2015

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

Discussing job mobility within unrelated industries is interesting as most workers moved from unrelated industrial divisions to the current job in the large and medium scale manufacturing sector. The most interesting analysis is looking at the economic sectors where workers previously engaged in the labour market. From Table 4.3, it can be inferred that the highest proportion of unrelated job mobility comes from workers who had a previous job in the manufacturing sector as well (Sector 3), comprising almost 30 per cent of total unrelated job movers. This implies that job mobility in the manufacturing sector is less flexible toward different economic sectors. Even though workers can change jobs, most merely moved from a different job division to the current job, but still within the manufacturing sector. Another significant source of labour supply in the manufacturing sector is agriculture (Sector 1). About 20 per cent of movers in manufacturing jobs had experience working in agriculture. This shows the structural change in Indonesia. The third most significant supplier of labour for the manufacturing sector is the trade, hotel and restaurants sector. This sector contributed 17 per cent of total movers.

Furthermore, within the large and medium manufacturing industry, division 15 (food products and beverages) is the highest division accepting workers with experience working in different job divisions. It could be inferred that this sector has relatively high flexibility in facilitating job mobility. On the other hand, division 23 (coal, refined petroleum products and nuclear fuel) is relatively restricted in accepting workers from different job divisions with only 0.54 per cent of movers from total unrelated movers.

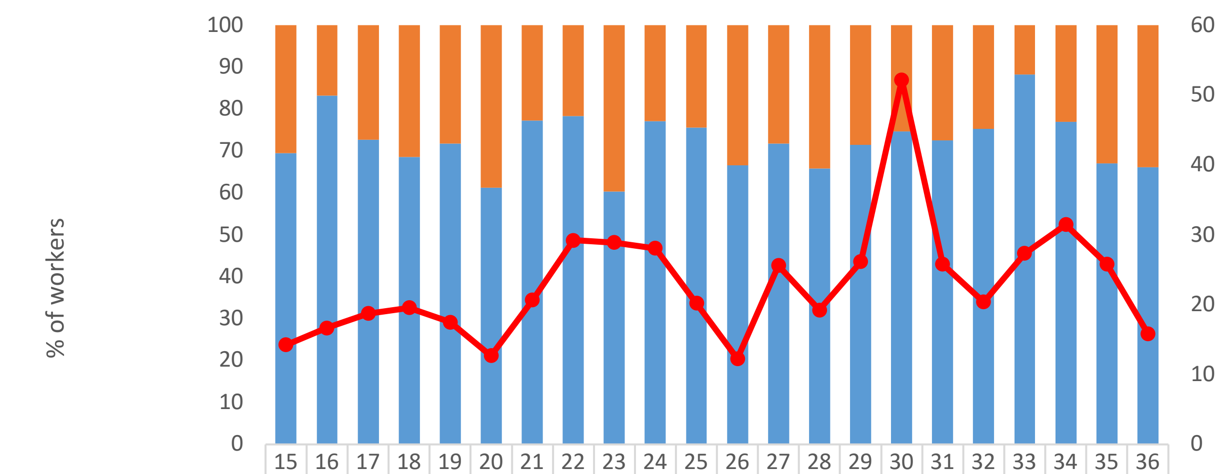
Table 4.3. Job mobility distribution under unrelated industries movement, in the average period 2007-2015

Current Job		Previous job (in economic sectors)									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Overall**
15	Food products and beverages	3.93	0.28	3.74	0.81	2.19	3.53	0.78	0.98	2.85	**19.08**
16	Tobacco	0.43	0.06	0.43	0.13	0.23	0.66	0.1	0.07	0.4	**2.51**
17	Textiles	0.95	0.06	1.54	0.12	0.41	1.67	0.21	0.06	0.75	**5.76**
18	Wearing apparel	2.29	0.07	1.83	0.13	0.92	2.92	0.21	0.18	0.94	**9.49**
24	Chemicals and chemical products	1.03	0.1	1.45	0.22	0.34	0.41	0.22	0.18	0.48	**4.43**
25	Rubber and plastics products	0.89	0.07	1.5	0.22	0.28	0.5	0.07	0.25	0.34	**4.12**
26	Other non-metalic mineral products	1.07	0.04	1.51	0.67	0.44	2.23	0.29	0.35	0.51	**7.13**
27	Basic metals	0.48	0.01	0.54	0.15	0.16	0.18	0.1	0.07	0.13	**1.83**
28	Fabricated metal products, except machinery and equipment	0.84	0.07	1.54	0.12	0.26	0.53	0.13	0.32	0.31	**4.12**
29	Machinery and equipment n.e.c	0.26	0.03	0.45	0.04	0.16	0.16	0.06	0.04	0.1	**1.32**
30	Office, accounting, and computing machinery	0.04	0.34	0.51	0.01	0.41	0.01	0.03	0.01	0.15	**1.53**
31	Electrical machinery and apparatus n.e.c	0.16	0.03	0.41	0.04	0.06	0.15	0.03	0.03	0.04	**0.95**
32	Radio, television and communication equipment and apparatus	0.41	0.01	1.66	0.04	0.13	0.15	0.1	0.04	0.28	**2.83**
33	Medical, precision and optical instruments, waches and clocks	0.04	0.13	0.25	0.03	0.18	0.01	0.12	0.04	0.04	**0.85**
34	Motor vehicles, trailers and semi-trailers	0.25	0.03	0.53	0.01	0.07	0.06	0.07	0.06	0.09	**1.17**
35	Other transport equipment	0.94	0.04	2.19	0.15	0.15	0.31	0.25	0.15	0.28	**4.44**
36	Furniture and manufacturing n.e.c	1.6	0.22	3.27	0.26	0.97	0.98	0.3	0.65	0.85	**9.1**
Overall		**19.29**	**2.01**	**29.48**	**3.97**	**8.86**	**17.07**	**4**	**4.69**	**10.62**	**100**

Note: [1] Agriculture, livestock, forestry and fishery, [2] mining and quarrying, [3] manufacturing industry, [4] electricity, gas and water supply, [5] construction, [6] trade, hotel and restaurants, [7] transport and communication, [8] finance, real estate and business services, [9] services.

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

The second type of labour mobility discussed in this paper is spatial mobility. Due to the limitations of the data available in the survey, geographical mobility here merely takes account of non-permanent workers' mobility, which covers population aged 15 years and above whose place of residence and work location are administratively different (Statistics Indonesia, 2018). On average, from 2007 to 2015, 23 per cent of total manufacturing workers lived in a different regency or municipality from their workplace. Moreover, within the divisions of industry, office, accounting, and computing machinery sector (ISIC 30) had the highest proportion of non-permanent migrant with more than 50 per cent of its workers moved spatially. Among workers whose residential areas were different from their work location, most of the labour force are commuting workers. On average, 68 per cent of total migrant workers commuted from their house to their workplace. The condition of geographical mobility in the manufacturing sector is presented in Figure4. 4.



	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
Noncommuting	30	17	27	31	28	39	23	22	40	23	24	33	28	34	29	25	27	25	12	23	33	34
Commuting	70	83	73	69	72	61	77	78	60	77	76	67	72	66	71	75	73	75	88	77	67	66
Geo-mobility	14	17	19	20	17	13	21	29	29	28	20	12	26	19	26	52	26	20	27	31	26	16

Figure 4.4. Geographical mobility period from 2007-2015

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

The distribution of commuting workers in Indonesia's manufacturing sector across provinces is also fascinating to discuss. This is because the proportion of commuting workers may show the different costs of mobility across areas in Indonesia. This relates to regional development, including infrastructure development, agglomeration and access to transportation. As captured in Figure 4. 5, in relatively more developed areas, the proportion of commuting workers is higher. The highest proportion of commuting workers is in Java and North Sumatera. It can be argued that in those areas, public transportation and infrastructure are better than in other regions. These regions had, on average, 14 per cent of total expenditure spent on infrastructure in the period over 2007-2015 (the World Bank, 2020).

Moreover, in terms of transportation, these regions are supported by relatively well-developed roads, with an average length of district roads of 8800 km for Java and 1800 km for North Sumatera.

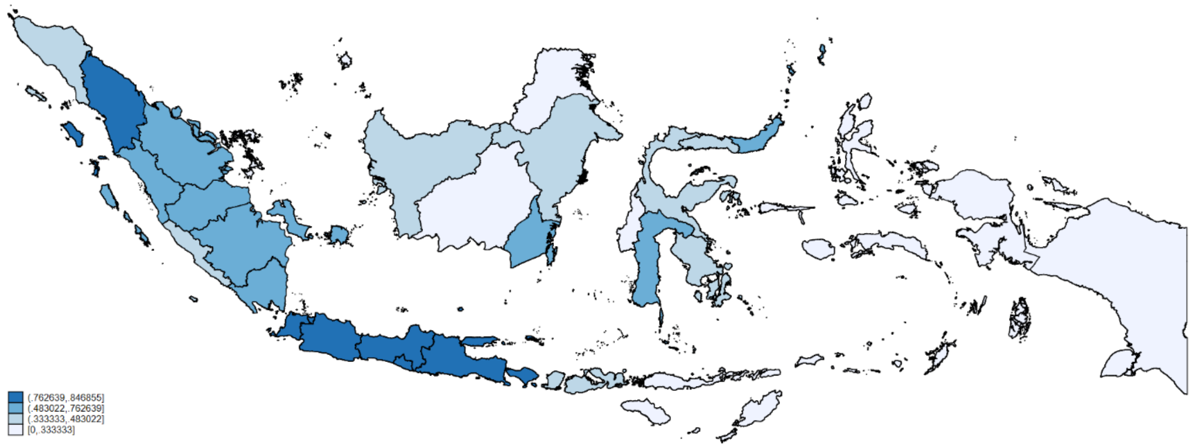


Figure 4.5. The proportion of commuting workers based on geographical dispersion period 2007-2015

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

From the above information, there are some key issues explaining why the Indonesian case fits with the research questions in this paper. First, Indonesia still experiences a high level of wage inequality. Secondly, this country still highly depends on the manufacturing sector in terms of value-added as this sector contributes significantly to Indonesia's GDP. Unfortunately, this high level of output cannot yet be distributed to most Indonesian workers as this sector merely absorbs a low and stagnant level of labourers. This may imply that labour market restrictions exist in Indonesia's manufacturing sector. In fact, a unique labour market characteristic, labour mobility, has also confirmed that geographical mobility has significant influence only in some areas. Furthermore, job mobility in the manufacturing sector has also been restricted as the movement mostly happens among the manufacturing sector itself. Based on these issues, it is arguably essential to analyse how manufacturing jobs and labour mobility affect wage disparity. Moreover, by knowing the relationships among variables, policy implications dealing with wage inequality eradication and labour market restrictions in the manufacturing sector could be drawn.

4.4 Data and Methodology

<u>4.4.1 Data</u>

In order to answer the research questions, data from Indonesia's labour force survey have to be synchronised with the information from the large and medium manufacturing survey. This is because labour characteristics such as labour mobility as well as labour characteristics affecting wages can only be explained in detail by the labour survey. On the other hand, information about the manufacturing industry is collected from manufacturing surveys. Because of the synchronisation and the availability of labour mobility information, this research unit of analysis is an industry group (3-digit level of ISIC) over the period 2007-2015. In the process of synchronisation, the two surveys, defined paid workers in this research as all workers in manufacturing firms working more than 35 hours per week. This definition follows Osterreich (2013) to overcome the problem of limited information about the size of the firm where the labourers worked. The inclusion of defined workers will be matched with firm characteristics gathered from the Indonesian yearly large and medium manufacturing survey because to reduce the effects of small and micro firms' conditions.

For the modelling specifications, there are two dependent variables used in this research, namely conditional wage inequality and unconditional wage inequality. Conditional wage inequality (σ) is estimated by the standard error of the wage regression (Winter-Ebmer and Zweimüller, 1999). This indicator shows how wages received by workers diverges after controlling similar observable worker characteristics such as education, age, gender, and skills. For sensitivity purposes, the wage inequality in this paper is also measured by the unconditional indicator. Unlike conditional measurement, the unconditional indicator measures wage dispersion among workers with different observable characteristics. In this research, the Gini index of wages in each industry group is used as the unconditional measurement. As shown in Table 4.4, generally, unconditional and conditional wage inequality have a positive relationship in an industry group. This means that an industry group with high unconditional wage disparity tends to have a high conditional inequality indicator as well.

Table 4.4. Correlation between conditional and unconditional inequality

ISIC		Correlation	P-value
15	Food products and beverages	0.32	0.03**
16	Tobacco	0.94	0.0002***
17	Textiles	0.04	0.84
18	Wearing apparel	- 0.59	0.06*
19	Tanning and dressing of leather	0.62	0.006**
20	Wood and products of wood except furniture and plating materials	0.31	0.21
21	Paper and paper products	0.57	0.11
22	Publishing, printing and reproduction of recorded media	0.17	0.44
23	Coal, refined petroleum products and nuclear fuel	0.80	0.002***
24	Chemicals and chemical products	0.04	0.85
25	Rubber and plastics products	0.25	0.33
26	Other non-metallic mineral products	- 0.17	0.2
27	Basic metals	- 0.17	0.4
28	Fabricated metal products, except machinery and equipment	0.73	0.0006***
29	Machinery and equipment n.e.c	- 0.08	0.69
30	Office, accounting, and computing machinery	0.08	0.85
31	Electrical machinery and apparatus n.e.c	0.14	0.36
32	Radio, television and communication equipment and apparatus	0.64	0.0003***
33	Medical, precision and optical instruments, watches and clocks	-0.09	0.72
34	Motor vehicles, trailers and semi-trailers	0.70	0.0004***
35	Other transport equipment	0.60	0.003***
36	Furniture and manufacturing n.e.c	0.66	0.003***

Source: Author's estimations.

There are several variables of interest in this paper. The effect of manufacturing jobs is measured by the number of manufacturing workers in each industry group. This variable is then broken down into several groups of workers based on their educational background to analyse what kinds of manufacturing jobs affects wage inequality. The educational background is divided into three groups: low education workers containing workers who attended primary school, unfinished school or never attended school; high school education workers are workers who completed high school; and tertiary education workers whose minimum education is a diploma.

Another crucial variable in this research is labour mobility. Labour mobility is measured by geographical mobility and job mobility. Geographical mobility is defined as non-permanent workers' mobility, which covers the population aged 15 years and above whose place of residence and workplace are different administratively. Spatial mobility is also estimated by differencing commuting and non-commuting workers. Commuting workers are defined as workers who move geographically and commute to their daily work. Meanwhile, job mobility is defined as any workers who stopped or moved jobs to one year before working in their current job. Job mobility is estimated in more detail by dividing into three different types of industry, which are similar industry (movement within the same 3-digit ISIC classification), related industry (movement within the same 2-digit ISIC excluding similar industry movement) and unrelated industry (job movement to a different 2-digit ISIC).

Besides the variable of interest, unique and time-varying factors of industry groups and workers' characteristics in the industry have also been included in the estimations. For the industry group, the variables that are used are capital condition, an industrial group based on technology applied in the production, type of capital ownership, export condition, as well as Java-located factor. Moreover, the proportions of workers based on productive age, skills, gender and wage conditions are included to capture workers' condition in industry groups. Table 4.5 presents the means and standard deviations of variables used in the estimations. Moreover, a multicollinearity test has been performed to ensure that no problem of high collinearity exists in the estimation.

