This item is the archived peer-reviewed author-version of:

Catching-up, structural transformation, and inequality : industry-level evidence from Asia

Reference:

Martorano Bruno, Park Donghyun, Sanfilippo Marco.- Catching-up, structural transformation, and inequality : industry-level evidence from Asia
Industrial and corporate change - ISSN 0960-6491 - 26:4(2017), p. 555-570
Full text (Publisher's DOI): <https://doi.org/10.1093/ICC/DTW039>
To cite this reference: <https://hdl.handle.net/10067/1358390151162165141>

Catching-up, structural transformation, and inequality: Industry level evidence from Asia

Bruno Martorano,

Institute of Development Studies, University of Sussex (UK), E-mail: b.martorano@ids.ac.uk

Donghyun Park

Asian Development Bank, Manila (Philippines), E-mail: dpark@adb.org

Marco Sanfilippo*

University of Bari (Italy) and Institute of Development Policy and Management, University of Antwerp

(Belgium), E-mail: marco.sanfilippo@uantwerp.be

*Corresponding author

Abstract

This paper empirically investigates the effect of structural transformation on wage inequality in Asia, using industry-level data for three skill groups of workers. While structural transformation, associated with technological progress, productivity catching-up, and capital deepening, has contributed to Asia's sustained growth, its effect on income inequality remains uncertain. Our results show that the process of economic transformation has exacerbated inequality in the region by increasing the relative share of high-skilled workers in total compensation. This is mainly due to a shift towards more productive – and more intensive in the use of skilled labour – activities both within and between industries. However, we also find that policy responses, especially investments in education, mitigate the increase in inequality.

Keywords: Productivity, catching-up, structural transformation, wage gap, Asia

JEL codes: E24; L16

Acknowledgements

We would like to thank two anonymous referees for their helpful suggestions. Financial support from the Asian Development Bank (grant N. 123499) is gratefully acknowledged.

1. Introduction

Rapid globalization and diffusion of new technologies have brought about extensive structural transformation of economies across the world. While the structural changes improved productivity and bolstered economic growth, more of the gains have accrued to owners of capital rather than workers, and to skilled workers rather than unskilled workers, in both advanced and developing economies (ILO, 2014). Most Asian countries are clearly part of such global trends. Over the last decade, output growth in the region has exceeded employment, and productivity outgrew wages (especially outside China, ILO, 2012).

Such trends are consistent with existing theoretical literature, which shows that productivity catch-up with advanced economies can result in higher inequality (Zhu and Trefler, 2005; Chusseau and Hellier, 2012). Several mechanisms, in particular technological upgrading and globalization, can explain this relationship. A close association between higher productivity and technical change has significant implications for the demand and composition of domestic skills, which, in turn, affects wage inequality.

Within this context, it is worthwhile to analyse the experiences of some Asian countries since they have several unique features. While structural change facilitated catch-up with advanced economies and contributed to unprecedented improvement in living standards and poverty reduction, the impact on inequality remains uncertain. As pointed out by Zhuang et al. (2014: 3), the drivers of Asia's catching-up and rapid growth, i.e. technological change, globalization and market-oriented reforms, also exacerbated inequality. However, many Asian economies still rely heavily on labour-absorbing manufacturing, in contrast to the ongoing process of "premature de-industrialization" in developing countries described by Rodrik (2015). McMillan et al. (2014) and Timmer et al. (2014) document that, unlike other developing regions, productivity growth in Asia has taken place largely within, rather than between, sectors, i.e. through more rapid efficiency gains in existing activities rather than as a shift of labour from low- to high- productivity sectors. This pattern is consistent with the "comparative advantage-following" argument recently put forth by proponents of the new structural economics approach (Lin, 2012). As a matter of fact, East Asian growth was characterized by labour-saving technological progress (World Bank, 1993) and high levels of investments in human and physical capital (Aizenman et al., 2012).

In this paper we aim to uncover new evidence on the relationship between structural transformation, catching-up, and wage inequality in Asia. By doing so, we hope to contribute to the existing literature in different ways. First, we perform our empirical analysis at both the country- and the industry- level. Compared to studies that only look at the country level (e.g. Avalos and Savvides, 2006; Bigstein and Munshi, 2014), our analysis accounts also for heterogeneity across sectors. Furthermore, in contrast to previous industry-level studies, which are confined to a subset of high-technology industries within the manufacturing sector (Martorano and Sanfilippo, 2015), we extend the analysis to all the main industries of the economy, fully accounting for both the within- and between-sector dimensions of structural transformation.

Second, we use different variables to proxy structural transformation. While we account separately for the capital intensity of each sector, our key measures of structural transformation considers each industry's productivity catch-up as well as the overlap between the sectorial structure of the economy and the benchmark of high-income OECD economies. This not only allows for looking at both within- and between-sector dimensions of structural transformation (Timmer et al., 2014), but it also provides a better sense of each country's pattern of economic development and the extent to which catching up affects inequality.

Lastly, we highlight the role of country-specific factors, including education policies, in mitigating the negative effects of structural transformation on the wage gap between skilled and the unskilled workers.

For our empirical analysis, we use data from the Social Economic Accounts (SEA) of the World Input Output Database (WIOD) project for five major Asian countries (China; India; Indonesia; South Korea and Taiwan) over the period 1995-2009. Our results show that the process of economic transformation has widened wage inequality by increasing the relative share of high-skilled workers in total labour compensation. This is mainly due to a shift towards more productive – and more intensive in the use of skilled labour – activities both within and between industries. This pattern is difficult to reverse since it is intrinsically linked to the process of economic development. However, selective policy interventions can partly offset the negative effect of economic upgrading and structural changes on wage inequality. A key policy lesson which emerges from the Asian experience is that policies to augment the supply of human capital and thus accommodate the rising demand for

skilled labour can mitigate, directly and indirectly, the negative consequences of catching-up.

