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**Promoting Growth-Enhancing Structural Change: Evidence from a Panel of African, Asian, and Latin American Countries**

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# Promoting Growth-Enhancing Structural Change: Evidence from a Panel of African, Asian, and Latin American Countries

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**Abstract**

In what the authors name "a first pass through the data", McMillan et al. (2014) have recently addressed the question: what determines the magnitude of growth-enhancing structural change - defined as gains to average labor productivity resulting from a reallocation of labor across sectors? This paper extends their cross-section work to a panel data set of 5- and 10-year intervals from 1970 to 2010 for 29 (mostly developing) countries. Controlling for a wide range of control variables and time-invariant unobserved heterogeneity, the results present support for growth-enhancing structural change to be the outcome of a conditional domestic convergence process towards, what I term, a country's idiosyncratic state of efficient allocation. The regressions further indicate that the removal of labor market rigidities and improvements in gender equality in education correlate with larger gains from structural change in a statistical and economical meaningful way. However, these relationships are not found in countries with large (gender) inequality in education or strong labor market rigidities, respectively. The study also shines some light on the channels through which the variables potentially affect gains from structural change.

JEL Codes: O10, O14, O47

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# 1 Introduction

Many poor countries employ large parts of their labor force in the agricultural sector at low levels of productivity. This stylized fact has crucial implications. Across countries, it offers to be a key explanation for the variation in living standards in the world (Caselli, 2005; Restuccia et al., 2008; Duarte and Restuccia, 2010). Within countries, large productivity differences between agriculture and the remaining economy indicate that labor is misallocated across sectors and that structural change - that is, the reallocation of workers across sectors - can significantly contribute to labor productivity growth (Temple and Wößmann, 2006; Vollrath, 2009; McMillan et al., 2014; Gollin et al., 2014; Herrendorf and Schoellman, 2015). Motivated by this, McMillan et al. (2014) have recently conducted a "first pass through the data" to identify potential determinants of growth-enhancing structural change for a cross-section of 38 countries for the period 1990-2005.

This paper extends the work by McMillan et al. (2014) in several ways. I begin by elaborating on the theory to consider growth-enhancing structural to be the outcome of a domestic convergence process towards, what I term, a country's *state of efficient allocation.* Here, labor is optimally allocated across sectors given the respective economic environment. The subsequent empirical analysis then focuses on two issues: One, assessing evidence for conditional convergence. Two, examining the role played by labor market rigidity, formal education and (gender) inequality in education[1] for a country's gains from structural change.

Importantly, the paper makes two propositions that guide the empirical investigation. First, I argue that the effect of changes in either the pool of sufficiently educated workers or the legislative rigidity of the labor market on gains from structural change depends on the precondition that the other component does not represent a constraining factor. To be more specific, I hypothesize that improvements along the education dimension will only translate into gains from structural change conditional on the fact that the labor market is not characterized by strong rigidities. Vice versa, a flexibilization of the labor market does only spur growth-enhancing structural change, if there is a pool of sufficiently educated workers. Second, I argue that unobservable country-characteristics determine a country's state of efficient allocation. As it is well known from standard growth regressions, cross-country results can potentially suffer from omitted variable bias in the presence of unobserved heterogeneity. Moreover, cross-country regressions do not address the policy relevant question how *changes* in a country's record of growth-enhancing structural change are related to *changes* in a set of variables.

[1]This paper considers two types of inequality in education: 1) overall inequality and 2) gender inequality in education. I will use the expression "(gender) inequality" when a statement is targeted towards both types of inequality.