Table 4.5. Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Dependent variable				
Conditional inequality (σ) Unconditional inequality (Gini index)	0.16 0.30	0.12 0.10	0.03 0.1	0.97 0.76
Variable of interests				
Number of manufacturing workers	126,534	180,562	486	1,299,068
Workers with low education (proportion)	0.40	0.19	0	1
Workers with high school education (proportion)	0.50	0.18	0	1
Workers with tertiary education (proportion)	0.10	0.11	0	1
Workers with geographical mobility (proportion)	0.23	0.14	0	1
Workers with job mobility (proportion)	0.08	0.10	0	1
Commuting workers (proportion)	0.16	0.13	0	1
Non-commuting workers (proportion)	0.07	0.10	0	0.75
Workers with similar job mobility (proportion)	0.00	0.01	0	0.11
Workers with unrelated job mobility (proportion)	0.05	0.06	0	1
Workers with related job mobility (proportion)	0.00	0.01	0	0.08
Control variables				
Workers at the age limit (proportion)	0.32	0.12	0	1
Woman workers (proportion)	0.27	0.20	0	1
Workers receiving lower wage than median wage (proportion)	46.21	9.40	0	79.64

Variable	Mean	Std. Dev.	Min	Max
Blue collar workers	0.77	0.16	0	1
Labour-capital ratio	11.71	1.87	5.52	23.19
Capital-output ratio	8.23	147.54	0.00	3,438.14
Low technology firms (proportion)	0.37	0.47	0	1
Medium technology firms (proportion)	0.31	0.44	0	1
High technology firms (proportion)	0.28	0.43	0	1
Combined ownership firms (proportion)	0.88	0.11	0.36	1
Domestic ownership firms (proportion)	0.88	0.11	0.33	1
Local government ownership firms (proportion)	0.01	0.02	0	0.33
Central government ownership firms (proportion)	0.02	0.06	0	0.67
Foreign ownership firms (proportion)	0.17	0.15	0	0.73
Exporting firms (proportion)	0.11	0.09	0	0.44
Firms located in Java (proportion)	0.84	0.14	0.32	1
Number of observations	545			

Source: Author's estimations.

4.4.3 Methodology

The first objective in this research is to analyse the effects of manufacturing jobs on wage inequality in the Indonesian manufacturing sector. To answer this research question, the econometric models used are:

$$y_{it} = \beta + \beta_0\ y_{it-1} + \beta_1 Z_{it} + \beta_2 X_{it} + \delta_i + \eta_t + \varepsilon_{it} \quad (4.1)$$

The above equation predicts the linear relationship between manufacturing jobs and wage inequality. In this research, the quadratic relationship has also been estimated to analyse whether, at some point, the positive effects of manufacturing jobs on wage inequality may dominate or be dominated by the adverse effects. These estimations are made to prove the descriptive plot (Figure 4.6 and 4.7), which shows that a quadratic relationship may occur between wage inequality and the number of workers.

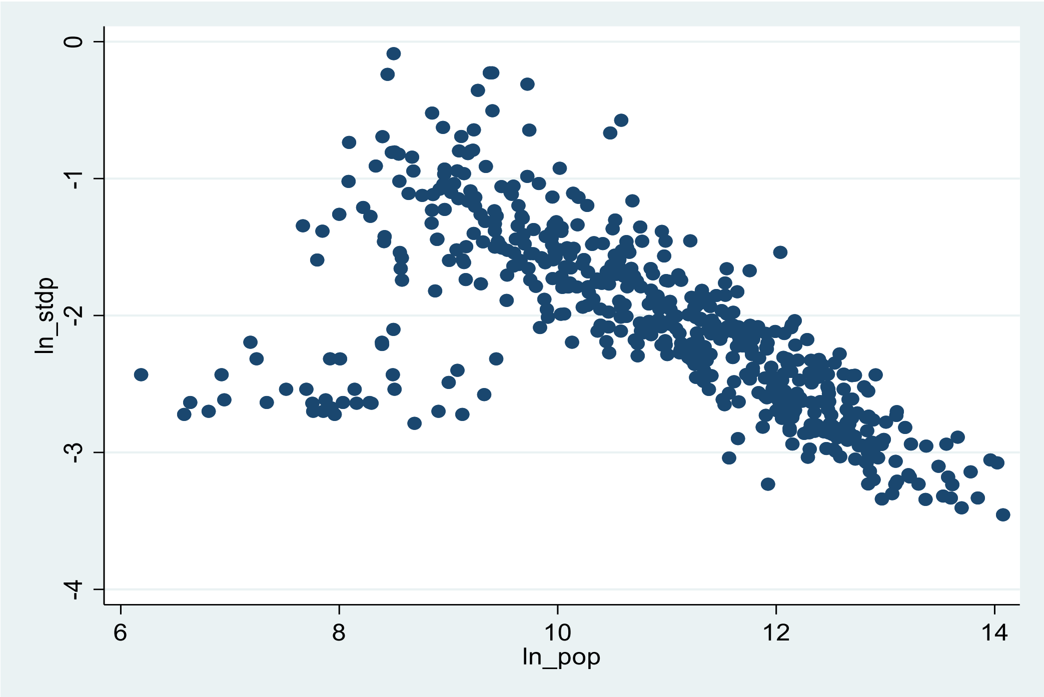


Figure 4.6. Relationship between conditional wage inequality and number of workers

Source: Author's estimations.

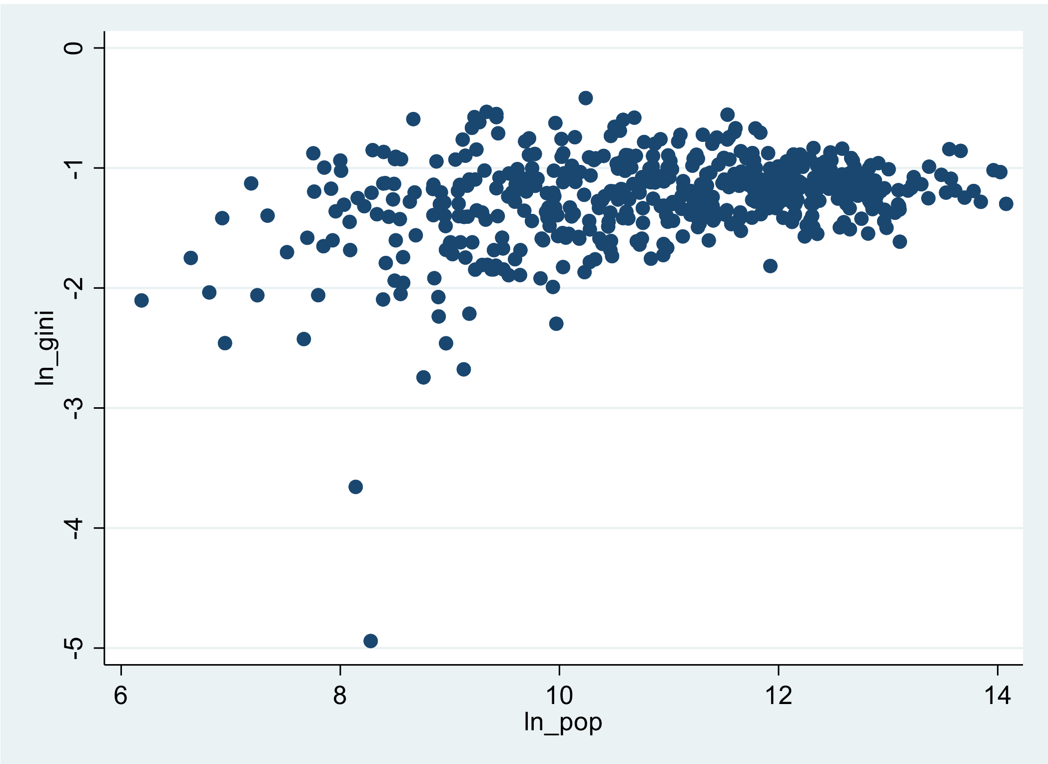


Figure 4.7. Relationship between unconditional wage inequality and number of workers

Source: Author's estimations.

The quadratic relationship between wage inequality and the number of workers can be written as:

$$y_{it} = \beta + \beta_0 \ y_{it-1} + \beta_1 Z_{it} + \beta_2 Z_{it}^2 + \beta_3 X_{it} \ + \delta_i + \eta_t + \varepsilon_{it} \ (4.2)$$

For the industry group i =1,…, N and time periods t= 1,…, T, where y_{it} is the logarithm of conditional or unconditional wage inequality indicators, σ and Gini index respectively. Z_{it} is the logarithm of the number of workers employed in the manufacturing sector at industry group level, X_{it} is a vector of control variables, δ_i is a time-variant industrial characteristic, η_t is a time-specific effect, and ε_{it} is an error term. Lagged explanatory variables are also utilised in the estimations as a robustness analysis.

The second research question of this essay is how labour mobility affects wage inequality in the industrial sector. The econometrics models for answering that question are

$$y_{it} = \alpha + \alpha_0 \ y_{it-1} + \alpha_1 GM_{it} + \alpha_2 JM_{it} + \alpha_3 X_{it} \ + \delta_i + \eta_t + \varepsilon_{it} \quad (4.3)$$

The non-linear relationship between labour mobility and wage distribution is also interesting to analyse as it explains up to what level positive or negative effects of labour mobility dominate effects on wage inequality. The quadratic relationships can be written as follow,

$$y_{it} = \alpha + \alpha_0 \ y_{it-1} + \alpha_1 GM_{it} + \alpha_2 GM_{it}^2 + \alpha_3 JM_{it} + \alpha_4 JM_{it}^2 + \alpha_5 X_{it} \ + \delta_i + \eta_t + \varepsilon_{it} \ (4.4 \ )$$

Where i is an industrial group, t is periods, y_{it} is the conditional or unconditional wage inequality indicators, σ and Gini index respectively. GM_{it} represents geographical mobility measured by the proportion of workers whose workplace and residence are in different administrative areas, JM_{it} reflects job mobility in the labour market measured by the proportion of workers who had changed job within one year before working in the current job, X_{it} is a vector of control variables, δ_i is a time-variant industrial characteristic, η_t is a time-specific effect and ε_{it} is an error term. In order to accommodate the hypothesis of whether the effects of job mobility are also affected by the size of manufacturing, the number of workers employed in each industrial group is also added as one of the control variables into the main models, 4.3 and 4.4. However, based on the results (Appendix 4A.4), the number of people employed and its interactions with interest variables are statistically insignificant. Hence, analysis in this paper is based on main regressions (Equation 4.1 to 4.4). Furthermore, additional estimations using lagged explanatory variables are also done in this paper in order to get a more robust analysis.

Equations 4.1 to 4.4 contain endogeneity problems as the lagged dependent variable may correlate with the error terms. Hence, those equations are estimated by two-step system GMM in dynamic panel data models. This is because the application of the standard OLS or fixed effects least squares to the endogenous model will result in downward bias and even inconsistent estimation because of the Hurwicz bias (Nickell, 1981). It is also difficult to find a strong instrument variable. The particular type of GMM, which is a two-step system GMM, is chosen in this paper because this approach eliminates the problem of small sample bias coming from a small number of individuals (Soto, 2009), which is the case in this paper. Moreover, there are some other advantages of using system GMM in the panel data analysis. First, system GMM uses more moment conditions than difference GMM so it will perform better with nearly non-stationary data (Blundell and Bond, 1998). Second, system GMM will result in more consistent estimators as it does not depend on the second-order serial correlation assumption. Nevertheless, difference GMM has also been utilised in Appendix 4A.3 as a test of sensitivity analysis. Endogenous variables in the main analysis are instrumented by lagged 2 for wage inequality and lagged 1 for manufacturing jobs and labour mobility variables. In fact, different lags are also implemented to provide a robustness check. As it can be seen in Appendix 4.5, different lag applications have similar results as the main analysis. Moreover, the use of orthogonal deviations also confirms the result of primary analysis.

To provide more sensitivity analysis, this paper also implements other robustness checks. First is the implementation of different levels of datasets. In terms of different levels of datasets, this paper uses datasets with different levels of classification structures. In these estimations, instead of using a group of industries (3-digit ISIC), a branch of industrial classification (5-digit ISIC) is used. As the industrial branch has more detailed classification, this data represents more disaggregated industrial activities that reflect more unique observations. The only drawback regarding the analysis is that the data sets are only available from 2007 to 2010. The 5-digit datasets are estimated by the same methodology as the main analysis. Another different dataset implementation is the use of provincial-level data.

The second robustness check is the use of external instrument variables that are estimated by the 2SLS technique. It can be argued that the manufacturing jobs variable is not an exogenous variable, so it is instrumented by the manufacturing employment share over time developed by Bartik (1991). This instrument predicts the share from two sources, which are the initial composition of workers across industry classes (4-digit ISIC) within the industry group (3-digit ISIC) in the base year (t0) and the aggregate labour share in the manufacturing sector across industries over time for the whole national labour force. Formally, the instrument variable showing predicted employment share can be calculated as:

$$\mathrm{Z}_{\mathrm{it=}} \sum_{\mathrm{j=1}}^{\mathrm{J}} \frac{\text{Total workers}_{\mathrm{jt0}}}{\text{Total workers}_{\mathrm{ito}}} \cdot \left(\frac{\text{Total workers}_{\mathrm{jt}}}{\text{Total workers Nt}} - \frac{\text{Total workers}_{\mathrm{jt0}}}{\text{Total workers Nto}} \right)$$

Where Z is predicted manufacturing jobs, *i* is 3-digit ISIC industries, *j* is 4-digit ISIC industries, *to* is the base year, in this case, 2007, and *N* is national level.

The above instrumental variable is used as a change in employment at the national level will affect certain industries where these industries were heavily concentrated in the early period (t_0) relative to the rest of the sectors. Moreover, this instrumental variable is considered as an exogenous factor to the unobserved factors that affect wage inequality over time in each group of industries.

By implementing the similar idea that manufacturing jobs are instrumented by the employment share indicator developed by Bartik (1991), the relationships between labour mobility and wage inequality have also been estimated by the IV technique with different instrumental variables. Geographical mobility and job mobility are instrumented by the past settlement instrument popularised by Card (2009). The idea of the past settlement instrument is similar to the shift-share (Bartik) concept, combining individual-level economic composition with shifts on an aggregate level to predict variation in a dependent variable. The instruments used for geographical mobility (GM) and job mobility (JM) are:

$$\mathrm{GM}_{\mathrm{it=}} \sum_{o=1}^{O} \frac{\text{Total moving workers}_{\mathrm{iot0}}}{\text{Total moving workers}_{\mathrm{ito}}} \cdot \frac{\text{Total moving workers}_{\mathrm{Nt}}}{\text{Total workers}_{\mathrm{it-1}}}$$

$$\mathrm{JM}_{\mathrm{it=}} \sum_{j=1}^{J} \frac{\text{Total moving workers}_{\mathrm{ijt0}}}{\text{Total moving workers}_{\mathrm{ito}}} \cdot \frac{\text{Total moving workers}_{\mathrm{Nit}}}{\text{Total workers}_{\mathrm{it-1}}}$$

Where *i* is 3-digit ISIC, *o* is the district of origin, *to* is the base year which is 2007, *N* is the national level, and *j* is 4-digit ISIC. All identification strategies are estimated by using Stata 16 (StatataCorp, 2019).

4.5 Results and discussion

4.5.1 Effects of manufacturing jobs on wage inequality.

To answer the first question of how jobs in manufacturing affect wage inequality, the number of workers in manufacturing is estimated to explain wage inequality. From Table 4.6, it can be seen that manufacturing jobs have a significant and positive effect on wage inequality, under both conditional and unconditional measurements. This estimation implies that when firms or industry group hire more labour, the wage is more skewed.

Table 4.6. Effects of manufacturing jobs on wage inequality (linear relationship)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =ln_ σ			DEP =ln_GINI		
L.ln_ σ	0.49***	-0.10*	0.01**			
	(0.04)	(0.06)	(0.005)			
L.ln_gini				0.33***	0.10*	0.21*
				(0.038)	(0.06)	(0.084)
ln_Z	0.09***	0.01	0.03***	0.05***	0.03	0.05*
	(0.017)	(0.030)	(0.008)	(0.012)	(0.074)	(0.022)
_cons	-0.52	0.32	0.44	-2.22***	-2.54	-2.07**
	(0.500)	(0.533)	(0.243)	(0.395)	(1.395)	(0.732)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.63	0.31		0.33	0.23	
F-stat	43.88	18.33		11.69	12.99	
Number of instruments			58			58
Hansen statistic-P value > z			0.87			0.99
Diff Hansen test			0.65			0.88
AR2- P value > z			0.86			0.24
Weak instrument test (K- p-value)			0.35			0.12
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Source: Author's estimations.