The remainder of the paper is structured as follows. Section 2 reviews the literature on the determinants of wage inequality. Section 3 presents the data, model and methodology used for our empirical analysis. Section 4 reports and discusses our results. Section 5 concludes.

2. Literature Review

There is a large literature on factors affecting the relative demand for skilled workers, and thus the distributional consequences for skilled versus unskilled workers, with an initial focus on advanced economies (Acemoglu, 1998; 2002; Wood, 1995; Card and di Nardo, 2002). More recently, a growing strand of literature has investigated the determinants of wage inequality in emerging and developing countries too. Pushed by productivity catch-up with more advanced economies and by structural transformation, sustained economic growth in many developing countries has generally resulted in rising inequality due the higher demand for skills (Berman and Machin, 2000; Chusseau and Hellier, 2012).

What are the main mechanisms through which productivity growth and structural transformations cause higher levels of wage inequality? Technology is certainly a major channel. Higher productivity associated with technological change has obvious implications for the distribution of wages between skilled and unskilled workers. According to the Skill Biased Technological Change (SBTC) hypothesis, high technology-intensive activities employ relatively more skilled workers. Technological upgrading may result thus in a shift in the relative demand curve for skills, exacerbating wage inequality (Card and di Nardo, 2002). Shift of demand towards more skilled workers due to technological change is also evident in middle and low- income countries (Berman and Machin, 2000). For example, Hur et al. (2005) show that the technological upgrading in Korean industrial sectors increased the demand for skills in the second half of the 1990s. Liu et al. (2013) report that the introduction of new technologies increased wage levels in Taiwanese industry. Similarly, Berman et al. (2005) show that the increase in the demand for skilled labour in India since the 1990s was mainly driven by skill-biased technological change.

Significantly, Berman and Machin (2000) point out that the fact that such shifts are mainly driven by the within industry component is itself a prerequisite to the SBTC hypothesis, and highlights the case of Korea as a clear example. Using household level data, Kijama (2006) finds that the increase in the skill premium in post-reform India can be largely explained by a robust increase in the demand of skills (tertiary-educated workers) due to within-industry SBTC.

A shift toward higher productivity activities affects income distribution between capital and labour, reducing the relative share of the latter. The SBTC hypothesis posits that high complementarity between capital and skills will further raise the demand for skilled workers and their relative wages. Looking at Chilean firms, Pavnick (2003) finds that capital deepening raises the relative demand for skilled workers. Studies on Asian countries yield similar findings. Ramaswamy (2008), for instance, shows that changes in capital-output ratio increased wage inequality in the Indian manufacturing sector in 1981-2004.

In general, developing countries import technology and technological change. As such, a number of studies (Goldberg et al., 2010; Vivarelli, 2012; Mitra and Jha, 2015; Charfeddine and Mrabet, 2015) evokes globalization, and the associated transfer of technologies through trade and FDI, as the leading causes of wage inequalities (Wood, 1995; Robbins, 2003). However, this argument has been widely debated at both the theoretical and the empirical levels (see Kurokawa, 2014, for a review). The Stolper-Samuelson corollary of the Heckscher-Ohlin theory of trade points out that opening up to foreign trade will equalise the remuneration of factors of production across countries, leading to an increase in the demand (and so the wages) for unskilled labour in developing countries (Wood, 1995). There are indeed a number of studies (Attanasio et al., 2004; Avalos and Savvides, 2006; Mamoom and Murshed, 2012) which provide empirical support for the Stolper-Samuelson hypothesis.

However, more recent evidence seems to suggest the opposite (Meschi et al., 2011; Charfeddin and Mrabet, 2015). This group of studies also shows that the effect of trade on wage inequality in developing countries is magnified when the trade partner is an advanced economy (Meschi and Vivarelli, 2009). Influential contributions include Feenstra and Hanson (1997) and Zhu and Trefler (2005). Both papers theoretically and empirically show that greater openness results in a shift of

relatively less skilled production from the North to the South. However, such production is more skill intensive in the South.

Meschi and Vivarelli (2009) suggests that complementarity between SBTC and openness is realistic if assumptions of homogeneous production functions and identical technologies between countries are relaxed. In that case, greater openness will induce SBTC due to greater transfer of technologies from advanced to developing countries. For instance, Lee and Wie (2015) show that in Indonesia the adoption of advanced technology introduced through imports and foreign direct investment shifted labour demand in favour of skilled workers, increasing wage inequality since 2000. Vivarelli (2012) explains that this process is more likely to occur for middle- rather than low-income countries, considering the different levels of absorptive capacities. Interestingly, Zhu and Trefler (2005) show that the faster a country catches up, the worse the wage inequality, due to a more rapid shift towards skill intensive production transferred from the North.

To conclude this short review, it is worth mentioning a recent contribution by Buera et al. (2015) emphasizing the compositional effects of structural change. Supported by long run evidence from a group of advanced economies, the authors show that structural change will inevitably reallocate resources towards more skill-intensive industries, thus widening the wage gap between skilled and unskilled workers. According to the authors, such resource reallocation is an inevitable consequence of economic development and, interestingly, will push up the skill premium even in the absence of technological change.

3. Data and empirical framework

In this section, we describe the data, model and methodology used in our empirical analysis.

3.1. Data and main indicators

Our data come from the Socio-Economic Accounts (SEA) of the WIOD project¹ (Timmer et al., 2015), which provides information on employment, wages, capital and output at the industry level for 40 countries over the period 1995-2009. Data on the number of hours worked and their relative compensations, originally

¹ Available at: http://www.wiod.org/new_site/home.htm

sourced from national labour force surveys and censuses, are reported by skills (low; medium and high), defined according to the International Standard Classification of Education (ISCED)².