To answer this question, I follow McMillan et al. (2014) and decompose growth in average labor productivity over a period into productivity gains within sectors and gains that result from a reallocation of workers across sectors. In a second step, I use the obtained contribution of structural change as my dependent variable to examine potential determinants of the magnitude of growth-enhancing structural change. A major contribution of this study is that, oppose to McMillan et al. (2014), I perform my analysis on a panel data set of 5- and 10-year intervals ranging from 1970 to 2010 for 29 (mostly developing) countries, while still drawing on employment and value added data which are disaggregated for nine sectors representing the total economy. The combination of a nine-sector disaggregation of the economy, a time span of four decades, as well as the high number of developing countries in the sample represents a distinctive feature of my study compared to previous empirical work on structural change, which has for most parts focused on a three-sector disaggregation of the economy or a restrictive set of advanced countries due to data limitations (see for example Herrendorf et al. (2014) and references therein).

This study makes several extensions to the work of McMillan et al. (2014). First, the longer time period enables to examine the within variation in the data. Second, by applying fixed-effects panel estimation, I am able to, at least partially, control for potential omitted variables bias due to unobserved heterogeneity. Third, my empirical set up allows for a certain level of parameter heterogeneity. More precisely, I estimate the relationship between selected variables and the dependent variables separately for two groups of countries which I classify based on their labor markets rigidness, overall education level, or (gender) inequality in education. Finally, I shed some light on the channels through which the observed drivers affect growth-enhancing structural change. I do so by applying an extension to the decomposition methodology used in McMillan et al. (2014) which differentiates between gains that result form a shift of workers into sectors with higher *levels* of productivity and sectors with higher productivity growth *rates* (de Vries et al., 2015).

The empirical analysis leads to the following main findings. The regressions present evidence for growth-enhancing structural change to be the outcome of a conditional domestic convergence process towards each country's idiosyncratic state of efficient allocation. In line with what is found in classic growth econometrics work, the estimated coefficient size is considerably larger in my fixed-effects specifications compared to the cross-section estimation in McMillan et al. (2014). Looking at different sources of labor mobility barriers in particular, improvements in the overall level of formal education seem not to be linked to larger gains from structural change within countries over time.

Opposite to this, removing labor market rigidities and reducing gender inequality in education appear to play a role. Both the short- and medium-term regressions point to an economically meaningful and statistical robust correlation between lower gender gaps and productivity gains from structural change. However, the results also show that this relationship does not hold within the group of countries characterized by more rigid labor markets. Likewise, the positive link between labor market flexibilization and growth-enhancing structural change is not unconditional, as it is not found in countries with large (gender) inequality in education in neither the short- nor medium-term regressions. Digging deeper, I find that in countries with lower (gender) inequality in education, flexibilization appears to facilitate workers to shift into sectors with higher productivity levels. Although this relationship is also found, on average, among countries with larger (gender) inequality in education, there is much more variance. Moreover, in this latter group, flexibilization is associated with workers shifting into sectors with below-average productivity growth in a statistical significant way, which suggests that the workers who have been reallocated enter these new sectors with lower marginal productivity. This finding highlights the potential drawbacks linked to a labor market flexibilization and emphasizes that if a country intends to promote growth-enhancing structural change by reducing labor market rigidities, an economic environment in which educational equally prevails is a necessary precondition.

This study links to several strands in the literature. The first strand relates to recent research on the agricultural productivity gap. As found in different studies, not only average productivity, but also average wages are lower in agriculture relative to the non-agricultural sectors in almost every country in the world, especially in developing countries (Gollin et al., 2014; Herrendorf and Schoellman, 2015; Cai and Pandey, 2015). As wages are assumed to be payed by the marginal productivity of workers, this suggests a misallocation of labor across sectors, but at the same time also indicates the potential for future growth-enhancing structural change. Related, but taking an ex-post approach, a set of recent studies apply different decomposition techniques to quantify the contribution of structural change to labor productivity growth across different countries and time periods (Timmer and de Vries, 2009; IADB, 2010; McMillan et al., 2014; de Vries et al., 2015). What emerges from this literature is that the magnitude with which structural change contributes to labor productivity growth varies, not only across countries, but also within countries over time. Both literature strands therefore motivate a better understanding of how countries can facilitate income gains that stem from the reallocation of workers across sectors.