The positive relationship between firms size and wage inequality doesn't happen to be a linear relationship. An inverted U-shaped relationship between the two variables is evident in the Indonesian manufacturing sector, as represented in Table 4.7. This implies that the number of workers hired increases wage inequality, regardless of whether conditional or unconditional measurement is used. Nevertheless, at some point, when the number of workers is relatively high, wage inequality will drop with both measurements. This means that hiring more labour above the maximum level will reduce wage dispersion. From figures in the appendix (Figure 4A1. And 4A.2) it can be seen that, on average, the optimum number of workers in the industry group causing an increase in conditional disparity is 20,000 and 29,000 people for conditional and unconditional inequality. At any number of workers hired above these optimum points, wage inequality within industry group will decrease. However, the value of these maximum points should be interpreted with care, given the multicollinearity problem between wage dispersion variables in level and squared. This quadratic relationship has also been found when lagged independent variables are used to explain effects on wage disparity, as shown in Appendix 4A.2.

Table 4.7. Effects of manufacturing jobs on wage inequality (a quadratic relationship)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =ln_ σ			DEP =ln_GINI		
L.ln_ σ	0.33***	-0.11*	0.02**			
	(0.043)	(0.06)	(0.009)			
L.ln_gini				0.31***	0.07*	0.21***
				(0.039)	(0.04)	(0.054)
ln_Z	1.19***	0.28*	0.20**	0.30*	0.90*	0.39***
	(0.167)	(0.130)	(0.072)	(0.133)	(0.455)	(0.15)
ln_Z^2	-0.06***	-0.01*	-0.01***	-0.02*	-0.05**	-0.019**
	(0.008)	(0.006)	(0.003)	(0.006)	(0.022)	(0.007)
_cons	-7.37***	-0.87	-0.79	-3.54***	-6.57**	-4.25***
	(1.006)	(0.829)	(0.488)	(0.801)	(2.376)	(0.93)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.67	0.17		0.31	0.25	
F-stat	49.96	25.95		11.35	11.48	
Number of instruments			59			59
Hansen statistic-P value > z			0.85			0.93
Diff Hansen test			0.75			0.65
AR2- P value > z			0.82			0.24
Weak instrument test (K p-value)			0.19			0.49
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets

Source: Author's estimations.

By looking at the optimum points from the regressions, it is also important to analyse which industrial groups are hiring numbers of workers less than the threshold points. Figure 4.8 illustrate two different conditions concerning the number of workers hired in each industry group. The first condition, which is represented by a bar chart, is the top ten group of the industries contributing labour absorption in the Indonesian manufacturing sector. From the chart, it can be seen that most workers are engaged in low technology industries, with the highest labour absorption in group 181 or the group of garments except fur apparel. The only medium-low technology industry in the top ten is the group of plastic product (sector 252). The second aspect illustrated in the chart is the group of industries that have numbers of workers less than the optimum point of conditional and unconditional wage inequality. Based on conditional inequality, there are 23 industry groups that have fewer than 2000 people, which are presented by red-dotted markers in Figure 4.8.

Meanwhile, according to the Gini index, there are 28 industries hiring workers at less than the optimum point that can reduce wage disparity. These industries are presented by red and black dotted markers in Figure 4.8. Industry groups that fall into the non-optimum size of workers are dominated by medium and high technology industries. There are only four low technology industries hiring less than the thresholds, namely dairy products, cotton, dressing and dyeing, and reproduction of recorded media industry.

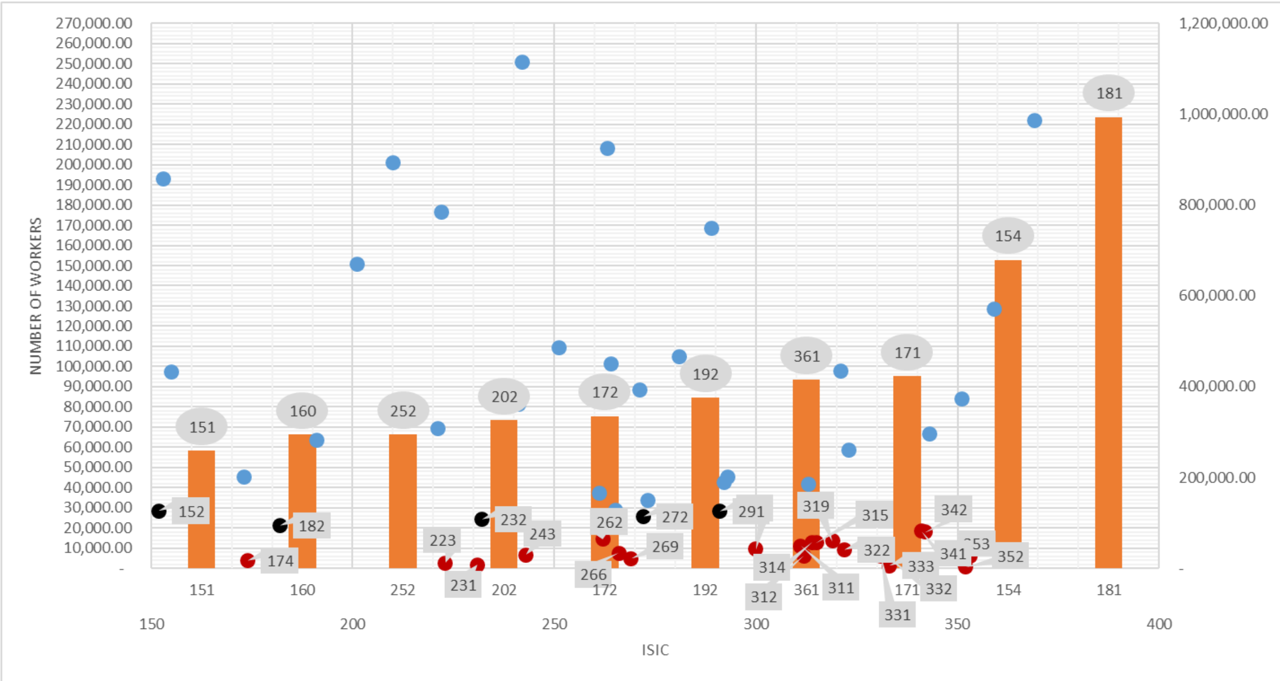


Figure 4.8. Average number of workers in each industry group

Source: Author’s calculation based on Indonesia’s labour force survey 2007-2015

A possible reason that wage inequality increases when firms grow, but when the size is relatively big, is that workers heterogeneity decreases. It has been argued (Davis and Haltiwanger 1995, Fox, 2004 and Lallemand and Ryck, 2006) that when firms are relatively small, they implement relatively more diversified technology and have more heterogeneous workers. In contrast, when firms grow in terms of size, they apply more standardised technology that requires more homogenous workers, particularly a certain level of skill in order to utilise the technology.

The argument about worker diversity differing across firm size has been evident in the Indonesian manufacturing sector. From Figure 4.9, it can be seen that workers’ skill diversity index is higher when the number of workers is smaller. On the other hand, when firm size grows, the index is decreasing. The negative correlation between the diversity index and manufacturing jobs implies that smaller size industry group tend to have more heterogeneous workers, leading to more diversified wages. In contrast, as bigger firms need more homogenous skills of workers to operate specific technology, the wage paid is relatively more compressed.

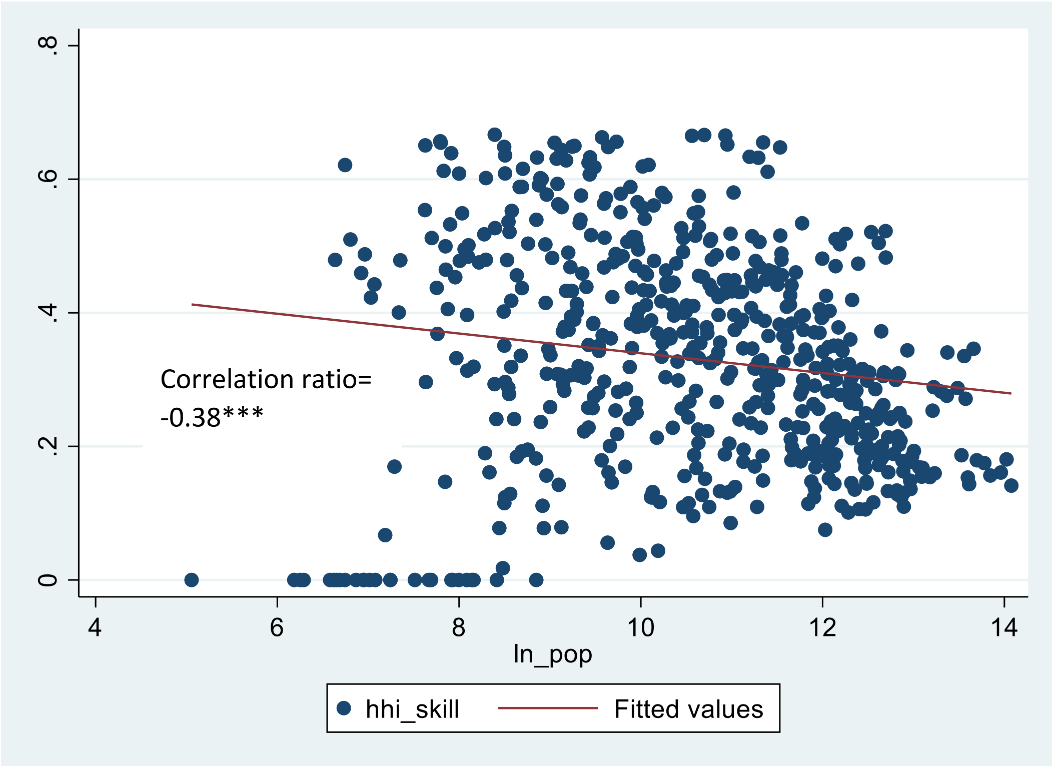


Figure 4.9. Workers' skill diversity and number of workers

Source: Author's calculation based on Indonesia's labour force survey.

Note: Workers skill diversity is measured by $HHI_{it} = 1 - \sum_{m=1}^{Mit} s_{mit}^2$ where s_m is the share of workers that falls into each category m skill of group i at time t. This index is equal to zero if only one category is represented in the firm. The higher the index more heterogeneous skill having in the firm.

Other possible reasons explaining why wage inequality drops when the number of workers is relatively big is related to clustering and wage rate compliance. According to Song et al. (2019), workers are clustered based on their wages. Bigger firms that pay their workers high will be clustered with high-paid workforces. Furthermore, the bigger the firms, the higher the wage rate compliance leading to greater wage compression (Davis and Haltiwanger, 1995). These arguments can also be seen in the Indonesian manufacturing sector. From Figure 4.10, it can be seen that a relatively high proportion of workers receiving wage less than the industrial group median is found mainly in the low class of firm size from 1st to 4th decile. Furthermore, evidence about wage compliance indication can be seen from Figure 4.11. This figure plots the proportion of workers receiving wage at least as high as the minimum wage. The figure shows that in the low class of the industrial group, some groups have zero proportion of workers receiving at least the minimum wage, 1st and 2nd decile. This implies that smaller industrial groups, there are groups that pay all their workers lower than the minimum wage. In contrast, in bigger industries, there is no case for paying all workers with wages less than the minimum rate. At least 20% of workers receive a wage equal to or more than the minimum wage.

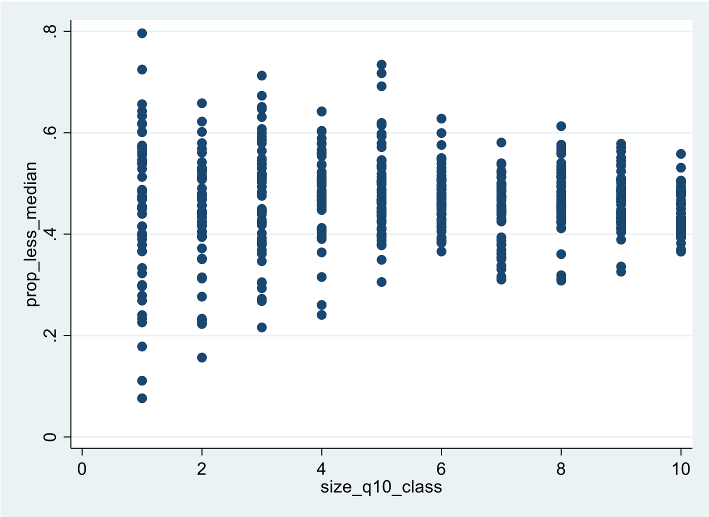


Figure 4.10. The proportion of workers receiving less than the median wage and size of the industry

Source: Author’s calculation based on Indonesia’s labour force survey.

Notes: x-axis is classes of firm size in deciles. Y-axis is the proportion of works receiving wage lower than the group median.

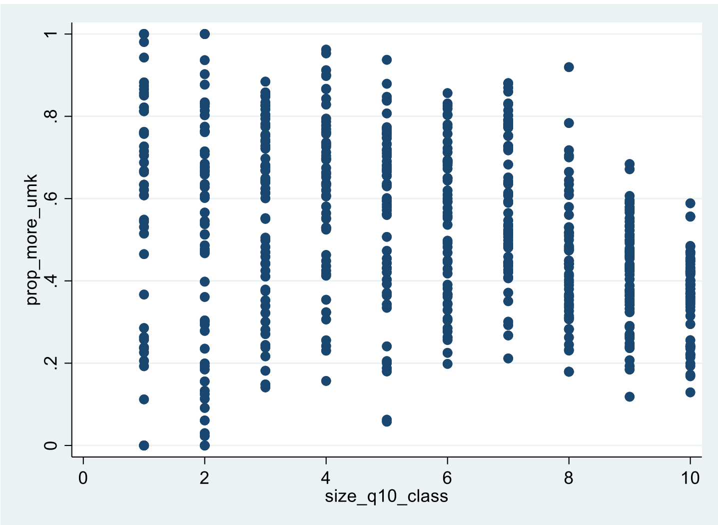


Figure 4.11. The proportion of workers receiving less than the median wage and size of the industry

Source: Author’s calculation based on Indonesia’s labour force survey.

As job absorption has a significant role in the Indonesian manufacturing sector, as explained above, it is arguably important to discuss what type of workers based on their education affects wage disparity. By implementing a quadratic estimation (Table 4.8), it is estimated that only the proportion of lower and high school educated workers has statistically significant effects on wage dispersion, although the relationship has different shapes. The proportion of workers having lower education (maximum junior high school level) has a U-shaped relationship with conditional wage inequality. This means that when the proportion increases up to the threshold, which is 39 per cent, wage inequality drops. However, if an industry hires low-educated workers above that limit, wage disparity will increase.

In contrast, the ratio of workers who graduated from senior high school has a significant inverted – U- shaped relationship with conditional and unconditional wage disparity. This implies that when the industry hires workers beyond the threshold, which is 52 per cent for conditional and 59 per cent for unconditional inequality, job absorption will reduce wage inequality. The proportion of workers having tertiary education does not have significant effects on wage inequality. This may be due to the relatively insignificant proportion among the total workers on average. The estimations about manufacturing jobs based on education background provide additional evidence that the problem of the low-level human capital in Indonesia's manufacturing sector remains a big issue, and needs to be resolved for better outcomes, including inequality within the sector.