Five Asian countries are available from the original dataset³. They include two high-income Newly Industrialized Economies (NIEs) (Korea and Taiwan), a large, middle-income ASEAN economy (Indonesia), and China and India, two fast-growing giants. Industries cover the three main sectors of the economy, primary, manufacturing and services, and are generally reported – unless where some re-aggregation was necessary – at the 2-digit code of the ISIC classification, revision 3 (see Table A1 in the appendix for a list of the industries included)⁴.

3.1.1. Wage gap

Based on such information, we construct our dependent variable, the wage gap, as the ratio of the hourly wage of high-skill workers (*skilled_wage*) to the sum of the wages of medium- and low-skill workers (*unskilled_wage*). Formally,

$$wage_gap_{i,j,t} = skilled_wage_{i,j,t} / unskilled_wage_{i,j,t} \quad (1)$$

where i, j and t identify country, industry and year, respectively.

Evidence on inequality levels shows some differences among our sample of Asian countries. China initially had lower wage inequality levels, but experienced a marked widening over time (Figure 1). Rising disparities between urban and rural areas, as well as growing wage gaps between skilled and unskilled workers within urban areas, contributed to the worsening of the wage gap (Li et al, 2012).

FIGURE 1 HERE

² Though to the best of our knowledge the data are probably more comprehensive sources comparing countries across sectors in such a consistent way, some bias must be taken into account due, for instance, to the lack of reliable information on informal and self-employed workers, whose role might be substantial in some emerging economies such as India. For more information on the way these workers were covered by the data, see the country notes reported in the background paper by Erumban et al. (2012)

³ While Japan is also included in SEA, we exclude it from our analysis considering its stable presence in the group of high-income OECD countries as well a less recent process of structural transformation.

⁴ Non-market service industries (from L to P in Table A1) were dropped from the sample due to their potential role of outliers in countries highly exposed to market forces and international integration.

India and Indonesia have the highest levels of wage inequality. Interestingly, Indonesian wage inequality has remained stable. This seems supported by complementary evidence on the country's overall inequality levels (di Gropiello and Sakellariou, 2010). A possible explanation is that the Asian crisis affected urban wages more than rural wages (Jomo, 2006). On the other hand, East Asian countries, which enjoyed some positive spillover effects of rapid growth on income distribution during the years of the East Asian Miracle (World Bank, 1993), have somewhat better levels of inequality.

We also decompose changes in the wage gap in its two main components. The first one is the within-industry skill upgrading while the second one is the between-industry component, which measures the changes in the size of an industry over time. Formally:

$$\Delta wage\ gap_j = within_j + between_j \quad (2)$$

$$within_j = \sum_{i=1}^N \Delta wage\ gap_i \times emp_j \quad (3)$$

$$between_j = \sum_{i=1}^N \Delta emp_i \times wage\ gap_i \quad (4)$$

where j identifies the industry, while emp represents the share of industry j employment in total employment.

Table 1 shows that the rise of wage inequality has been largely driven by within-industry variations (with the exception of India), confirming evidence in the existing literature, including on some Asian countries (Berman and Machin, 2000, on Korea). This pattern supports the view that the evolution of wage gap has been driven by technology changes, which is consistent with the SBTC hypothesis, rather than by the reallocation of workers towards more skill intensive industries. It is also consistent with the pattern of productivity growth in the region as documented by McMillan et al. (2014).

TABLE 1 HERE

3.1.2. *Catching- up*

In the absence of detailed information on technology adoption by industry, we try to capture the technological dimension by combining information about changes in within sector productivity and the distribution of value added between sectors, i.e. looking at the pattern of structural transformation over time.

Rather than using absolute values of productivity for each country in our sample, we compare their performance to a benchmark represented by the average value of a group of high-income OECD countries.⁵ We first construct an indicator of real industry labour productivity as the ratio of value added to the total number of workers in each Asian country. We then construct our benchmark as the average of the OECD group, and express our variable as the ratio of the two. Our main indicator of structural transformation, the productivity catch up index, is then calculated as the log difference of the productivity ratio between t and t-1.

$$catch_up^{oecd}_{i,t} = \log \left(\frac{\frac{productivity_{i,t}}{productivity_{OECD,t}}}{\frac{productivity_{i,t-1}}{productivity_{OECD,t-1}}} \right) \quad (5)$$

Evidence on the patterns of productivity growth and catching-up in Asia over the decades is striking. Since the mid-1990s, Asian economies experienced rapid growth and extensive structural transformation. Productivity growth has been uneven across countries and industries. In 1995-2009, China and India enjoyed the highest growth of productivity, which is plausible in light of their low initial income levels. Korea and Taiwan managed to keep their productivity levels stable, which is also plausible in light of their already high levels (Figure 2). Indonesia, on the other hand, lost ground. After a rebound in the early 2000s, productivity declined visibly in the manufacturing sector and fell modestly in the service sector, with the exception of some industries such as transport and communications (World Bank, 2014).

FIGURE 2 HERE

⁵ Countries included are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, Portugal, Spain, Sweden, UK and USA.

The overall increase of productivity observed in absolute terms in Figure 2 has not necessarily led to faster catching-up with advanced economies, highlighting interesting differences in the direction of structural change across countries. Not surprisingly, China stands out as the country with productivity improvements large enough to catch up with advanced countries in practically all sectors of the economy, regardless of their labour, capital or knowledge intensity (Figure 3 – panel a). India, on the other hand, has been able to close the gap more modestly and mostly in services, especially knowledge intensive ones such as financial intermediation and business services (Figure 3 – panel b). The drivers of Korean growth are mostly manufacturing industries in which the country developed a comparative advantage while in Taiwan growth was driven by high-skill services. Finally, our data confirm that the poor performance of Indonesia was due to poor performance of manufacturing industries (see Appendix Figure 1).