A large literature has examined driving forces of structural change. However, both formal models as well as empirical estimations often focus on examining drivers of non-balanced growth across sectors in terms of value added or employment shares (among others, Kongsamut et al., 2001; Caselli and Coleman, 2001; Jaumotte and Spatafora, 2007; Acemoglu and Guerrieri, 2008; Ngai and Pissarides, 2007; Dabla-Norris et al., 2013). This paper differs from these studies by linking drivers of structural change directly to their impact on labor productivity growth, instead of looking at sectoral shares as the outcome variable. Moreover, it specifically looks the role of gender bias in education, a factor that has received only little attention in the above literature. Finally, the empirical findings contribute to a better understanding of the channels through which gender equality in education can promote economic growth (see for example, Klasen, 2002; Klasen and Lamanna, 2009) .

# 2 Growth-Enhancing Structural Change and Barriers to Labor Mobility: Theory and Evidence

## 2.1 Structural change as a domestic convergence process

A good starting point to think about the drivers of growth-enhancing structural change is to think of a domestic convergence process. Simply put, growth-enhancing structural change is outcome of labor shifting across sectors with different levels of marginal labor productivity. Gaps in marginal labor productivity state that, for instance, an additional farmer generates less output compared to an additional worker in the mining industry. This implies that labor is misallocated across sectors and that a reallocation of workers from less (agriculture) to more (mining) productive sectors would increase labor productivity growth (that is, growth-enhancing structural change) until the marginal product of labor is equalized across sectors. Hence, growth-enhancing structural change can be seen as a domestic convergence process in which a country does not converge to a steady state income level, but growth-enhancing structural change occurs up to, what I term, a *state of efficient allocation* where labor is optimally allocated across sectors conditional on the respective economic environment.[2][3]

What determines a country's state of efficient allocation? A short answer is labor market frictions, which can make the reallocation of workers across sectors very costly, leading to an optimal allocation of workers in which differences in marginal productivity across sectors are still present. To present a magnitude, Artuc et al. (2015) estimate that the mobility costs of switching sectors can amount to up to three or four times of a worker's annual earnings

[2] I restrict my statement to the equality of marginal labor productivity across sectors. This does not imply that there are no further efficiency losses due to a misallocation of labor across sub-industries or even firms (see for example, Banerjee and Duflo 2005; Restuccia et al. 2008; Bartelsman et al. 2013; Restuccia and Rogerson 2013).

[3] There is also a strand in the literature on structural change that argues that structural change is not the actual root of productivity growth by *assuming* that at each moment labor is allocated efficiently between sectors. This literature sees structural change as a result of changes in non-homothetic consumer preferences and technological progress linked to growth (see for example, Herrendorf et al. (2014) and the references therein).

in many developing countries.[4] Hence, it can be economically rational for a worker not to shift into a higher paying job, if the associated costs of reallocation exceed the expected wage gains. The same holds true for the employer-side, who will abstain from hiring more labor if large fix mobility costs plus wages exceed the expected marginal labor output. Note that the term "mobility costs" can be understood as the total burden of labor market frictions. Frictions can have many sources, including worker specific factors such as subsistence factors, transportation costs, or information barriers to migration (Gollin et al., 2007; Gollin and Rogerson, 2014; Artuc et al., 2015) In this paper, I take a macroeconomic perspective and restrict my analysis to aggregated, or country-level, factors.

First empirical findings that suggest that domestic convergence is not an unconditional process come from the cross-section analysis by McMillan et al. (2014). The authors proxy the domestic convergence term with the employment share of agriculture, drawing on the stylized fact that it is the agricultural sector that employs a large share of labor with low productivity in developing countries. Their results indicate that starting out with a larger share of the labor force being employed in agriculture may increase the potential for structural-change induced growth, but the mechanism is conditional on not having a strong comparative advantage in primary products. The economic reasoning behind this is that the mining and utility sector has a very limited capacity to generate substantial employment, which limits the positive contribution of structural change associated with a participation in international markets. The findings in McMillan et al. (2014), offer an explanation for the variation in the record of growth-enhancing structural change across countries. Their analysis does, however, not directly address the important policy question of how *changes* in factors can explain *changes* in the magnitude of growth-enhancing structural change within a single country over time. Moreover, it does not account for unobserved country-characteristics that determine the economic environment in which structural change takes place.