Table 4.8. Effects of manufacturing jobs based on education types on wage inequality (quadratic relationships)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP = σ			DEP =GINI		
L. σ	0.37***	-0.10**	0.12**			
	(0.04)	(0.05)	(0.06)			
L.gini				0.40***	0.08	0.27**
				(0.04)	(0.08)	(0.11)
p_lower	-0.5*	-0.32*	-1.59***	-0.09	-0.10	-0.28
	(0.12)	(0.18)	(0.40)	(0.16)	(0.21)	(0.50)
p_lower_sq	0.01***	0.005**	0.02***	0.002	0.003**	0.01
	(0.001)	(0.002)	(0.004)	(0.001)	(0.001)	(0.00)
p_high	0.47**	0.58***	1.18***	0.34***	0.52***	1.04*
	(0.17)	(0.18)	(0.41)	(0.13)	(0.19)	(0.58)
p_high_sq	-0.004**	-0.01***	-0.01***	-0.003**	-0.004***	-0.01*
	(0.002)	(0.002)	(0.004)	(0.002)	(0.001)	(0.005)
p_ter	0.06	0.07	0.09	0.3***	0.39***	0.01
	(0.17)	(0.16)	(0.33)	(0.1)	(0.13)	(0.38)
p_ter_sq	-0.001	-0.002	-0.003	-0.004**	-0.003	0.004
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)
_cons		0.23	-0.11		-0.21	-0.21
		(0.27)	(0.34)		(0.37)	(0.52)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.41	0.25		0.33	0.28	
F-stat	13.13	4.06		9.37	10.86	
Number of instruments			63			63
Hansen statistic-P value > z			0.99			0.59
Diff Hansen test			0.96			0.36
AR2- P value > z			0.45			0.19
Weak instrument test (K p-value)			0.25			0.18
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Source: Author's estimations.

4.5.2 Effects of labour mobility on wage inequality.

The second aim of this paper is to know how labour mobility, geographically and across industries, affects wage inequality. From Table 4. 9, it can be seen that job and spatial mobility generally do not have significant effects on wage disparity in the Indonesian manufacturing sector when estimated by a linear model. From all the estimations, job mobility only has a significant relationship with unconditional inequality. It has a positive relationship which implies that labour movement between groups of the industry will increase wage disparity. The effects of labour mobility on disparity may depend on the size of manufacturing. To address this idea, manufacturing size and interaction with labour mobility variables have been included as additional control variables. As shown in Appendix 4A, those variables are not statistically significant; hence the primary analysis below is based on the main model.

Table 4.9. Effects of labour mobility on wage inequality (linear relationship)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP = σ			DEP =GINI		
L. σ	0.38***	-0.09	0.01			
	(0.04)	(0.06)	(0.08)			
L.gini				0.46***	0.09	0.3**
				(0.04)	(0.07)	(0.1)
GM	-0.03	-0.02	-0.02	-0.03	-0.03	-0.04
	(0.04)	(0.08)	(0.14)	(0.03)	(0.06)	(0.1)
JM	0.08	0.08	0.05	0.05	0.09	0.41***
	(0.08)	(0.11)	(0.33)	(0.07)	(0.14)	(0.12)
_cons	0.03	0.39	0.63	-0.07	0.009	0.05
	(0.13)	(0.35)	(0.42)	(0.11)	(0.37)	(0.45)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.395	0.224		0.284	0.226	
F-stat	14.9	18.7		9.06	5.05	
Number of instruments			57			57
Hansen statistic-P value > z			0.89			0.73
Diff Hansen test			0.78			0.66
AR2- P value > z			0.79			0.92
Weak instrument test (K p-value)			0.26			0..43
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Source: Author's estimations.

Unlike the linear estimation, when labour mobility and wage inequality variables are estimated by quadratic estimation, non-linear relationships between those variables were statistically significant in the Indonesian manufacturing sector for the period 2007-2015 as shown in Table 4.10. It is estimated that spatial mobility will reduce wage inequality up to a certain level; once it goes beyond this level, disparity will rise. From the coefficients, it is found that the thresholds for the proportion of workers who move geographically are at 54 and 58 per cent for conditional and unconditional wage inequality, respectively. Unlike spatial mobility, job mobility among industry has an inverted U-shaped relationship with maximum level of 47 per cent for conditional disparity and 50 per cent for unconditional inequality. This means that when the proportion of workers who experience job movement goes beyond these levels, job mobility will reduce wage disparity among industries. The hypothesis of whether labour mobility depends on manufacturing size can only be evident in job mobility measurement with a negative and significant coefficient (as presented in Appendix 4A). This coefficient implies that manufacturing size will reduce the negative impact of labour mobility on disparity.

Table 4.10. Effects of labour mobility on wage inequality (a quadratic relationship)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP = σ			DEP =GINI		
L σ	0.37***	-0.07	0.12**			
	(0.04)	(0.05)	(0.05)			
L.gini				0.42***	0.08*	0.36***
				(0.04)	(0.05)	(0.08)
GM	-0.13	-0.21**	-0.51**	0.07	-0.06	-0.68**
	(0.10)	(0.11)	(0.21)	(0.08)	(0.09)	(0.29)
GM^2	0.23	0.32**	0.47**	-0.09	0.09	0.58*
	(0.12)	(0.13)	(0.22)	(0.10)	(0.11)	(0.31)
JM	0.12	0.24*	0.56*	0.38***	0.29**	0.56**
	(0.14)	(0.14)	(0.29)	(0.11)	(0.12)	(0.29)
JM^2	-0.06	-0.53***	-0.60*	-0.75***	-0.67***	-0.55***
	(0.20)	(0.20)	(0.35)	(0.16)	(0.17)	(0.21)
_cons	0.04	0.56**	0.16	-0.14	-0.06	0.34***
	(0.13)	(0.27)	(0.26)	(0.10)	(0.24)	(0.10)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.37	0.15		0.29	0.28	
F-stat	13.79	2.63		9.67	4.55	
Number of instruments			61			61
Hansen statistic-P value > z			0.99			0.88
Diff Hansen test			0.94			0.78
AR2- P-value			0.30			0.20
Weak instrument test (K p-value)			0.2			0.45
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.
Source: Author's estimations.

By analysing the threshold, it can be inferred that there are some industry groups that need to increase their labour intake coming from their own region. This is because the proportion of workers from outside the region is above the threshold that may hamper wage inequality. Figure 4.12 displays the average proportion of mobile workers in the manufacturing industry. This implies that the most attractive industry group for mobile workers is medium-high and high technology industries. Those industries which are represented by the orange and red dotted plot have proportions of workers beyond the threshold for conditional measurement only and both measurements respectively. From those industries, only group 223 (reproduction of recorded media industry) is classified as a low-technology industry but with a relatively high intake of mobile workers. These industry groups need to increase their job creation from domestic regions.

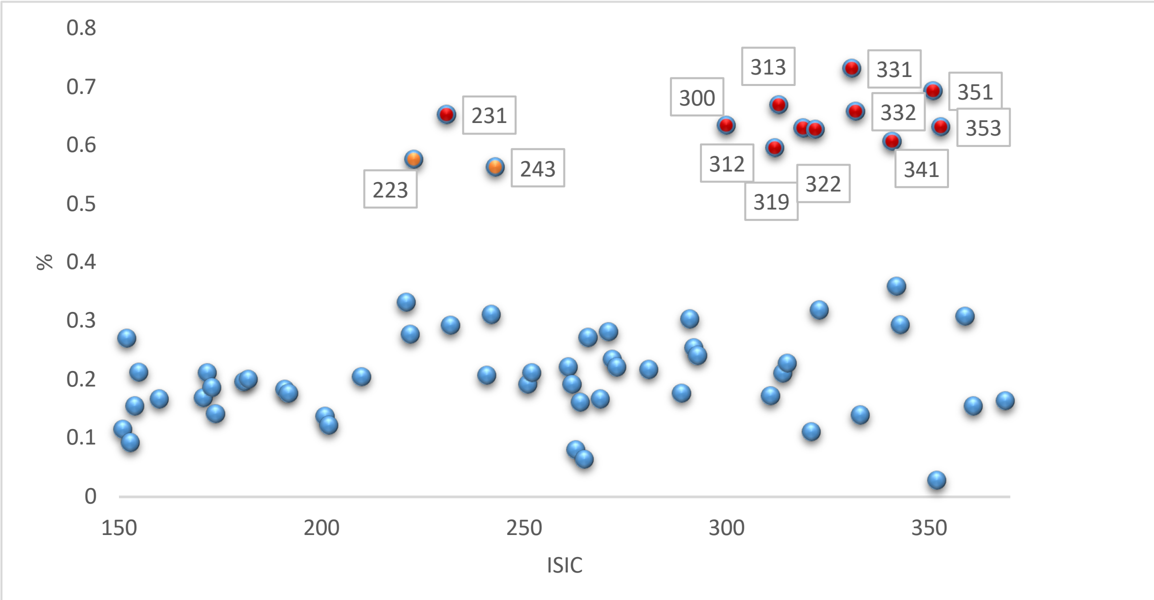


Figure 4.12. The proportion of workers moving from different regions

Source: Author’s calculation based on Indonesia’s labour force survey 2007-2015

Different patterns for job mobility phenomenon have been evident in the Indonesian manufacturing sector. For this type of mobility, a higher proportion of workers having experience from different jobs will promote equality in the industry. However, from all industry groups, only six groups pass the negative effect threshold. Those industries are illustrated by orange dots, which pass the limit based on conditional inequality only and green dots, which pass both measurements. The six industries are the cotton industry, coal-based industries, manmade fibres, television/radio transmitters: line communication apparatus, lighting equipment and electric lamps and metal product recycling. On the other hand, all other groups of industry need to be more open to workers with experience from different jobs. The proportion of workers with job mobility experience is illustrated in Figure4. 13.

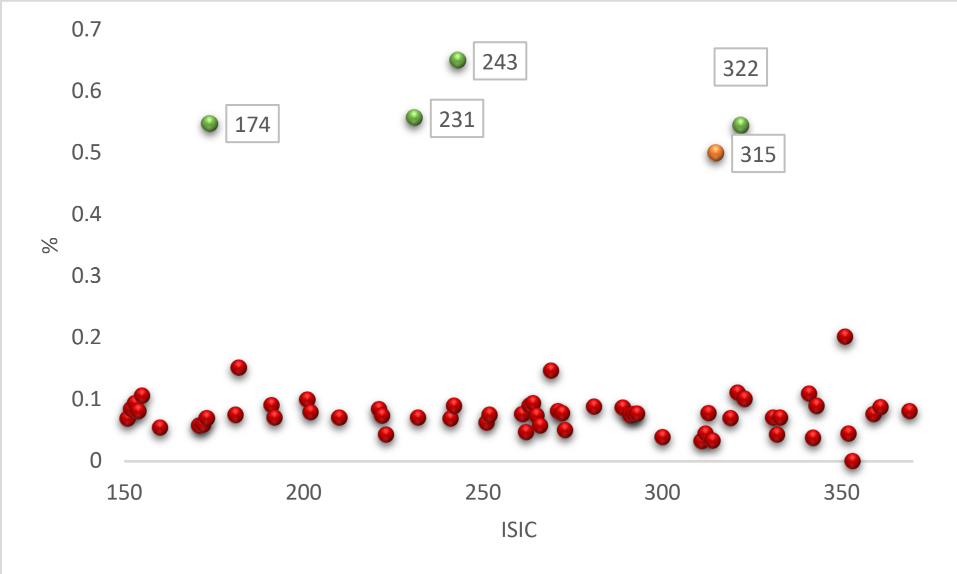


Figure 4.13. The proportion of workers moving from different regions

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

There are some possible reasons to explain why, at some point, spatial mobility in the labour market will reduce wage inequality but later will hinder the disparity. Based on Kanbur and Rapoport (2015), the positive impacts of geographical mobility on inequality are because this type of mobility will put downward pressure on wage in the destination area. The first factor causing wage pressure is that mobile workers generally move from low wage to high wage regions. Secondly, mobile workers that are dominated by low-skill workers will compress wages downward. These two factors are apparent in the Indonesian manufacturing sector. From Figure 4.14, it can be seen that more than 50 per cent of mobile workers move from low to high wage regions. It is also evident that workers who move geographically are dominated by workers in the low-skill job classification. The composition of labour mobility by skill can be seen in Figure 4.15. Furthermore, when labour mobility in terms of location is too high, it will increase wage inequality because of workers heterogeneity. If workers in the labour market are too heterogenous, it will cause asymmetrical effects and human capital redistribution that will increase disparity (Østbye and Westerlund, 2007; Elhorst, 2003). Moreover, Pan and Mukhopadhaya (2016) also argued that workers heterogeneity has a significant effect on wage disparity. Workers heterogeneity phenomenon can be found in Indonesia's labour market. The human capital represented by education background among mobile workers is relatively varied. It can be seen in Figure 4.16 that the proportion of mobile workers based on education is spread. There is no level of education that particularly dominates in the composition.

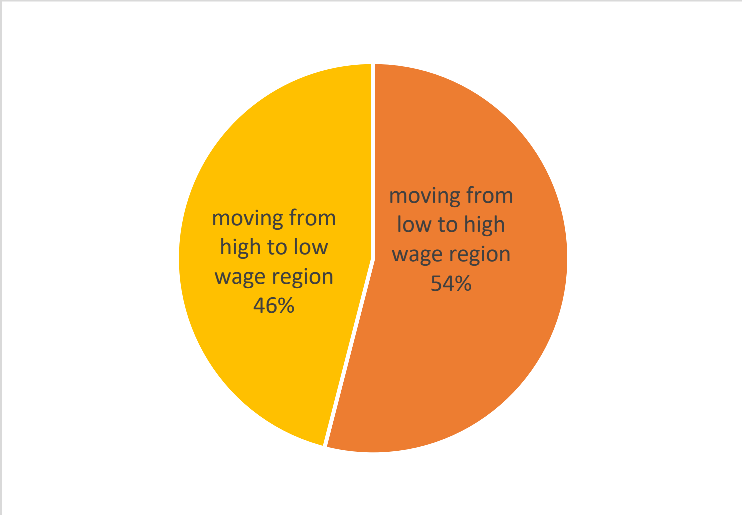


Figure 4.14. Percentage of workers moving geographically

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

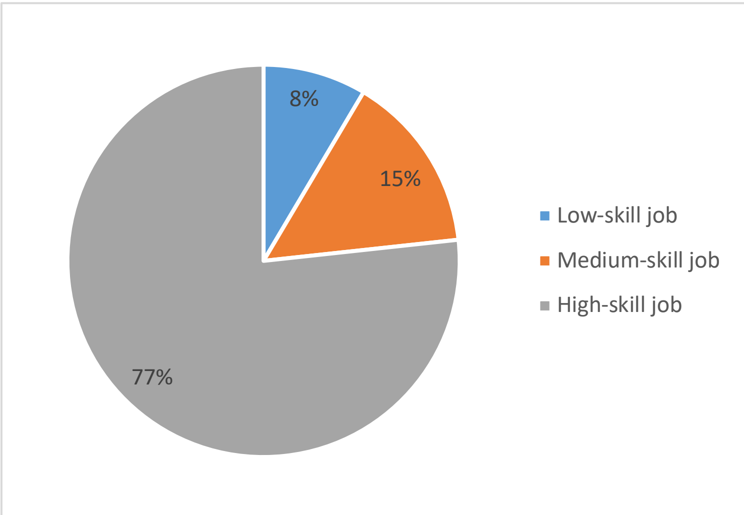


Figure 4.15. Percentage of workers moving geographically based on skill

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

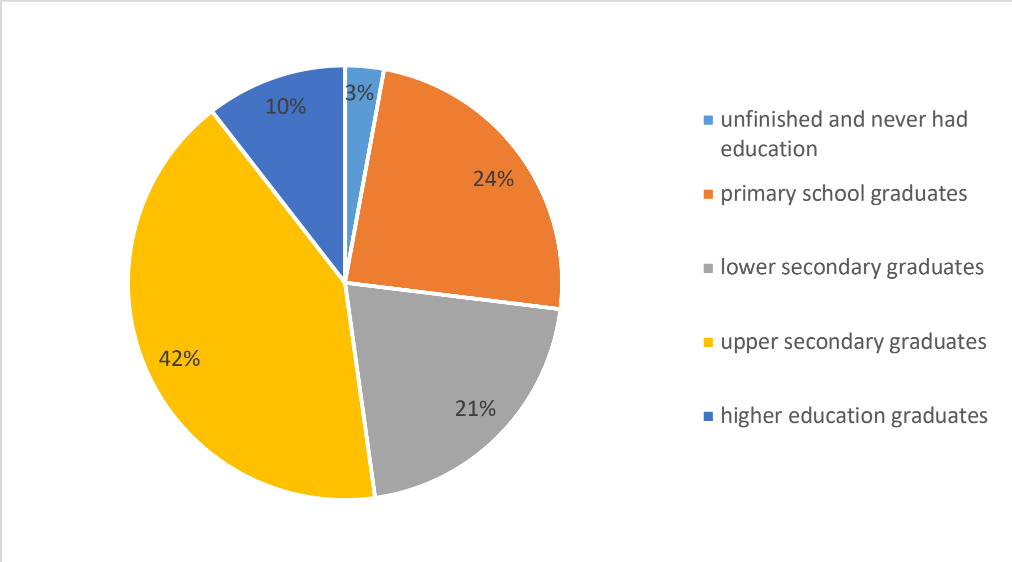


Figure 4.16. Percentage of workers moving geographically based on education background