FIGURE 3 HERE

3.2. Model and empirical specification

Having introduced the main variables of interest, this section spells out our empirical specification in more detail.

Our baseline specification formally links the wage gap (*wage_gap*), as defined in (1), with productivity catch up (*catch_up*^{*oeed*}), as defined in (5). As discussed, productivity growth may affect wage inequality through a number of mechanisms, especially technology diffusion and capital deepening. To rule out the effect of capital deepening, and isolate the technological change component, we control specifically for the capital intensity of each industry, measured as the ratio of the compensations of capital and labour (*kl*). In addition, to account for the relative size of each industry in the economy, and its influence on the wage distribution, we control for the share of each industry in total employment (*emp_share*).

Although we are fairly confident that within industry productivity change absorbs a large part of the gains in total productivity in our countries (as demonstrated in Table 4 of McMillan et al., 2014: 21), in additional specifications we try to account for a modified “between” effect. Once again, we take the OECD countries as benchmark. Using a metric of export similarity index based on Krugman (1991), we calculate a similarity index (KIS- Krugman Index of Similarity) by comparing the

relative share of each industry's value added in the economy. The similarity index is transformed to range between 0 and 1, with values close to 1 meaning a stronger similarity with the economic structure of the OECD:

$$KIS_{it} = 1 - \left(\frac{1}{2} \sum_{i=1}^I |va\ share_{i,it} - va\ share\ OECD_{i,it}| \right) \quad (6)$$

Overall, we expect productivity catch-up, capital intensity, and similarity index to worsen the wage gap, in light of their effect on the skill bias of technological change, complementarity between capital and skilled workers, and shift of production towards high-skill activities. This is what we consistently observe in the recent growth pattern of advanced economies. However, technological change via productivity growth and capital deepening might not necessarily be labour biased, but labour saving (Vivarelli, 2012; Lawrence, 2015), depending on the characteristics of the countries and industries.

We also include some additional controls that can have short-run effects on wage inequality. We first control for the level of per capita GDP (gdp_pc) in order to account for the different income levels of the five countries. Income differences may matter since wage inequality tends to rise with higher levels of economic development. Second, we account for the supply side, which is central in the SBTC hypothesis. An increase in the supply of skilled labour force will, in fact, result in lower skill premia in view of the so-called substitution effect, at least in the short run (Acemoglu, 2002). More specifically, we introduce a variable (edu) that account for the relative supply of highly skilled workers, which is measured as the ratio of working age population with secondary and tertiary education to working age population with primary or no education.

In all our estimations we adopt a dynamic specification by adding the lagged dependent variable ($wage_gap_{t-1}$) on the right hand side. Our decision to run a dynamic specification is mainly driven by the path-dependent pattern of the wage gap, which is normally driven by structural factors that are unlikely to vary in the short run. In addition, we include a full set of country (η_i), industry (θ_i) and time (θ_t) fixed effects to account for all the potential unobservable factors likely to influence the distribution of wages in our sample. Our complete specification is therefore the following:

$$wage_gap_{it} = \alpha_0 + \alpha_1 wage_gap_{it-1} + \alpha_2 catch_up^{pecd}_{i,t} + \alpha_3 kl_{it} + \alpha_4 emp_share_{it} + \alpha_5 gap_pc_{it} + \alpha_6 edu_{it} + \eta_i + \delta_t + \theta_t + u_{it} \quad (7)$$

All variables expressed in monetary values, such as value added and wages, have been deflated using their respective price index (available from the SEA database) and reported in common currency using the same exchange rate adopted to make I/O tables consistent across the different countries covered by the WIOD (see Timmer et al., 2015). All variables are transformed in natural logarithms. Summary statistics of the variables are reported in Table A2 in the appendix.

3.3. Methodology

Our empirical specification described in (7) presents a number of potential biases. The inclusion of a lagged dependent variable among the covariates forces us to correct for autocorrelation in the error term. Another relevant issue is endogeneity. This has to do with the presence of the lagged dependent variable, as well as other covariates. More specifically, an omitted variable bias can affect our estimates due to, for instance, the inability of our measures of structural transformation to adequately capture technological change. This would affect both catch-up and inequality, and cause potential endogeneity of the former variable (Zhu and Trefler, 2005).

We therefore employ estimators based on the Generalized Method of Moments (GMM). The first is the “Difference GMM”, proposed by Arellano and Bond (1991). This estimator transforms the original equation into first differences and endogenous variables are instrumented using lags of their own levels. Exogenous regressors are included in the instrument matrix in first differences. The second method is the “System GMM” estimator proposed by Blundell and Bond (1998), which uses the lagged differences in order to instrument the level equation. This method improves the efficiency of the estimation and allows the introduction of additional instruments.

We treat the catch up, the capital to employment ratio, and the employment share as endogenous, using their first three lags as instruments. The lagged dependent variable is considered endogenous as well and, due to the failure of the Arellano – Bond test to detect autocorrelation up to order 5, we use its sixth lag and beyond as instruments.