So, what drives the domestic convergence process within countries? Keeping the analogy to the classical growth regressions, I consider factors that potentially affect a country's state of efficient allocation. I distinguish between three types of factors. First, factors that are directly related to the mobility of the workforce. Second, a set of factors that potentially impact the expansion of employment in more productive sectors by affecting the economic environment more broadly. For instance, changes in either the investment rate, foreign direct investments (FDI), or the exchange rate can provide (dis)incentives in more productive sectors to expand

[4] Artuc et al. (2015) have recently calculated labor mobility costs across the world using data on labor allocations and wages in the manufacturing sector. Based on their calculation, labor mobility costs amount to an equivalent of 3.71 and 2.76 times the annual wage in developing and developed countries respectively. Empirical evidence based on detailed micro data comes from Lee and Wolpin (2006). Using data for the U.S. over the 1968–2000 period, the author estimate that the monetary cost of changing sectors were as large as 75 percent of annual earnings.

their economic activity. Third, time-invariant unobservable country characteristics. A good example are social norms, such as the class system in India, that discriminates certain groups from migrating into more productive sectors within countries. In my regressions, I focus on the factors that directly determine the mobility of workers, while controlling for unobserved heterogeneity and a large set of potential determinants. To be specific, I consider formal education, gender inequality in education, and legislative labor market regulation as factors that represent labor market frictions on a macroeconomic level. The remaining discussion in this section is therefore devoted to these three variables and their potential role for growth-enhancing structural change.

## 2.2 The role of labor mobility barriers

### 2.2.1 *Formal education*

Examining the role played by education in the context of growth-enhancing structural change is motivated by one stylized fact in particular. Workers employed in agriculture have on average lower levels of formal education. In fact, this difference can explain a considerable portion of the observed productivity gap between agriculture and the non-agricultural sectors (Gollin et al., 2014; Herrendorf and Schoellman, 2015). One interpretation of this empirical finding is that the non-agricultural sectors demands, at least on average, a higher level of human capital to conduct the tasks and use the technology related to each sector. The non-agricultural wage premium reflects the cost of acquiring the necessary skills. Education then functions as a form of "occupational mobility ticket". At low levels, it allows workers to move out of low productive farm work, while at higher levels it is the key to enter into highly productive sectors, such as business services. Increasing educational attainment in the population thus means to increase overall labor mobility, which is expected to promote growth-enhancing structural change.

This idea is consistent with the theoretical framework developed in Caselli and Coleman (2001) and used to explain structural transformation and regional convergence in the U.S.. In their model, workers decide between investing in skill acquisition to move into the manufacturing sector or staying a farm worker. Based on this setup, the authors show that a reduction in education costs induce an increasing proportion of the labor force to move out of the (unskilled) agricultural sector and into the (skilled) non-agricultural sector.

Empirically, a set of cross-section studies show that higher levels of education correlate with lower shares of employment in agriculture and a larger share of workers working in schooling-intensive sectors. Jaumotte and Spatafora (2007) find a significant positive relationship between increases in the shift of workers out of agriculture and average years of educational attainment. Using tertiary as well as secondary enrollment rate as proxies for the education level of the population, the quantile-regressions in Dabla-Norris et al. (2013) point to a statistically significant relationship between the populations education level and the expansion of services as well as more sophisticated manufacturing products. Similar, Ciccone and Papaioannou (2009) show that employment growth in schooling-intensive industries was significantly faster in economies with higher education levels and greater education improvements based on data for 37 manufacturing industries for around 40 countries in the 1980s. Finally, detailed evidence on the direct link between increases in educational attainment and gains from a reallocation of labor across sectors to economic growth comes from Lee and Malin (2013) for China. Using micro-level data and an empirical growth-accounting framework that allows for the endogenous selection of education and sector of employment, the researcher's estimates imply that an individual who has completed middle school is 41.8 percentage points more likely to work in the non-agricultural sector than one who has not. Moreover, their findings suggest that 11 percent of aggregate growth in output per worker from 1978 to 2004 in China is accounted for by increased education, with 9 percent coming through the labor-reallocation channel.