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

There is also a possible factor that can explain why most industrial groups in Indonesia are still in the position where job mobility hinders wage disparity. The possible reason is related to the mismatch factor. As argued by Park (2019), skill mismatch will create labour mobility frictions that negatively affect wage distribution. The skill mismatch hypothesis can also be found in the Indonesian manufacturing labour market. Based on Presidential Law Number 8 the Year 2012 about jobs and competencies, the minimum education level required for level 3 occupations, which is technicians and associate professionals, is a diploma (Indonesia, 2012). However, from Figure 4.17, it can be observed that the majority of workers in level 3 occupations have upper-secondary level education, which is lower than a diploma. Similar to that, in level 2 occupations, which is professionals, the Indonesian government requires minimum education at undergraduate or tertiary level. However, based on the data (Figure 4.18), 43 per cent of workers at this level still have less than he tertiary level of education. These two figures may reflect that skill mismatch has been a concern in the Indonesian manufacturing sector.

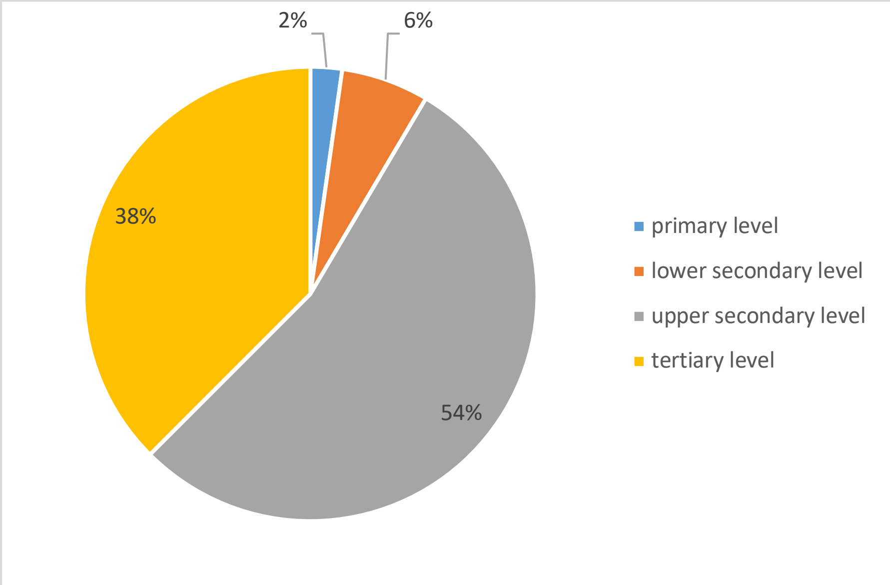


Figure 4.17. Level 3 occupation (Technicians and associate professionals) based on educational background

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

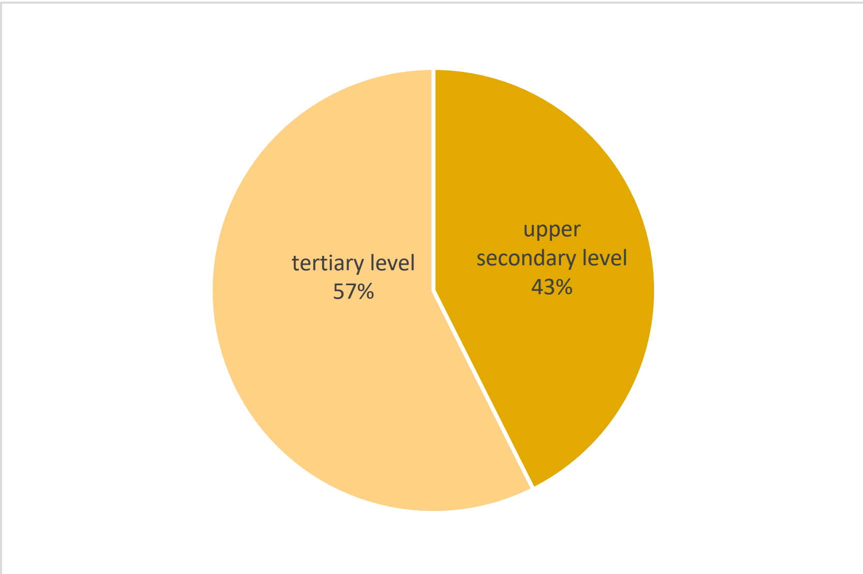


Figure 4.18. Level 2 occupation (Professionals) based on educational background

Source: Author's calculation based on Indonesia's labour force survey 2007-2015

Analysing more details, types of geographical and occupational mobility are also essential. Spatial mobility is estimated by the proportion of commuting and non-commuting workers. And job mobility is decomposed into three types of mobility. All estimations are in linear function as the quadratic function estimations are not statistically significant. Based on the regression, it is found that commuting does not have significant effects on wage disparity in the industrial group. On the other hand, some types of occupational movement have a significant relationship with wage dispersion. It is estimated that the proportion of workers with previous experience in similar and related industries brings positive impacts on wage disparity. The effects of specific types of labour mobility on wage disparity are displayed in Table 4.11.

Table 4.11. Effects of labour mobility on wage inequality (based on specific types of mobility)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP = σ			DEP =GINI		
L. σ	0.37***	-0.09*	0.16**			
	(0.04)	(0.05)	(0.06)			
L.gini				0.45***	0.17*	0.31**
				(0.04)	(0.07)	(0.10)
p_comm	0.05	-0.01	-0.05	-0.02	-0.03	-0.17*
	(0.05)	(0.05)	(0.10)	(0.04)	(0.05)	(0.10)
p_noncomm	-0.01	0.08	-0.06	0.06	0.04	-0.03
	(0.05)	(0.06)	(0.12)	(0.04)	(0.06)	(0.09)
p_sim	-0.90*	-0.11	-5.60**	-0.35	-1.00**	-2.58**
	(0.49)	(0.49)	(2.50)	(0.41)	(0.35)	(1.33)
p_rel	-0.35	-0.38	-9.13***	0.44	-0.17	-6.72*
	(0.81)	(0.77)	(2.95)	(0.67)	(0.47)	(3.64)
p_un	-0.03	-0.07	0.12	-0.04	-0.05	-0.23
	(0.08)	(0.08)	(0.19)	(0.07)	(0.14)	(0.17)
_cons	0.07	0.39	0.90**	-0.06	0.09	0.38
	(0.13)	(0.27)	(0.36)	(0.11)	(0.39)	(0.37)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.37	0.23		0.29	0.14	
F-stat	13.17	3.74		7.95	5.47	
Number of instruments			62			62
Hansen statistic-P value > z			0.97			0.97
Diff Hansen test			0.94			0.96
AR2- P value > z			0.65			0.58
Weak instrument test (K p-value)			0.43			0.36
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Source: Author's estimations.

4.5.3 Robustness Check

4.5.3.1 Implementation of different data-sets

4.5.3.1.1 Using 5-digit ISIC datasets

Table 4.12 shows that in both conditional and unconditional wage inequality, an inverted-U-shaped relationship between manufacturing jobs and wage dispersion exists in the new dataset. The parameters reveal that the relationships are statistically significant in the estimation of standard deviation and Gini index variables. It is logically correct to argue that in the more disaggregated data of the manufacturing industry, hiring more labour will reduce wage inequality as long as the number of workeris relatively high. This argument supports what has been found in the primary analysis.

Table 4.12. Quadratic relationships between manufacturing jobs and wage inequality in the manufacturing industry using 5-digit ISIC

	OLS	FE	SYS GMM	OLS	FE	SYS GMM
	DEP= ln_σ			DEP=ln_GINI		
L.ln_ σ	0.72***	-0.39***	0.30***			
	(0.023)	(0.063)	(0.104)			
L.ln_gini				0.16***	0.38***	0.053
				(0.034)	(0.062)	(0.083)
ln_Z	0.003	0.019	0.057**	0.05***	0.05*	0.05***
	(0.058)	(0.020)	(0.03)	(0.012)	(0.022)	(0.010)
ln_Z^2	-0.002	-0.001	-0.004**	-0.002***	-0.003*	-0.002***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
_cons	-1.132	0.22	-0.134			
	(1.14)	(0.26)	(0.29)			
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.74	0.31		0.18	0.21	
F-stat	12.9	7.06		9.16	5.19	
Number of instruments			49			49
Hansen statistic-P value > z			0.64			0.16
Diff Hansen test			0.62			0.14
AR2- P value > z			0.47			0.22
Weak instrument test (K p-value)			0.26			0.67
Number of groups	307	307	307	307	307	307
N	858	858	858	858	858	858

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Source: Author's estimations.

Control variables are similar to the main regressions.

Similar to what is found in the manufacturing jobs estimations, labour mobility has a similar pattern in the new dataset estimations as in the primary one. Estimation results expose that spatial labour mobility has a U-shaped relationship pattern with wage dispersion. On the other hand, job mobility and wage inequality are correlated in an inverted U-shaped pattern. These two different patterns of relationships are statistically significant only in the estimation of the Gini Index. The estimations for labour mobility and wage inequality are presented in Table 4.13.

Table 4.13. Quadratic relationship between labour mobility and wage inequality in the manufacturing industry using 5-digit ISIC

	OLS	FE	SYS GMM	OLS	FE	SYS GMM
	DEP= σ			DEP=GINI		
L.σ	0.59***	-0.39***	0.22			
	(0.029)	(0.065)	(0.869)			
L.gini				0.30***	-0.33***	0.02
				(0.03)	(0.04)	(0.09)
GM	-0.000	-0.001	-1.29	-0.31***	-0.16**	-0.25*
	(0.03)	(0.04)	(1.76)	(0.05)	(0.06)	(0.12)
GM^2	0.02	0.002	0.92	0.43***	0.23**	0.34*
	(0.03)	(0.06)	(1.82)	(0.06)	(0.07)	(0.13)
JM	0.11	0.16	0.78	0.22	0.41	0.31
	(0.31)	(0.14)	(12.75)	(0.56)	(0.58)	(0.89)
JM^2	-0.21	-1.13	-8.51	-0.43***	-0.23**	-0.34*
	(2.4)	(0.68)	(16.25)	(0.06)	(0.07)	(0.13)
_cons	0.06	0.09	6.48	0.61	0.09	6.48
	(0.21)	(0.22)	(9.36)	(0.21)	(0.22)	(9.36)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.51	0.19				
F-stat	41.32	5.74				
Number of instruments			51			51
Hansen statistic-P value > z			0.87			0.24
Diff Hansen test			0.88			0.32
AR2- P value > z			0.43			0.14
Weak instrument test (K p-value)			0.97			0.77
Number of groups	307	307	307	307	307	307
N	858	858	858	858	858	858

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Control variables are similar to the main regressions.

Source: Author's estimations.

4.5.3.1.2 Using provincial-level datasets

The existence of a quadratic relationship between labour absorption and wage inequality in the manufacturing sector has also been estimated using provincial-level data over the same time frame, 2007-2015. In this robustness check, the aim is to see whether wage inequality in the manufacturing sector at the regional level is also affected by the number of people employed in this sector. Based on the estimations, it can be inferred that manufacturing jobs at a regional level have similar effects on wage disparity as at the industrial level. This implies that with a relatively low number of people employed in manufacturing jobs, wage equality at the provincial level will worsen. However, with a relatively high level of manufacturing jobs available, wage inequality will drop. The estimated thresholds for the number of people employed that can reduce disparity are 22,026 and 28,283 for unconditional and conditional measurement, respectively. The estimations are presented in Table 4.14.

Table 4.14. Quadratic relationship between manufacturing jobs and wage inequality in the manufacturing industry using provincial data

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =ln_ σ			DEP =ln_GINI		
L.ln_ σ	0.87***	0.59***	0.63***			
	(0.03)	(0.05)	(0.04)			
L.ln_gini				0.58***	0.11	0.004
				(0.05)	(0.08)	(0.11)
ln_Z	0.03	0.55***	0.41**	0.02	0.33***	0.8*
	(0.06)	(0.12)	(0.14)	(0.03)	(0.08)	(0.43)
ln_Z^2	-0.001	-0.02***	-0.02*	-0.001	-0.02***	-0.04*
	(0.003)	(0.01)	(0.01)	(0.001)	(0.004)	(0.02)
_cons	-1.36	-4.00*	-2.94	0.69	-0.81	-5.84
	(1.17)	(1.90)	(1.84)	(0.61)	(1.28)	(4.45)
Provincial characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
Provincial Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.89	0.95		0.50	0.35	
F-stat	196.40	240.63		25.81	23.21	
Number of instruments			24			24
Hansen statistic-P value > z			0.35			0.58
Diff Hansen test			0.45			0.35
AR2- P value > z			0.18			0.23
Weak instrument test (K p-value)			0.87			0.74
Number of groups	33	33	33	33	33	33
N	264	264	264	264	264	264

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Control variables: Human Development Index, poverty rate, minimum wage rate, location quotient for the primary, secondary and tertiary sector. All control variables are at the provincial level.

Source: Author's estimations.

Effects of labour mobility have also been estimated by using provincial data as a robustness analysis. All the estimations are shown in Table 4.15. They reveal that in all estimations, a prominent inverted U-shaped relationship is only found in the relationship between occupational mobility and unconditional wage inequality. The same type of mobility also affects conditional wage disparity in a nonlinear pattern with a varied level of significance across the estimation techniques. Furthermore, a different type of labour mobility, spatial mobility, has also been found to have insignificant effects on regional wage inequality, conditional and unconditional measurement in most of the estimation techniques. However, if analysis is merely based on the sign of the parameters, it can be concluded that spatial mobility has the same U-shaped relationship pattern with wage inequality at the regional level as it has at the industrial level.