4. Empirical Results

In this section, we report and discuss our empirical results. Table 2 reports our regression results based on different econometric techniques, including OLS, Fixed effects (FE) and difference- and system-GMM. The lagged coefficient of the dependent variable is always positive and statistically significant. This provides strong evidence on path-dependent pattern of the dependent variable, which is consistent with previous studies based on aggregate data of developing countries (Meschi and Vivarelli, 2009). The size of the coefficient of the lagged dependent variable generated by the System GMM estimator falls between the higher bound of the OLS (Column 1) and the lower bound of the Fixed Effects (Column 2) model, as expected. Also, the AR and the Hansen tests provide evidence on the correct specification of the model. Considering the superior performance of the system-GMM compared to the others, for the rest of this section we will base our discussion on columns 4-6.

The catching up coefficient is positive and statistically significant in all specifications. According to our preferred specification, closing the productivity gap by 10% raises the wage gap by about 2%. This result is coherent with existing literature, assuming that productivity catch-up with advanced economies increases the demand for skills and widens wage inequality (Zhu and Trefler, 2005; Chusseau and Hellier, 2012). While there are several potential explanations, our evidence suggests that within-industry technological upgrading needs to be accounted as a key factor in our Asian sample. Significantly, our evidence indicates that this happens through productivity gains, which is relevant in light of the fact that most of structural change in the region is driven by increases in within-industry productivity (Timmer et al., 2014; McMillan et al., 2014), and many countries and industries are still far from the productivity frontier.

The previous finding is reinforced by the evidence on the positive and significant effect of capital intensity on inequality. The result supports complementarity between capital and skilled labour. Asian economies are not an exception to the rule since the growing intensification of capital in production during the last decades has favoured skilled over unskilled workers, pushing wage inequality up (ILO, 2014). In contrast, the relative size of industry is not significant, though the coefficient is still positive. This is not entirely surprising considering the context of our analysis, since over their development patterns many Asian countries have been

able to keep their comparative advantage in some traditional labour intensive industries, while simultaneously upgrading into more technology and capital intensive ones (Lin, 2012).

Having so far considered the within-industry dimension of structural change, in column 5 we also account for the between-industry dimension. To do so, we add a country specific variable (*kis*) measuring industry similarity with OECD countries. Our results are again in line with our expectations since they suggest that laggard countries transforming the structure of their economies in the direction of more advanced ones pay a price in terms of widening wage gap between the skilled and the unskilled. This result is consistent with recent findings by Buera et al. (2015), who show that between-sector structural transformation often leads to a shift to high value-added and more skill-intensive activities.

TABLE 2 HERE

Per capita GDP (*gdp_pc*) is positive and significant. Differences in the level of income matter since wage inequality tends to rise with higher levels of economic development. In particular, the pathway towards economic growth and structural transformation can affect the wage distribution by increasing the relative share of high-skilled workers in total labour compensation, which in turn tends to increase wage inequality.

In addition, Table 2 shows that the supply of highly skilled workers, measured as the ratio of working age population with secondary and tertiary education to working age population with primary and no education, is negatively correlated to wage inequality. This result confirms one of the central arguments of the SBTC hypothesis, i.e. that there is an inverse relation between the wage gap and the relative supply of skilled labour (the so-called *quantity effect*, see Acemoglu, 2002). As a result, the increase in the supply of skilled workers is expected to reduce the wage premium, *in the absence* of technological change.

However, whether education policies have a direct effect on wage inequality during periods of structural transformation remains to be seen. To check how education policies in Asia have responded to changes in the demand for skills due to structural transformation, we introduce an interaction term between the catch-up and education coefficients (*catch_up*edu*). The result, reported in column 6 of Table 2,

shows that the interaction term is negative and significant, meaning that a greater supply of workers with higher education can indeed mitigate the widening of the skill premium caused by productivity catch-up. This is consistent with theory and evidence from other countries (reported in Acemoglu, 2002), as well as the experience of some early members of the East Asian Miracle. For example, in South Korea education policies matched and indeed contributed to the evolution of economic structure over time.

Finally, in order to check the robustness of our results, we employed alternative measures of the dependent variables and found that most of the results are qualitatively similar to the baseline results regardless of whether the wage gap is calculated as the ratio of high to low-skilled workers or as the ratio of high to medium-skilled workers (Tables B1-B2 in the online Appendix).

5. Conclusions

Asia has grown visibly faster than other parts of the world during the past few decades. While extensive structural transformation, associated with technological progress, productivity growth, and capital deepening, contributed to Asia's sustained rapid growth, it may have exacerbated income inequality. This issue is of great interest for the region, where more inclusive growth has emerged as a top strategic priority in light of widening inequality. The central objective of this paper is to empirically investigate the effect of structural change on inequality in Asian countries. To do so, we used data for different industries and skill groups of workers for five major Asian economies from 1995 to 2009.

Our results suggest that the process of structural change and catch-up with advanced economies has indeed worsened wage inequality in Asian countries. Our evidence further confirms that high-skilled workers have benefited disproportionately from structural transformation. In line with theory and existing evidence, our findings lend empirical support to the skill bias of technological change, and complementarity between capital and skilled workers, in Asian countries. Therefore, while structural change is vital for Asia's economic dynamism and growth, it may have contributed to inequality in the region.

However, our evidence indicates that there is room for policy responses which can mitigate the adverse effect of structural transformation on wage inequality. In particular, boosting the supply of educated workers can limit the adverse effect if it

helps to meet the growing demand for skills, a consequence of structural change. This underlines the need for investments in education and human capital.