### 2.2.2 *Inequality in education*

Aside from the overall level of education in the population, also the distribution of education influences the occupational mobility of a country's workforce. Especially in developing countries, growth-enhancing structural change is likely to be not the consequence of a small elite of highly educated people shifting into high-productivity sectors. Instead, what rather drives the overall gains from reallocation is an increasing pool of sufficiently educated workers endowed with the skills demanded in more productive sectors. Or put differently, the share of the workforce holding an "occupational mobility ticket". After all, it is the shift out of agriculture in particular that leads to growth-enhancing structural change.

Three stylized facts, which hold true for many countries in the world, motivate to take a closer look at the gender bias in education in particular. First, a major, but shrinking, share of women works in the agricultural sector at low levels of productivity. Applying the same logic as above, a higher level of education among women should be associated with a larger share of women who are able to migrate into higher productivity sectors. Yet, and second, a woman's occupational choice is often affected by social stigmatization (Goldin, 1995). While male workers that have only a basic educational background can find work in more productive blue-collar jobs in mining, construction or brawn-intensive manufacturing, female employment in these sectors can be severely constraint by social norms. This is less the case for white-collar jobs. However, these jobs also require higher levels of schooling in general. Empirical evidence for the importance of education for women's occupational choices can be found in Klasen and Pieters (2012). Using data from Indian households, their results show that it is the class of highly educated women that reap the benefits of India's transformation process in form of attractive employment positions, while women with low levels of education are rather pushed into workplaces by the necessity to generate additional household income.

The third stylized fact states that women earn lower wages than men across all sectors and occupations (UN, 2015). Although this can be a consequence of simple discrimination, there is also an economic argument for it. Assuming that females and males have equal quantities of brains, but males bring more brawn to the labor market, men will earn higher wages relative to women as long as there is some demand for brawn-intensive labor. Women therefore have a comparative advantage in sectors that draw relative intensively on brain compared to brawn. This means that from an input cost perspective, male labor and female labor are imperfect substitutes. Moreover, if employers discriminate female labor (for example, based on socio-cultural habits) and are willing to pay higher wages for male labor, this discrimination premium becomes increasingly costly the smaller the gender gap in education is. Educated female workers thus represent an attractive labor force in brain-intensive sectors and should eventually lead rent-oriented firms in high-productive service sectors to employ more women. In fact, there is empirical cross-section evidence that gender gaps in pay can also lead to comparative advantages in trade of female-labor intensive manufacturing industries, and that this advantage is increased the lower the inequality in education is within the respective country (Busse and Spielmann, 2006). This is not to say that gender gaps in pay are in any sense desirable, particularly not from a normative perspective. Combined with a reduction in the gender gap in education between men and women, however, a comparative advantage of women in high-productivity sectors could promote growth-enhancing structural change.

### 2.2.3 *Labor market rigidity*

A lack of education is not the only barrier to a reallocation of workers across sectors. Legislative labor regulations, such as firing costs or laws on employment security, affect the speed at which labor adjustments take place. For instance, Ciccone and Papaioannou (2009) show that if companies consider employment conditions as inflexible, this can lead to slower inter-sectoral reallocation within manufacturing, as firms decide to invest in capital deepening instead of new workplaces. Further support is found in Nickell et al. (2008), who find that countries with more stringent employment protection policies experience slower adjustment towards their long-run equilibrium production structure.