Table 4.15. Quadratic relationship between labour mobility and wage inequality in the manufacturing industry using provincial data

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP = σ			DEP =GINI		
L. σ	0.87***	0.66***	0.65***			
	(0.032)	(0.051)	(0.038)			
L.gini				0.58***	0.16	0.088
				(0.048)	(0.090)	(0.096)
GM	-0.012	-0.006	-0.002	-0.008	-0.014*	-0.015
	(0.011)	(0.008)	(0.010)	(0.006)	(0.007)	(0.014)
GM^2	0.001	0.001	0.000	0.001	0.002***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
JM	0.006	0.020*	0.024	0.007	0.027***	0.040**
	(0.016)	(0.011)	(0.015)	(0.009)	(0.010)	(0.018)
JM^2	-0.000	-0.002*	-0.005*	-0.001	-0.004***	-0.004*
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
_cons	-1.17	-0.79	0.21**	0.81	0.23	0.14**
	(1.14)	(1.92)	(0.1)	(0.60)	(1.08)	(0.07)
Provincial characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
Provincial Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.88	0.94		0.49	0.31	
F-stat	163.92	191.51		21.65	20.84	
Number of instruments			31			31
Hansen statistic-P value > z			0.85			0.90
Diff Hansen test			0.84			0.90
AR2- P value > z			0.88			0.67
Weak instrument test (K p-value)			0.55			0.36
Number of groups	33	33	33	33	33	33
N	264	264	264	264	264	264

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Control variables: Human Development Index, poverty rate, minimum wage rate, location quotient for the primary, secondary and tertiary sector. All control variables are at the provincial level.

Source: Author's estimations.

4.5.3.2 Implementation of external instruments

The results of OLS and the second stage regressions of the IV technique are presented in Table 4.16. The first stage regressions, shown in the appendix, indicate that the instrument is highly correlated with the actual employment share. This strong indication of the instrument is also supported by the weak identification test presented in Table 4.16. Moreover, the use of the instrument variable is valid as manufacturing jobs variables are statistically not exogenous. Based on the diagnostic tests, it can be argued that the IV technique is valid and robust. The regression parameters show that quadratic relationships between manufacturing jobs and wage inequality-conditional and unconditional measurement are evident and statistically significant. This implies that IV regression supports the results of the main findings based on dynamic panel regression.

Table 4.16. Quadratic relationship between manufacturing jobs and wage inequality in the manufacturing industry using external instruments (Second stage regression)

	ln_ σ		ln_gini	
	OLS	IV	OLS	IV
ln_Z	1.45**	3.74**	1.33***	4.05
	(0.55)	(1.77)	(0.33)	(6.06)
ln_Z^2	-0.08***	-0.2**	-0.07***	-0.18
	(0.03)	(0.09)	(0.02)	(0.28)
_cons	-9.5***		-8.05***	
	(3.47)		(1.86)	
Workers characteristics	Yes		Yes	
Industry characteristics	Yes		Yes	
Year Dummies	Yes		Yes	
ISIC dummies	Yes		Yes	
F-stat	8.60***	6.54***	8.22***	3.56
Weak identification test (F test)		19.93		19.93
Stock-Yogo 5% critical values		11.59		11.59
Overidentification test (Chi-sq P val)		0.15		0.4045
Endogeneity test (Chi-sq P val)		0.03**		0.02**
Number of observation	478	478	478	478

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Control variables are similar to the main regressions.

Source: Author's estimations.

From Table 4.17 it can be seen that IV techniques are robust for both conditional and unconditional measurements by observing all the statistical diagnostic tests. The regressions results are the same as the dynamic panel estimation results, where both spatial and occupational labour mobility have different shapes of non-linear relationship with wage inequality. Geographical mobility has a U-shaped relationship with conditional and non-conditional inequality. In contrast, occupational mobility has an inverted U-shaped correlation with wage disparity. These results strengthen the argument that geographical mobility needs to be controlled if it is beyond the threshold as it will increase inequality. On the other hand, an increase in job mobility between sectors needs to be encouraged to reduce wage inequality.

Table 4.17. Quadratic relationship between labour mobility and wage inequality in the manufacturing industry using external instruments (Second stage regression)

	OLS	IV	OLS	IV
	stdp		gini	
GM	-0.14	-1.87*	-0.009	-1.51***
	(0.18)	(1.1)	(0.16)	(0.48)
GM^2	0.24	2.7*	0.05	2.1***
	(0.23)	(1.53)	(0.21)	(0.72)
JM	0.19	0.64*	0.078	1.185**
	(0.15)	(0.37)	(0.11)	(0.5)
JM^2	-0.74*	-1.81*	-0.02	-2.702**
	(0.4)	(1.1)	(0.21)	(1.24)
Workers characteristics	Yes		Yes	
Industry characteristics	Yes		Yes	
Year Dummies	Yes		Yes	
ISIC dummies	Yes		Yes	
F-stat	7.29***	1.83***	10.46***	2.5***
Weak identification test (F test)		13.46		13.455
Stock-Yogo 5% critical values		11.04		11.04
Overidentification test (Chi-sq P val)		0.22		0.63
Endogeneity test (Chi-sq P val)		0.09*		0.0003***
Number of observation	478	478	478	478

Notes: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in brackets.

Control variables are similar to the main regressions.

Source: Author’s estimations.

4.6 Conclusion

Despite the ability to generate relatively high productivity, Indonesian manufacturing has still experienced steady growth in wage inequality with low and stable job creation and labour mobility. Hence, it is arguably important to analyse how job absorption and labour mobility affect wage distribution in this sector. By using various dimensions and techniques, it is found that manufacturing jobs and wage inequality have an inverted U-shaped relationship, implying that a relatively low level of job absorption will harm wage distribution. However, when the number of workers employed is more than the threshold, it will reduce inequality. Possible factors may explain why job absorption still increases wage inequality in relatively smaller sized firms include the workers' heterogeneity seen in smaller industries. On the other hand, workers are more homogenous as the size grows bigger as they implement more established technology than smaller sized industries. Moreover, when industries grow, they appear to comply with minimum wage policy.

Labour mobility, in this paper, is measured in two ways, spatial mobility and job mobility. Estimations reveal that spatial mobility has a U-shaped relationship pattern with wage inequality. The negative relationship at the level below the threshold is a result of downward pressure effects. The pressure occurs because movers are from low to high regions and low-skill workers. Moreover, the positive relationship when the level of mobility is beyond the limit is caused by asymmetrical problems of workers' heterogeneity. Job mobility has affected wage inequality differently. Even though estimations reveal a robust inverted U-shaped relationship, most industrial groups fall in the area where job mobility hinders wage inequality. This seems to be because of skill mismatch problems that exist in the Indonesian manufacturing sector labour market.

The most critical implication from all the above empirical findings is the problem of low human capital quality in the Indonesian manufacturing sector, which urgently needs to be solved. It is found that job creation can reduce wage inequality. Notably, hiring more educated workers will elevate the role of job creation in reducing inequality. When the quality of labour increases, demand for labour coming from the medium-high technology sector will increase. However, it is noted that this particular sector still hires workers lower than the point where job creation can reduce inequality. In terms of labour mobility, an increase in human capital quality in labour supply will also eliminate the adverse effects of labour mobility on wage distribution due to the asymmetrical problems of workers' heterogeneity and skill mismatch.

4.A Appendix 4

Table 4A.1. Group of industry based on Indonesian Standard Industrial Classification Codes (KBLI) 2000

NO	KBLI	Description
1	151	Processed meat, fish, fruits, vegetables, oil and fat
2	152	Dairy products
3	153	Grain mill products: starches and animal feed
4	154	Other food products
5	155	Beverages
6	160	Tobacco products
7	171	Spinning, weaving and finishing of textiles.
8	172	Made-up textile articles, except apparel; carpets
9	173	Knitted and crocheted fabrics and articles
10	174	Cotton Industry
11	181	Garments except fur apparel
12	182	Dressing and dyeing of fur; processing of fur
13	191	Tanning , dressing and processing of leather
14	192	Footwear
15	201	Sawmilling
16	202	Products of wood, woven rattan, bamboo, etc
17	210	Paper and paper products
18	221	Publishing
19	222	Printing and related services activities, including photo copy
20	223	Reproduction of recorded media
21	231	Coal based industries
22	232	Oil Refineries, oil manufacturing, and products from oil refining and natural gas
23	233	Processing of nuclear fuel
24	241	Basic chemicals
25	242	Other chemicals
26	243	Manmade fibres
27	251	Rubber and rubber products
28	252	Plastic products
29	261	Glass and glass products
30	262	Porcelain products
31	263	Clay products
32	264	Cement, lime and gypsum and their products
33	265	Stone products
34	266	Asbestos products
35	269	Non-metallic mineral products n.e.c.
36	271	Basic iron and steel
37	272	Basic precious and non-ferrous metals
38	273	Metal foundries
39	281	Structural metal products; tanks; steam generators
40	289	Other metal products, and metalworking services
41	291	General purpose machinery

42	292	Special purpose machinery
44	293	Domestic appliances n.e.c.
44	300	Office, accounting, and computing equipment
45	311	Electric motors, generators, and transformers
46	312	Electricity distribution and control apparatus
47	313	Insulated wire and cable
48	314	Accumulators, primary cells and batteries
49	315	Lighting equipment and electric lamps
50	319	Other electrical equipment n.e.c.
51	321	Electronic valves, tubes etc.
52	322	Television/radio transmitters; line communication apparatus
53	323	Radio and television receivers and associated products
54	331	Medical, measuring, testing appliances, etc. excludes optical instruments
55	332	Optical instruments and photographic equipment
56	333	Watches and clocks
57	341	Automobiles
58	342	Automobile bodies, trailers, and semi-trailers
59	343	Automobile parts and accessories
60	351	Ship/Boat building and repair
61	352	Train manufacturing, spare parts and related equipment
62	353	Aircraft manufacture equipment and repair
63	361	Furniture
64	369	Jewellery and related industries

Appendix 4A. 2– Using all lagged independent variables

Table 4A.2.1. Effects of Manufacturing Employment on Wage Inequality (Linear)

	OLS	FE	SYS_GMM	DIFF_SYS	OLS	FE	SYS_GMM	DIFF_SYS
	DEP =LN_STDP				DEP =LN_GINI			
L.ln_stdp	0.55***	-0.041	0.004	-0.094				
	(0.041)	(0.092)	(0.13)	(0.120)				
L.ln_gini					0.30***	0.13*	0.27***	0.30***
					(0.039)	(0.067)	(0.064)	(0.077)
L.ln_Z	0.097***	0.17	0.25***	0.132	0.05***	0.099	0.05*	0.27*
	(0.018)	(0.096)	(0.040)	(0.097)	(0.012)	(0.074)	(0.020)	(0.116)
_cons	0.078	-0.89	0.17		-2.38***	-5.11**	-3.97***	
	(0.480)	(1.199)	(0.865)		(0.394)	(1.559)	(0.975)	
Workers Characteristics	YES				YES			
Industry Characteristics	YES				YES			
Year Dummies	NO	YES	YES	YES	NO	YES	YES	YES
ISIC Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Adjusted R squared	0.68	0.26			0.35	0.13		
F-stat	51.24	38.64			13.34	47.72		
Hansen statistic-P value > z			0.79	0.65			0.46	0.29
AR2- P value > z			0.54	0.91			0.98	0.15
Weak instrument test			0.98	0.43			0.24	0.86
Number of groups	66	66	66	66	66	66	66	66
N	478	478	478	408	478	478	478	408

Table 4A.2.2. Effects of manufacturing employment on wage inequality (quadratic)

	OLS	FE	SYS_GMM	DIFF_SYS	OLS	FE	SYS_GMM	DIFF_SYS
	DEP =LN_STDP				DEP =LN_GINI			
L.ln_stdp	0.44***	-0.06	-0.03	-0.08				
	(0.05)	(0.09)	(0.13)	(0.12)				
L.ln_gini					0.29***	0.10	0.27***	0.29***
					(0.04)	(0.07)	(0.07)	(0.08)
L.ln_Z	0.80***	0.20	1.03***	1.17*	0.37**	1.28**	0.80**	1.66***
	(0.17)	(0.36)	(0.29)	(0.53)	(0.13)	(0.41)	(0.25)	(0.47)
L.ln_Z2	-0.04***	-0.02	-0.06***	-0.06*	-0.02*	-0.06**	-0.04**	-0.07**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
_cons	-4.72***	-2.54	-6.19***		-4.06***	-10.46***	-7.60***	
	(1.03)	(2.15)	(1.74)		(0.78)	(2.57)	(1.87)	
Workers Characteristics		YES				YES		
Industry Characteristics		YES				YES		
Year Dummies	NO	YES	YES		NO	YES	YES	
ISIC Dummies	NO	YES	YES		NO	YES	YES	
Adjusted R squared	0.70	0.38			0.35	0.34		
F-stat	53.01	34.90			13.13	49.24		
Hansen statistic-P value > chi2			0.90	0.35			0.54	
AR2- P value > z			0.79	0.94			0.99	0.199
Number of groups	66	66	66	66	66	66	66	66
N	478	478	478	408	478	478	478	408

Table 4A.2.3. Effects of manufacturing employment on wage inequality based on education (linear)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =LN_STDP			DEP =LN_GINI		
L.ln_stdp	0.53***	-0.13	-0.003			
	(0.04)	(0.08)	(0.10)			
L.ln_gini				0.276***	0.0852	0.208*
				(0.04)	(0.08)	(0.08)
L.ln_primary	0.01	0.01	0.03*	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L.ln_sec	0.02	0.02	0.02	0.02	0.03*	0.03*
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
L.ln_high	-0.02	-0.07	-0.05	-0.0002	-0.06*	-0.0003
	(0.02)	(0.04)	(0.04)	(0.01)	(0.03)	(0.03)
L.ln_ter	-0.005	-0.03*	-0.04***	-0.02	-0.03	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
_cons	-0.70	-3.16***	-2.21*	-2.29***	-4.12**	-3.14***
	(0.53)	(0.77)	(0.97)	(0.40)	(1.32)	(0.90)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.61	0.11		0.33	0.20	
F-stat	35.18	23.97		11.38	59.65	
Number of instruments			56			56.00
Hansen statistic-P value > z			0.98			0.69
AR2- P value > z			0.18			0.14
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Table 4A.2.4. Effects of manufacturing employment on wage inequality based on education (quadratic)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =LN_STDP			DEP =LN_GINI		
L.ln_stdp	0.328***	-0.167*	-0.124			
	(7.36)	(-2.14)	(-1.14)			
L.ln_gini				0.273***	0.0870	0.233**
				(6.80)	(1.00)	(2.58)
L.ln_primary	0.0597*	0.0292	0.0713*	0.0344	0.0352	0.0355
	(2.21)	(0.70)	(2.20)	(1.69)	(1.14)	(1.29)
L.ln_sec	0.00463	-0.0190	0.0456	0.0287	0.0318	0.0592
	(0.13)	(-0.43)	(1.07)	(1.03)	(0.78)	(1.57)
L.ln_high	0.264***	0.287***	0.357***	0.0117	0.0319	-0.0166
	(4.45)	(3.46)	(3.91)	(0.26)	(0.44)	(-0.16)
L.ln_ter	0.0787**	0.111***	0.102***	0.0295	0.0700*	0.0701*
	(2.77)	(5.06)	(4.20)	(1.34)	(2.33)	(2.37)
L.ln_prim2	-0.00692*	-0.00547	-0.00989*	-0.00367	-0.00366	-0.00447
	(-2.03)	(-1.08)	(-2.39)	(-1.43)	(-0.95)	(-1.26)
L.ln_sec2	-0.000227	0.00539	-0.00264	-0.00111	0.000415	-0.00312
	(-0.05)	(1.22)	(-0.64)	(-0.33)	(0.08)	(-0.71)
L.ln_high2	-0.0205***	-0.0222**	-0.0303***	0.000896	0.00253	0.00455
	(-3.81)	(-3.33)	(-4.11)	(0.22)	(0.33)	(0.56)
L.ln_ter2	-0.00687*	-0.0103***	-0.00855**	-0.00120	-0.00556	-0.00652
	(-2.04)	(-3.71)	(-3.20)	(-0.45)	(-1.71)	(-1.82)
_cons	-2.626***	-3.308***	-3.816***	-2.493***	-3.894**	-2.975**
	(-4.78)	(-3.73)	(-4.14)	(-5.92)	(-3.01)	(-3.18)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES		NO	YES	
ISIC Dummies	NO	YES		NO	YES	
N	478	478	478	478	478	478