References

- Acemoglu, D. (1998), "Why do new technologies complement skills? Directed technical change and wage inequality", *Quarterly Journal of Economics*, 113, 1055-1989.
- Acemoglu, D. (2002) "Technical change, inequality, and the labor market," *Journal of Economic Literature*, 40(1), pp. 7–72. doi:10.1257/jel.40.1.7.
- Aizenman, J., Lee, M. & Park, D. (2012) "The Relationship between Structural Change and Inequality: A Conceptual Overview with Special Reference to Developing Asia", ADBI Working Paper Series N. 396
- Almeida, R. K. (2010), "Openness and Technological Innovation in East Asia: Have They Increased the Demand for Skills?," Policy Research Working Paper Series No. 5272 (The World Bank).
- Arellano, M. & S. Bond (1991), "Some Tests of specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *The Review of Economic Studies*, 58, 277–97.
- Attanasio, O., Goldberg P., and N. Pavcnik (2004). "Trade Reforms and Wage Inequality in Colombia." *Journal of Development Economics*. 74, 331-366.
- Avalos, A., & Savvides, A. (2006), "The Manufacturing Wage Inequality in Latin America and East Asia: Openness, Technology Transfer, and Labor Supply", *Review of Development Economics*, 10(4), 553-576.
- Berman, E. & Machin, S. (2000), "Skill-Based Technology Transfer around the World", *Oxford Review of Economic Policy*, 16(3), 12-22.
- Berman, E., Bound, J. & Machin, S. (1998), "Implications Of Skill-Biased Technological Change: International Evidence", *The Quarterly Journal of Economics*, 113(4), 1245-1279.
- Berman, E., Somanathan, R., & Tan, H. W (2005). "Is Skill-Biased Technological Change Here Yet? Evidence from Indian Manufacturing in the 1990's". *Annales d'Économie et de Statistique*, 299-321.
- Blundell, R. & S. Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models", *Journal of Econometrics*, 87, 115–43.

- Buera, F. J., Kaboski, J. P., & Rogerson, R. (2015). "Skill biased structural change." (No. w21165). National Bureau of Economic Research.
- Card, D., & di Nardo, J.E. (2002) "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles", *Journal of Labor Economics*, 20(4), 733-783.
- Charfeddine, L., & Mrabet, Z. (2015). "Trade liberalization and relative employment: further evidence from Tunisia." *Eurasian Business Review*, 5(1), 173-202.
- Chusseau, N. & Hellier, J. (2012) "Inequality in Emerging Countries", ECINEQ Working Paper N. 2012-256.
- di Gropiello, E. & Sakellariou, C. (2010). "Industry and Skill Wage Premiums in East Asia." The World Bank, Policy Research Working Paper Series No. 5379.
- Erumban, A., Gouma, R., de Vries, G., de Vries, K., & Timmer, M. (2012). WIOD Socio-Economic Accounts (SEA): Sources and Methods. Groningen, April.
- Feenstra, R. C. & Hanson, G. H. (1997) Foreign direct investment and relative wages: evidence from Mexico's maquiladoras, *Journal of International Economics*, 42(3-4): 371-393.
- Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., & Topalova, P. (2010). "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India". The *Quarterly journal of economics*, 125(4), 1727-1767.
- Hur, J. J., Seo, H. J., & Lee, Y. S. (2005). "Information and communication technology diffusion and skill upgrading in Korean industries". *Economics of Innovation and New Technology*, 14(7), 553-571.
- ILO (2012), Asia-Pacific Labour Market Update, April 2012, Geneve: ILO
- ILO (2014), Supplement to the ILO's Global Wage Report 2014/15: Wages in Asia and the Pacific: Dynamic but uneven progress, Geneve: ILO
- Jomo, K. S. (2006), "Growth with Equity in East Asia?", DESA Working Paper No. 33.
- Kijama, Y. (2006). "Why did wage inequality increase? Evidence from urban India 1983-99," *Journal of Development Economics*, 81, 97-117
- Krugman, P. (1991), *Geography and Trade*, Cambridge (US): MIT Press.

- Kurokawa, Y. (2014) "A Survey of Trade and Wage Inequality: Anomalies, Resolutions and New Trends," *Journal of Economic Surveys*, 28(1): 169-193.
- Lawrence, L.Z. (2015). "Recent Declines in Labor's Share in US Income: A Preliminary Neoclassical Account", Peterson Institute Working Paper N. 10/2015
- Lee, J. W., & Wie, D. (2015). Technological change, skill demand, and wage inequality: Evidence from Indonesia. *World Development*, 67, 238-250.
- Lin, J.Y. (2012) *New Structural Economics – A framework to re-thinking development and policy*, Washington, DC: the World Bank.
- Liu, J. L., Huang, C. H., & Yang, C. H. (2013). "Technological Change, Job Risk, and Wage Premium: Evidence from Taiwan". *The Developing Economies*, 51(2), 186-202.
- Mamoon, D., & Murshed, S. (2012). "Education bias of trade liberalization and wage inequality in developing countries." *The Journal of International Trade and Economic Development: an international and comparative review*, 21(3), 1-33.
- Martorano, B. & Sanfilippo, M. (2015), "Structural change and wage inequality in the manufacturing sector: long run evidence from East Asia", *Oxford Development Studies*, 43(2): 212-231.
- McMillan, M., Rodrik, D. & Verduzco-Gallo, I. (2014) "Globalization, Structural Change, and Productivity Growth, with an Update on Africa," *World Development*, 63: 11-32.
- Meschi, E. & Vivarelli, M. (2009). Trade and income inequality in developing countries. *World Development*, 37, 287-302.
- Meschi E., Taymaz E., & Vivarelli, M. (2011). "Trade, technology and skills: evidence from Turkish microdata," *Labour Economics*, 18, S60-S70.
- Mitra, A. & Jha, A.K. (2015). "Innovation and employment: a firm level study of Indian industries." *Eurasian Business Review* 5, 45-71.
- Pavcnik, N. (2003). "What explains skill upgrading in less developed countries?" *Journal of Development Economics*, 71, 311-328.

- Ramaswamy, K.V. (2008). "Wage inequality in Indian manufacturing: Is it trade, technology or labour regulations?," Indira Gandhi Institute of Development Research, Mumbai Working Papers 2008-021.
- Robbins, D. (2003). "The impact of trade liberalization upon inequality in developing countries: a review of theory and evidence." Working Paper no. 13. Geneva: International Labour Organization.
- Rodrik, D. (2015) "Premature Deindustrialization," NBER Working Paper No. 20935.
- Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R. & de Vries, G. J. (2014), "Slicing Up Global Value Chains" *Journal of Economic Perspectives*, 28(2), 99-118.
- Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R. & de Vries, G. J. (2015), "An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production", *Review of International Economics*, 23: 575–605.
- Vivarelli, M. (2012). "Innovation, employment and skills in advanced and developing countries: A survey of economic literature". IZA Discussion Paper N. 6291, IZA: Bonn.
- Wood, A. (1995). "How trade hurt unskilled workers." *Journal of Economic Perspectives*, 9, 57-80.
- World Bank (1993), *The East Asian Miracle: Economic Growth and Public Policy*, Oxford: Oxford University Press.
- World Bank (2014), Indonesia: Avoiding the Trap, the World Bank office Jakarta.
- Zhu, S.C. & Trefler, D. (2005) "Trade and inequality in developing countries: a general equilibrium analysis", *Journal of International Economics*, 65 (2005): 21–48.
- Zhuang, J., Kanbur, R. & Rhee, C. (2014), "Rising Inequality in Asia and Policy Implications", ADBI Working Paper 463. Tokyo: Asian Development Bank Institute.

Figures

Figure 1. Average levels of wage gap in Asian countries, 1995-2009

Source: Authors' elaboration on SEA database

Note: the wage gap reported in this graph is constructed as the simple average of each industry's wage gaps. More details are provided in Section 3.1.1.

Figure 2. Changes in productivity level between 1995 (x-axis) and 2009 (y-axis)

Source: author's elaboration on SEA database

Note: Each dot represents one of the industries included in the SEA database (see Table A1)

Figure 3. Changes in productivity catch-up with OECD in China (panel a) and India (panel b) between 1995 (x-axis) and 2009 (y-axis)

Source: Author's elaboration on SEA data

Notes: The productivity ratio has been constructed comparing levels of productivity by country and industry with the corresponding average levels recorded by high-income OECD countries. More details on the construction of the index are provided in Section 3.1.2.

Tables

Table 1. Within/between industry decomposition of the national wage gap, 1995-2009

	within	between	overall	within/overall
China	0.041	0.009	0.050	0.825
Indonesia	0.530	0.004	0.534	0.993
India	0.023	0.025	0.047	0.476
Korea	0.058	0.028	0.087	0.674
Taiwan	-0.012	0.000	-0.012	1.000

Source: authors' elaboration on SEA data

Table 2. Main Results

VARIABLES	(1) OLS	(2) FE	(3) GMM_DIFF	(4) GMM_SYS	(5) GMM_SYS	(6) GMM_SYS
L.lnwage_gap	0.866*** [0.040]	0.503*** [0.032]	0.206*** [0.044]	0.507*** [0.041]	0.451*** [0.040]	0.532*** [0.044]
dcatch_up	0.019 [0.013]	0.034*** [0.012]	0.009 [0.012]	0.026** [0.011]	0.018* [0.010]	0.044*** [0.017]
kl	0.000 [0.001]	-0.001 [0.001]	-0.007 [0.008]	0.007** [0.003]	0.008** [0.004]	0.004* [0.003]
emp_share	-0.001* [0.000]	0.005** [0.002]	0.015*** [0.005]	0.001 [0.002]	0.001 [0.002]	0.000 [0.002]
kis_va					0.662*** [0.231]	
lgdp_pc	-0.016*** [0.004]	0.144*** [0.015]	0.086** [0.043]	0.051* [0.027]	-0.032 [0.053]	0.062*** [0.023]
edu	-0.005** [0.002]	-0.017*** [0.003]	-0.044*** [0.012]	-0.035*** [0.007]	-0.011 [0.008]	-0.034*** [0.007]
catch_up*edu						-0.018*** [0.006]
Constant	0.146*** [0.034]	-1.304*** [0.128]		-0.488** [0.241]	-0.118 [0.374]	-0.582*** [0.206]
Observations	2,072	2,072	1,924	2,072	2,072	2,072
R-squared	0.846	0.358				
Country effects			Y	Y	Y	Y
Industry effects			Y	Y	Y	Y
Year effects			Y	Y	Y	Y
ar1p			0.00438	2.41e-05	2.21e-06	7.04e-06
ar2p			0.0135	0.0214	0.0207	0.0249
ar3p			0.00742	0.00135	0.00101	0.00136
ar4p			0.00633	0.0138	0.0167	0.0139
ar5p			0.318	0.786	0.745	0.950
Hansen - p			0.000989	0.702	0.998	0.996
N. instruments			116	200	240	238

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

APPENDIX A

Figure A1. Changes in productivity catch up with OECD countries- 1995 (x-axis) and 2009 (y-axis)

Source: Author's elaboration on SEA data

Notes: The productivity ratio has been constructed comparing levels of productivity by country and industry with the corresponding average levels recorded by high-income OECD countries. More details on the construction of the index are provided in Section 3.1.2.