Table 4A.2.5. Effects of labour mobility on wage inequality (linear)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =LN_STDP			DEP =LN_GINI		
L.ln_stdp	0.534***	-0.117	-0.0601			
	(13.83)	(-1.70)	(-0.56)			
L.ln_gini				0.283***	0.106	0.240***
				(7.09)	(1.41)	(3.31)
L_GM	-0.0467***	-0.0446*	-0.0944***	0.0134	0.00232	-0.0103
	(-3.82)	(-2.23)	(-4.54)	(1.40)	(0.11)	(-0.42)
L.JM	-0.00950	0.0208	-0.00426	0.0176**	0.0163	0.0209
	(-1.20)	(1.37)	(-0.33)	(2.97)	(1.19)	(1.74)
_cons	-0.639	-1.938*	-2.489**	-2.263***	-3.123*	-2.664***
	(-1.26)	(-2.14)	(-2.65)	(-5.90)	(-2.55)	(-3.46)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES		NO	YES	
ISIC Dummies	NO	YES		NO	YES	
N	478	478	478	478	478	478

Table 4A.2.6. Effects of labour mobility on wage inequality (quadratic)

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =LN_STDP			DEP =LN_GINI		
L.ln_stdp	0.445***	-0.123	-0.151			
	(10.24)	(-1.73)	(-1.13)			
L.ln_gini				0.267***	0.114	0.246**
				(6.67)	(1.51)	(3.25)
L.GM	0.0263	-0.154*	-0.434**	-0.0312	-0.0623	-0.160*
	(0.78)	(-2.65)	(-2.69)	(-1.22)	(-1.31)	(-2.45)
L.GM^2	-0.00567	0.0133*	0.0474**	0.00481*	0.00775	0.00921*
	(-1.91)	(2.13)	(2.61)	(2.25)	(1.65)	(2.54)
L.JM	0.0618**	0.0457	0.0346*	0.0595***	0.0461	0.0621*
	(2.73)	(1.80)	(0.02097)	(3.67)	(1.53)	(2.36)
L.JM^2	-0.00747**	-0.00406	-0.00367*	-0.00544**	-0.00444	-0.00664*
	(-2.89)	(-1.67)	(-0.00222)	(-2.98)	(-1.40)	(-2.31)
_cons	-1.108*	-1.920*	-1.834	-2.200***	-3.057*	-2.374**
	(-2.15)	(-2.13)	(-1.84)	(-5.71)	(-2.48)	(-3.27)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES		NO	YES	
ISIC Dummies	NO	YES		NO	YES	
N	478	478	478	478	478	478

Appendix 4A.3-Using Diff-GMM

Table 4A.3.1. Effects of manufacturing employment on wage inequality

	DEP =LN_STDP		DEP =LN_GINI	
L.ln_σ	-0.08	-0.06		
	(0.11)	(0.11)		
L.ln_gini			0.20	0.12
			(0.12)	(0.12)
ln_pop	0.15	1.07*	0.20	1.02*
	(0.25)	(0.69)	(0.12)	(0.44)
ln_pop_sq		-0.06*		-0.05*
		(0.03)		(0.02)
Workers Characteristics	YES		YES	
Industry Characteristics	YES		YES	
Year Dummies	YES	YES	YES	YES
ISIC Dummies	YES	YES	YES	YES
Number of instruments		58		59
Hansen statistic-P value > Chi	0.15	0.20	0.17	0.12
AR2- P value > z	0.86	0.81	0.30	0.53
weak iv test	0.54	0.58	0.16	0.87
Number of groups	66	66	66	66
N	408	408	408	408

Table 4A.3.2. Effects of labour mobility on wage inequality

	DEP =LN_STDP		DEP =LN_GINI	
L.ln_stdp	-0.11	-0.08		
	(0.15)	(0.59)		
L.ln_gini			0.18	0.05*
			(0.09)	(0.03)
GM	-0.03*	-0.29**	-0.15*	-0.48*
	(0.02)	(1.43)	(0.08)	(0.25)
GM2		0.38*		0.85*
		(0.2)		(0.45)
JM	0.19*	0.48*	0.35*	0.45*
	(0.1)	(0.25)	(0.19)	(0.24)
JM2		-0.36		-1.55*
		(0.19)		(0.82)
Workers Characteristics	YES		YES	
Industry Characteristics	YES		YES	
Year Dummies	YES	YES	YES	YES
ISIC Dummies	YES	YES	YES	YES
Number of instruments				
Hansen statistic-P value > Chi	0.18	0.19	0.63	0.76
AR2- P value > z	0.19	0.91	0.31	0.24
weak iv test	0.29	0.90	0.16	0.19
Number of groups	66	66	66	66
N	470	470	478	471

Figure 4A.1. Effects of manufacturing jobs on conditional wage inequality (quadratic relationship).

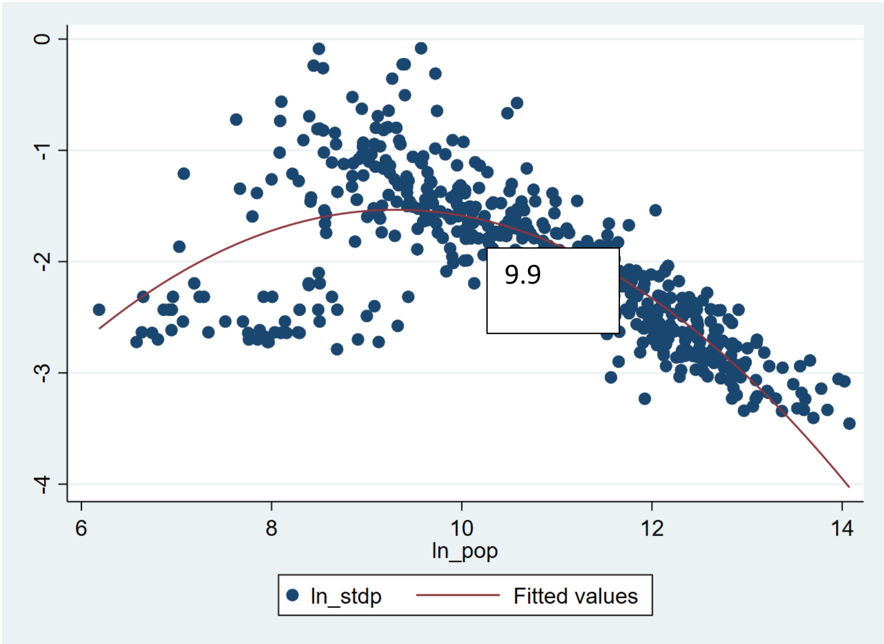
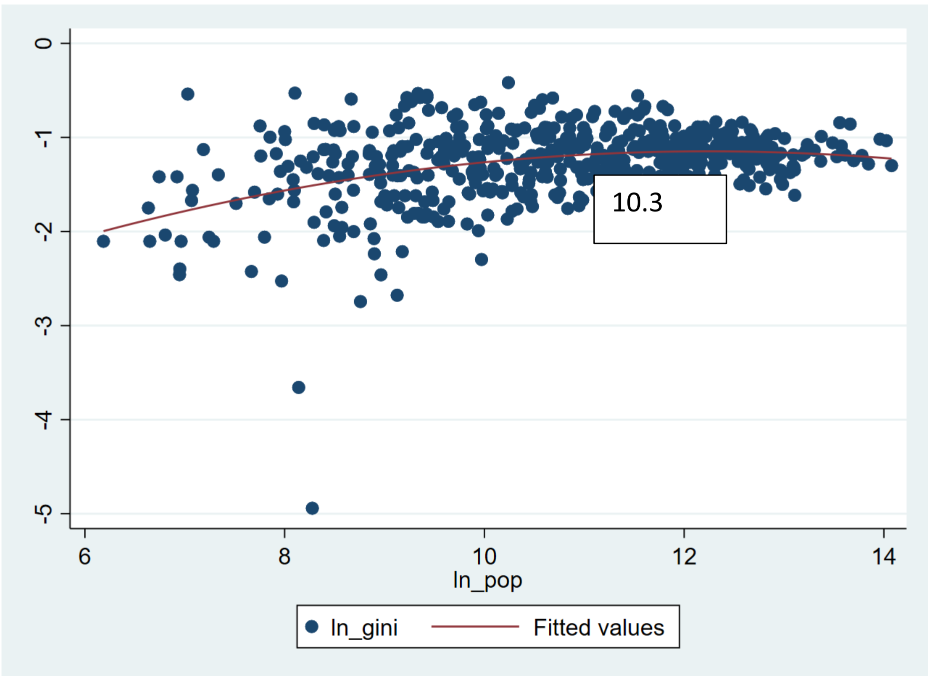


Figure 4A.2. Effects of manufacturing jobs on unconditional wage inequality (quadratic relationship).



Appendix 4A.4. Labour mobility with manufacturing size interaction

Table 4A.4.1. Liner relationship regressions

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =LN_STDP			DEP =LN_GINI		
L.stdp	0.32***	-0.095	-0.01			
	(0.04)	(0.06)	(0.09)			
L.gini				0.45***	0.09	0.32***
				(0.04)	(0.07)	(0.11)
p_moves	0.04	0.03	0.03	0.04	0.04	0.07
	(0.04)	(0.08)	(0.12)	(0.04)	(0.06)	(0.12)
p_jobmoves	-0.08	-0.08	0.09	-0.07	-0.1	-0.34**
	(0.08)	(0.12)	(0.32)	(0.07)	(0.15)	(0.17)
pop_percentage	0.93	1.24	1.57	0.13	1.65*	0.68
	(0.91)	(0.87)	(5.02)	(0.77)	(0.85)	(7.95)
pop_moves	-1.16	-0.63	-8.14	-0.85	-2.45	12.28
	(3.91)	(3.65)	(22.51)	(3.3)	(2.61)	(24.27)
pop_jobmoves	1.85	-1.25	-31.4	5.87	4.68	-44.25
	(10.03)	(6.07)	(92.7)	(8.48)	(7.94)	(100.45)
_cons	0.01	0.42	0.37	-0.08	0.04	0.002
	(0.13)	(0.35)	(0.49)	(0.11)	(0.37)	(0.99)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies	NO	YES	YES	NO	YES	YES
ISIC Dummies	NO	YES	YES	NO	YES	YES
Adjusted R squared	0.414	0.226		0.288	0.230	
F-stat	13.92	18.44		7.98	6.76	
Number of instruments			57			57
Hansen statistic-P value > z			0.97			0.98
AR2- P value > z			0.58			0.99
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Note: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets

Source: Author’s estimations.

Table 4A.4.2.Quadratic relationship regressions

	OLS	FE	SYS_GMM	OLS	FE	SYS_GMM
	DEP =LN_STDP			DEP =LN_GINI		
L.stdp	0.32***	-0.07	-0.02			
	(0.04)	(0.05)	(0.09)			
L.gini				0.41***	0.07	0.36***
				(0.04)	(0.05)	(0.08)
p_moves	-0.13	-0.25**	-0.32	0.09	-0.06	-0.76*
	(0.10)	(0.11)	(0.33)	(0.09)	(0.1)	(0.31)
p_jobmoves	-0.06	0.32**	1.79***	0.43***	0.37***	0.61
	(0.16)	(0.16)	(0.54)	(0.13)	(0.14)	(0.4)
p_moves2	0.22	0.35***	0.22	-0.09	0.1	0.63
	(0.12)	(0.13)	(0.33)	(0.1)	(0.11)	(0.33)
p_jobmoves2	-0.03	-0.62***	-2.09**	-0.79***	-0.76***	-1.39**
	(0.21)	(0.22)	(0.65)	(0.18)	(0.16)	(0.53)
pop_percentage	1.24	1.63	8.54	0.96	1.4	3.31
	(0.94)	(1.88)	(7.1)	(0.78)	(1.6)	(4.13)
pop_moves	1.09	3.87	14.08	-1.76	-0.9	18.57
	(4.11)	(5.17)	(25.46)	(3.39)	(4.6)	(14.5)
pop_jobmoves	0.34	-11.61	-312.3**	-7.69	-10.88	15.82
	(10.69)	(12)	(100.16)	(8.89)	(10.36)	(47.95)
_cons	0.02	0.59*	0.2	-0.14	-0.03	0.36***
	(0.13)	(0.27)	(0.37)	(0.11)	(0.24)	(0.11)
Workers Characteristics	YES					
Industry Characteristics	YES					
Year Dummies	NO	YES	YES			
ISIC Dummies	NO	YES	YES			
Adjusted R squared	0.42	0.13		0.32	0.26	
F-stat	12.97	2.39		8.57	4.23	
Number of instruments			57			
Hansen statistic-P value > z			0.25			0.4
AR2- P value > z			0.45			0.78
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Note: ***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets

Source: Author's estimations.

Table 4A.5. First stage of manufacturing job and wage inequality Table 4A.7.1

	σ		Gini Index	
	dep = ln_Z	dep=ln_Z^2	dep = ln_Z	dep=ln_Z^2
d	8.47***	184.31***	8.24***	181.2***
	(2.21)	(49.6)	(2.2)	(49.39)
d^2	-202.05**	4090.1**	-207.26**	-4160.26**
	(88.72)	(2051.24)	(88.69)	(2052.73)
Workers Characteristics	YES	YES	YES	YES
Industry Characteristics	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES
ISIC Dummies	YES	YES	YES	YES
F-stat	21.66***	16.81***	21.12***	16.51***
N	478	478	478	478

Note: d = Employment share predicted by Bartik equation (1991).

***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets
Source: Author's estimations.

	σ		Gini Index	
	dep =GM	dep=GM2	dep = JM	dep=JM2
ssi_gm	0.12	0.02	0.34***	0.14***
	(0.09)	(0.06)	(0.09)	(0.04)
ssi_gm2	-0.11**	-0.02	-0.17***	-0.07***
	(0.05)	(0.03)	(0.05)	(0.02)
ssi_jm	0.2*	-0.08	1.09***	0.34***
	(0.12)	(0.07)	(0.15)	(0.07)
ssi_jm2	0.34*	0.11	-1.4***	-0.42***
	(0.18)	(0.1)	(0.21)	(0.09)
Workers Characteristics	YES	YES	YES	YES
Industry Characteristics	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES
ISIC Dummies	YES	YES	YES	YES
F-stat	14.96***	12.76***	32.45***	22.65***
N	478	478	478	478

Note: ssi_gm = geographical mobility shift share; ssi_jm = job mobility shift share predicted by Card equation (2009).

***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets
Source: Author's estimations.

Appendix 4A.6. Other robustness for system GMM estimation

Table 4A.6.1. Effects of manufacturing employment on wage inequality (Linear relationship)

	DEP =LN_STDP			DEP =LN_GINI		
	1	2	3	1	2	3
L.ln_stdp	0.41***	0.02	0.45***			
	(0.06)	(0.08)	(0.14)			
L.ln_gini				-0.29*	-0.13	0.2**
				(0.17)	(0.16)	(0.09)
ln_Z	0.04***	0.08***	0.02	0.17***	0.14*	0.03*
	(0.01)	(0.03)	(0.02)	(0.06)	(0.08)	(0.02)
_cons	-0.59***	0.95*	0.39	-3.96***	-5.87*	1.73**
	(0.22)	(0.4)	(0.35)	(1.08)	(3,36)	(0.77)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies		YES			YES	
ISIC Dummies		YES			YES	
Number of instruments	57	55	59	57	55	59
Hansen statistic-P value > z	0.20	0.80	0.28	0.84	0.22	0.95
Diff-Hansen	0.28	0.78	0.27	0.19	0.30	0.98
AR2- P value > z	0.14	0.45	0.23	0.35	0.42	0.27
Weak IV (K)	0.19	0.28	0.18	0.92	0.38	0.18
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Note: 1 is the estimation using lagged 1 instrument variables for all endogenous variable; 2 is the estimation using lagged 2 instrument variables for all endogenous variable; 3 is the estimation using orthogonal option.