Table A1. Industries

Industry description	Industry code
Agriculture, Hunting, Forestry and Fishing	AtB
Mining and Quarrying	C
Food, Beverages and Tobacco	15t16
Textiles and textile	17t18
Leather, leather and footwear	19
Wood and Wood and Cork	20
Pulp, Paper, Paper, Printing and Publishing	21t22
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical	24
Rubber and plastics	25
Other Non-Metallic Mineral	26
Basic Metals and Fabricated Metals	27t28
Machinery, nes	29
Electrical and Optical Equipment	30t33
Transport Equipment	34t35
Manufacturing nec; Recycling	36t37
Electricity, Gas and Water Supply	E
Construction	F
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	50
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52
Hotels and Restaurants	H
Other Inland transport	60
Other Water transport	61
Other Air transport	62
Other Supporting and auxiliary transport activities; activities of travel agencies	63
Post and Telecommunications	64
Financial Intermediation	J
Real estate activities	70
Renting of m&eq and other business activities	71t74
Public Admin and Defence; Compulsory Social Security	L
Education	M
Health and Social Work	N
Other Community, Social and Personal Services	O
Private Households with Employed Persons	P

Table A2. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
wage_gap	2220	-.0953189	.3221975	-.7095095	2.006562
dcatch_up	2072	-.0274028	.2323027	-1.965934	1.075757
kl	2220	1.633553	2.631503	-.4006737	25.01004
emp_share	2250	2.824578	7.130734	0	62.38619
kis_va	2250	.5119324	.1285068	.2933046	.7230198
lgdp_pc	2250	8.901065	1.035193	7.304097	10.36433
edu	2250	2.167386	1.891463	.2903226	6.385524

APPENDIX B (online)

Table B1. Different dependent variable: High skilled wage/low skilled wage

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	ols_1	ols_fe	gmm_diff	gmm_sys	gmm_sys	gmm_sys
L.ln wage_gap_bis	0.887*** [0.031]	0.506*** [0.028]	0.272*** [0.040]	0.610*** [0.051]	0.617*** [0.046]	0.642*** [0.047]
dcatch_up	0.027 [0.016]	0.031** [0.013]	-0.001 [0.016]	0.029** [0.014]	0.02 [0.013]	0.046** [0.021]
kl	0.003* [0.002]	0.002 [0.002]	-0.001 [0.009]	0.019*** [0.005]	0.021*** [0.006]	0.015*** [0.005]
emp_share	-0.001 [0.000]	0.004 [0.003]	0.014*** [0.004]	0.001 [0.002]	0.002 [0.003]	0.000 [0.002]
kis_va					0.591** [0.234]	
lgdp_pc	-0.023*** [0.006]	0.161*** [0.020]	0.125* [0.065]	0.021 [0.035]	-0.077 [0.050]	0.027 [0.033]
edu	-0.002 [0.002]	-0.018*** [0.004]	-0.043*** [0.014]	-0.036*** [0.009]	-0.013 [0.013]	-0.035*** [0.008]
catch_up_edu						-0.016** [0.007]
Constant	0.302*** [0.075]	-1.036*** [0.168]		0.084 [0.318]	0.628* [0.377]	0.024 [0.292]
Observations	2,072	2,072	1,924	2,072	2,072	2,072
R-squared	0.881	0.359				
Country effects			Y	Y	Y	Y
Industry effects			Y	Y	Y	Y
Year effects			Y	Y	Y	Y
ar1p	.	.	0.000246	1.39E-07	1.46E-07	1.82E-07
ar2p	.	.	0.0169	0.0282	0.0292	0.0296
ar3p	.	.	0.0203	0.00712	0.00815	0.00848
ar4p	.	.	0.251	0.272	0.317	0.269
hansenp	.	.	0.0059	0.856	0.999	0.999
N. instruments	.	.	126	211	251	249

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table B2. Different dependent variable: High skilled wage/medium skilled wage

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	ols_1	ols_fe	gmm_diff	gmm_sys	gmm_sys	gmm_sys
L.ln wage_gap_tris	0.833*** [0.047]	0.503*** [0.040]	0.129*** [0.035]	0.455*** [0.036]	0.421*** [0.028]	0.477*** [0.036]
dcatch_up	0.015 [0.012]	0.038*** [0.012]	0.011 [0.011]	0.024** [0.011]	0.020* [0.011]	0.047*** [0.016]
kl	-0.001 [0.001]	-0.001 [0.002]	-0.008 [0.008]	0.000 [0.004]	0.000 [0.004]	-0.002 [0.003]
emp_share	-0.001** [0.000]	0.005*** [0.002]	0.015*** [0.005]	0.001 [0.002]	0.000 [0.002]	0.000 [0.002]
kis_va					0.759*** [0.226]	
lgdp_pc	-0.009*** [0.003]	0.132*** [0.014]	0.048 [0.042]	0.051** [0.023]	-0.059 [0.051]	0.063*** [0.020]
edu	-0.008*** [0.002]	-0.016*** [0.003]	-0.046*** [0.012]	-0.038*** [0.007]	-0.01 [0.007]	-0.036*** [0.007]
catch_up_edu						-0.020*** [0.005]
Constant	0.187*** [0.044]	-0.914*** [0.117]		-0.152 [0.201]	0.427 [0.353]	-0.266 [0.182]
Observations	2,072	2,072	1,924	2,072	2,072	2,072
R-squared	0.78	0.345				
Country effects			Y	Y	Y	Y
Industry effects			Y	Y	Y	Y
Year effects			Y	Y	Y	Y
ar1p	.	.	0.00663	0.000263	1.51E-05	7.20E-05
ar2p	.	.	0.00421	0.00868	0.00822	0.0125
ar3p	.	.	0.00282	0.000217	0.000111	0.000192
ar4p	.	.	0.0013	0.00744	0.0099	0.00697
ar5p	.	.	0.431	0.942	0.941	0.896
hansenp	.	.	0.000811	0.759	0.996	0.999
N. instruments	.	.	116	200	240	238

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1