***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets
Source: Author's estimations.

Table 4A.6.2. Effects of manufacturing employment on wage inequality (Quadratic relationship)

	DEP =LN_STDP			DEP =LN_GINI		
	1	2	3	1	2	3
L.ln_stdp	0.12***	0.03	0.02			
	(0.01)	(0.02)	(0.11)			
L.ln_gini				-0.18	-0.03	0.2**
				(0.14)	(0.14)	(0.09)
ln_Z	0.14**	0.39***	0.11*	0.47*	1.57*	0.66
	(0.07)	(0.14)	(0.06)	(0.27)	(0.85)	(0.23)
ln_Z^2	-0.007**	-0.02***	-0.007**	-0.02*	-0.08*	-0.001
	(0.003)	(0.007)	(0.003)	(0.01)	(0.04)	(0.01)
_cons	-1.07***	3.95***	-1.16	5.1***	-4.9	-1.88
	(0.36)	(1.08)	(0.43)	(1.65)	(4.04)	(1.47)
Workers Characteristics	YES			YES		
Industry Characteristics	YES			YES		
Year Dummies	YES			YES		
ISIC Dummies	YES			YES		
Number of instruments	64	61	59	64	61	59
Hansen statistic-P value > z	0.21	0.75	0.99	0.59	0.62	0.99
Diff-Hansen	0.21	0.64	0.96	0.63	0.64	0.98
AR2- P value > z	0.26	0.16	0.13	0.91	0	0.26
Weak IV (CLR)	0.7	0.87	0.97	0.56	0.51	0.18
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Note: 1 is the estimation using lagged 1 instrument variables for all endogenous variable; 2 is the estimation using lagged 2 instrument variables for all endogenous variable; 3 is the estimation using orthogonal option.

***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets
Source: Author's estimations.

Table 4A.6.3. Effects of labour mobility on wage inequality (Linear relationship)

	DEP =LN_STDP			DEP =LN_GINI		
	1	2	3	1	2	3
L.ln_stdp	0.31***	0.49***	0.06			
	(0.06)	(0.05)	(0.11)			
L.ln_gini				0.47***	0.46***	0.18**
				(0.06)	(0.06)	(0.09)
GM	-0.24*	-0.29*	-0.38*	-0.15*	-0.1*	-0.07
	(0.14)	(0.18)	(0.21)	(0.08)	(0.06)	(0.17)
JM	1.26***	0.51*	0.007	0.49**	0.55**	0.06
	(0.45)	(0.3)	(0.3)	(0.22)	(0.16)	(0.2)
_cons	0.1	0.14	0.31	0.06	0.06	0.02
	(0.14)	(0.13)	(0.41)	(0.11)	(0.12)	(0.35)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies		YES			YES	
ISIC Dummies		YES			YES	
Number of instruments	51	54	57	51	54	57
Hansen statistic-P value > z	0.96	0.98	0.96	0.98	0.92	0.99
Diff-Hansen	0.94	0.97	0.15	0.52	0.77	0.98
AR2- P value > z	0.15	0.8	0.87	0.32	0.38	0.51
Weak IV (K)	0.35	0.83	0.95	0.99	0.31	0.71
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Note: 1 is the estimation using lagged 1 instrument variables for all endogenous variable; 2 is the estimation using lagged 2 instrument variables for all endogenous variable; 3 is the estimation using orthogonal option.

***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets
Source: Author's estimations.

Table 4A.6.4. Effects of labour mobility on wage inequality (Quadratic relationship)

	DEP =LN_STDP			DEP =LN_GINI		
	1	2	3	1	2	3
L.ln_stdp	0.35***	-0.25***	0.12			
	(0.06)	(0.08)	(0.09)			
L.ln_gini				0.42***	0.46***	0.19*
				(0.1)	(0.06)	(0.1)
GM	-0.15*	-0.4*	-0.88**	-0.33*	-0.1*	-0.19
	(0.08)	(0.22)	(0.45)	(0.19)	(0.05)	(0.46)
GM^2	0.51**	0.43*	0.74	0.6**	0.17*	0.21
	(0.25)	(0.24)	(0.65)	(0.29)	(0.09)	(0.66)
JM	0.77**	0.9*	1.1*	0.71	0.58**	0.58
	(0.37)	(0.51)	(0.6)	(0.41)	(0.25)	(0.58)
JM^2	-1.76*	-2.86*	-3.13*	-0.6*	-1.56*	-2.5*
	(1.0)	(1.5)	(1.77)	(0.34)	(0.86)	(1.5)
_cons	0.18	1.56***	0.51	0.44	0.05	0.4***
	(0.2)	(0.51)	(0.37)	(0.43)	(0.11)	(0.13)
Workers Characteristics		YES			YES	
Industry Characteristics		YES			YES	
Year Dummies		YES			YES	
ISIC Dummies		YES			YES	
Number of instruments	58	55	61	58	55	61
Hansen statistic-P value > z	0.66	0.86	0.72	0.16	0.98	0.34
Diff-Hansen	0.68	0.77	0.82	0.45	0.92	0.2
AR2- P value > z	0.44	0.48	0.41	0.11	0.32	0.75
Weak IV (K)	0.88	0.58	0.22	0.99	0.17	0.17
Number of groups	66	66	66	66	66	66
N	478	478	478	478	478	478

Note: 1 is the estimation using lagged 1 instrument variables for all endogenous variable; 2 is the estimation using lagged 2 instrument variables for all endogenous variable; 3 is the estimation using orthogonal option.

***/**/* significant at the 1, 5 and 10 per cent level respectively. Robust standard errors are shown in the brackets
Source: Author's estimations.

Chapter 5 Conclusion and Policy Implications

The manufacturing industry has an important role in Indonesia's economy, which can be seen by its relatively high contributions to Indonesia's GDP. In fact, this sector greatly depends on large and medium scale industries to generate value-added. Despite the ability to generate relatively high productivity, Indonesian large and medium manufacturing industries have experienced problematic characteristics such as unstable and low output growth in recent decades, a steady growth in wage inequality and low, stable job creation and labour mobility.

Productivity growth is a crucial factor at the firm or industry level since it allows the firm or industry to compete with other sectors of the economy for limited resources and even improve their competitiveness in the marketplace. Although using more inputs in production can be one way to increase outputs, adding more inputs will not increase the income earned per unit of input. It is likely to result in lower average wages and lower rates of profit. Nevertheless, when output growth is achieved through productivity growth, with existing inputs, more output and income can be generated. If income per unit of input rises, additional resources are also attracted to production and can be profitably employed. Hence, it is crucial from a policy perspective to analyse the sources of output growth since it is important to observe whether output growth is due to input growth or productivity driven. Productivity or Total Factor Productivity growth can be generated by two important factors, technological progress and technical efficiency (Kalirajan and Shand, 1994; Kalirajan et al., 1996; Hulten et al., 2001)

Once it is known that labour efficiency that reflects labour productivity is relatively low, analysing factors that can increase or decrease labour productivity is crucial. It is argued by relative wages theory, fairness theory (Akerlof and Yellen, 1988) and tournament theory (Lazear and Rosen, 1981 and Lazear, 1989) that wage inequality has significant effects on productivity. Fairness theory argues that low wage inequality will increase labour productivity as workers become demotivated and reduce their efforts when they receive lower wages than their peers. It implies that 'fairness' in wage distribution will reduce the potential tendency of workers to perform hazardous actions for firms. In contrast, the tournament model argues that wage inequality is required to motivate workers to work more productively. However, the inequality needs to be maintained at a certain level to avoid the existence of predatory behaviour of 'hawks'-type workers that will decrease the firm's productivity.

Other problematic characteristics explored in this thesis include the relatively low job absorption and labour mobility in Indonesia's manufacturing sector. These characteristics are arguably important, affecting wage inequality that later on affects the productivity of the whole manufacturing sector. Job absorption and labour mobility have an important role in reducing wage inequality through wage compression (Pissarides and McMaster, 1990; Kanbur and Rapoport, 2005; Dorantes and Padial, 2007, and Belley et al., 2012). In contrast, these factors can also increase wage inequality because of asymmetrical problems coming from workers' heterogeneity (Burda and Wyplosz, 1992; Feser and Sweeny, 2003; Elhorst, 2003; Südekum, 2005; Epifani and Gancia, 2005; Partridge and Rickman, 2006; Østbye and Westerlund, 2007; Francis, 2009; Kambourov and Manovskii, 2009; Hoffmann and Shi, 2011; Soria et al., 2015; Stijepic, 2017; Park, 2019). The possibility of having positive and/or negative effects on wage inequality makes analysing Indonesia's job absorption and labour mobility in the manufacturing sector an important exercise to undertake from the policy perspective.

5.1 Summary of findings

This thesis has consisted of three papers that investigate the characteristics of Indonesia's large and medium manufacturing industries. The first paper (Chapter 2) measures total factor productivity (TFP) by decomposing it into technical efficiency and technological progress using varying parameter stochastic frontier analysis (VSFA). The results indicate that mean technical efficiency (TE) resulting from constant parameter stochastic frontier analysis (SFA) is higher than VSFA. Moreover, the TE rank of sub-sectors is more consistent based on VSFA, with the best performer being the sub-sector of repair and installation of machinery and equipment (ISIC 33). The TFP growth measured based on the VSFA in 2002-2014 was 4.3 per cent from 2000 to 2014 and decomposed mostly by technological progress experienced by firms. Considering sub-sector performance, the sub-sector that gained the highest TFP growth is the sub-sector of tobacco products. Another appealing result from the study is that labour efficiency reflecting labour productivity in Indonesia's manufacturing sector is relatively low, at 51 per cent during 2002-2014.

The second paper (Chapter 3) investigates the relationships between wage inequality and firm productivity, which is measured by labour productivity. Wage inequality measurements in this paper are conditional wage dispersion, which is estimated by wage regression from workers' characteristics data and unconditional wage dispersion, which is measured by the Gini index, and the maximum-minimum ratio of wages. This means that a relatively low wage inequality can motivate workers to work more productively. However, when wage inequality is beyond the thresholds, it will harm productivity. This implies that the findings support the ‘tournament’ argument in explaining relationships between wage inequality and productivity (Lazear and Rosen, 1981 and Lazear, 1989). The results are robust across many dimensions: panel data – fixed effects model, dynamic panel data – system-GMM, and two-stage least squares (2SLS) with standard deviations of income tax as the instrumental variables.

The last paper (Chapter 4) analyses how job absorption and labour mobility, which is measured by spatial and job mobility, affect wage inequality. By using various dimensions and techniques: different types of wage inequality measurement, conditional and unconditional wage disparity; various techniques such as OLS, FE, dynamic panel models with and without lagged independent variables, and instrumental variables (IV) techniques; and the use of different levels of data such as industrial group and regional level data, it is concluded that manufacturing jobs and job mobility significantly affect wage inequality in an inverted U-shaped pattern. This implies that manufacturing jobs and job mobility will reduce wage inequality when it is beyond the optimal levels. By contrast, spatial mobility has a significant U-shaped relationship with wage inequality. This suggests that hiring from domestic regions will elevate the role of mobility in reducing wage inequality.

5.2 Contributions and policy implications

This thesis has made several contributions. Chapter 2 is the first study decomposing TFP growth in Indonesia’s manufacturing sector with the assumption of non-neutrally shifts in production frontier functions. This means that heterogeneity between individual firms is treated explicitly to avoid misspecification bias when time-varying unobservable factors exist. Chapter 3 provides evidence about wage inequality and productivity relationship in the context of developing countries, which has rarely been observed in prior research. In terms of methodology, this chapter applies various types of wage inequality, both conditional and unconditional measurements, to provide robust results. Finally, Chapter 4 provides an in-depth analysis of how manufacturing jobs and labour mobility affect wage inequality by providing not only robust econometrics results but also possible reasons behind the relationship between manufacturing jobs, labour mobility and wage inequality, supported by descriptive analysis of rich datasets. Moreover, a simultaneous analysis between manufacturing jobs and labour mobility is also provided as it is argued that both factors can affect wage inequality simultaneously (Lewis, 1954).

The policy implications of the three studies are clear. The first study reveals that the value of TFP growth, which is decomposed into technological progress and technical efficiency, is widely divergent among industries. Therefore, to achieve stable and high TFP growth, increasing equal opportunities to utilise technological advancements across industries is crucial. Moreover, an increase in the level of human capital used in the sector is crucial to guarantee that optimal technology absorption can be achieved in a production process. The second study strengthens the argument on how human capital in Indonesia's manufacturing sector needs to be increased. Maintaining relatively low-level wage inequality and considering the existence of the 'hawks'- type of worker are general implications drawn in the study. The direct policy-related implication is that policy should address the problems of different quality of workers due to different access to good quality education among citizens.

Additional evidence on how human capital quality is crucial can be seen from the findings in the third paper. This paper reveals that hiring more educated workers will elevate the role of manufacturing jobs in reducing wage inequality. Moreover, demand for labour coming from medium-high technology industries, which fall in the area where wage inequality is still increasing, needs to be boosted so these industries will enjoy the role of manufacturing jobs in reducing wage inequality. Furthermore, an increase in human capital quality in labour supply will also eliminate the asymmetrical problems of workers' heterogeneity and skill mismatch coming from labour mobility effects.

5.3 Limitation and potential further research

There are limitations to these studies. First, these studies use empirical investigations and do not emphasise building a theoretical framework. Instead, I use some established theoretical concepts and approaches. For example, to measure TFP growth, I apply varying-parameter stochastic frontier analysis, as developed by Kalirajan and Obwona (1994). Moreover, to analyse the relationship between wage inequality and productivity, I test the hypothesis based on the 'fairness' theory developed by Akerlof and Yellen (1988) and the 'tournament' model established by Lazear and Rosen (1981) and Lazear (1989). Lastly, the relationships between manufacturing jobs, labour mobility and wage inequality can be found in many studies (Francis, 2009; Belley et al., 2012; Park, 2019; Song et al., 2019).

Second, this thesis utilised two types of surveys, yearly large and medium manufacturing industries surveys and data about workers' characteristics from the labour force survey. I had to use these two surveys as detailed information about workers' characteristics is not available from the manufacturing industries survey, so I needed to gather the information from the labour force survey. Because of this condition, I had to synchronise both surveys. Unfortunately, the identifiers are not firm-level characteristics. Instead, they are based on industry groups (3-digit ISIC). Hence, the main regressions are based on group industry level, not individual firm level.

Third, the identification strategies for the studies might not be perfect for overcoming all biases. For example, the application of varying parameter stochastic frontier has a challenge in the imposition of constant return to scale production function. Under this assumption, the estimation of frontier coefficients (β_j^*) would be complicated and intractable. As Kalirajan and Shand (1999) point out that 'Even when the condition of constant returns to scale is imposed on the mean response coefficients $\bar{\beta}_j$'s ,then due to the relationship that $\beta_j^* = max\{\bar{\beta}_j + v_{ij}\}$ the possibility that $\sum \beta_j^* > 1$ cannot be ruled out.' (p. 168). Hence, detailed econometrics methods, as well as additional robustness checks, are provided to reduce those biases. I hope these provide clear paths to improve empirical methods in future studies.

Some potential further studies have been identified. For future research, if data on employer-employee matching is available for Indonesia or other developing countries, it could be used to explore the effects of wage dispersion on firm productivity at the firm level more deeply. Moreover, gender gap issues in wages are still a problem, including in Indonesia, and exploring this issue as well as other environmental characteristics that may cause wage disparity will be beneficial to contributing to knowledge. Moreover, to provide more robust explanations about the reasons behind the relationships between manufacturing jobs, labour mobility, and wage inequality, empirical studies about how asymmetrical problems coming from workers' characteristics and skill mismatch could be further explored. Lastly, the hump-shaped relationships could be investigated to test whether the relationship between variables of interest and dependent variables is a quadratic or cubic pattern.

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