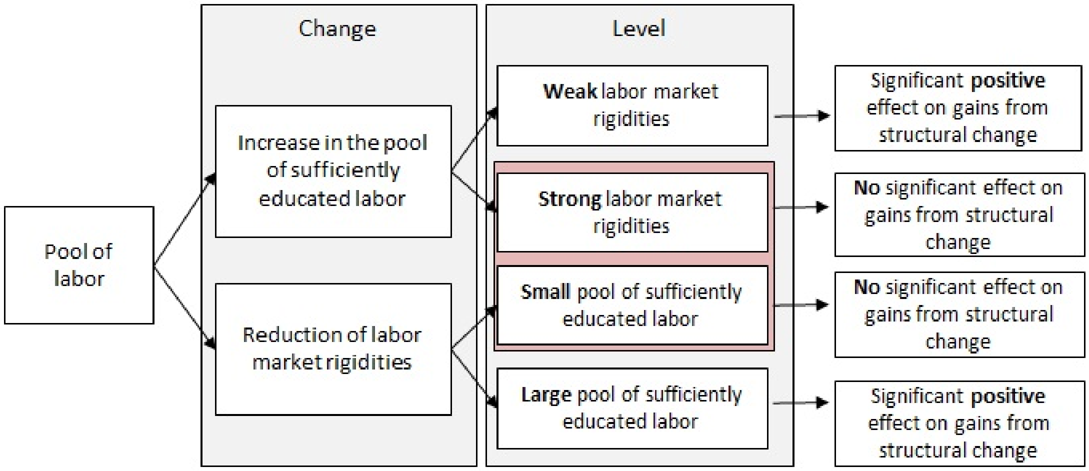
### 2.2.4 *Linking occupational mobility tickets and labor market rigidity*

Based on the arguments listed above, it seems plausible to expect that changes in one of the potential sources for labor mobility frictions (namely, overall education, (gender) inequality in education, or legislative labor market rigidities) are related to changes in the contribution of structural change to labor productivity growth. However, as I will elaborate in more detail below, this does not need to be the case in general. Instead, I will argue that the effect of changes along either dimension, the pool of sufficiently educated workers or the labor market legislation, depends on the precondition that the other dimension does not represent a constraining factor. To be more specific, I hypothesize that improvements along the education dimension will only translate into gains from structural change conditional on the fact that the labor market is not characterized by strong rigidities. Vice versa, a flexibilization of the labor market does only spur growth-enhancing structural change, if there is a sufficient pool of labor holding an occupational mobility.

To illustrate what I mean by this, consider an economy in which labor market regulation can be considered as rigid. Given such a setting, improvements in education and the distribution of education, which raise the occupational mobility of the labor force, might not translate into a large migration of workers across sectors, because the reallocation of labor is constrained by legislative rules. Opposite to this, the returns from improving occupational mobility of the labor force through formal education should be high in a setting where labor markets can be considered flexible.

The link between the legislative and the educational component of labor mobility barriers should also work the other way around. Consider a country that reforms its employment legislation in a way that makes it per se attractive for sectors to employ more labor. Given that the country under consideration has a workforce in which a large share is only poorly educated, and therefore, constraint in the range of tasks eligible to conduct, more productive sectors might not absorb much labor after all. Consequently, the magnitude of growth-enhancing structural change does not change by much. On the contrary, when there is a large pool of sufficiently educated workers which migration has been constraint by legislative labor market rigidities, a labor market reform should be followed by larger gains from structural change. Figure 1 summarizes the theory that I want to bring across here. That is, improving one dimension (pool of sufficiently educated labor or labor market rigidities) will not translate into significant gains from labor reallocation, if the other dimension is a constraining factor.

Figure 1: Schematic on constraining factors and growth-enhancing structural change




# 3 Data and Methodology

How do I test my theory empirically? This section answers this question in three parts. First, I outline how I calculate the contribution of structural change to labor productivity, that is, my dependent variable. Then, I discuss the data used and present some descriptive statistics on the growth contribution of structural change. Finally, the empirical specification is presented.

## 3.1 Measuring the growth contribution of structural change

This study applies a decomposition method to estimate the contribution of structural change to labor productivity growth. In short, the change in labor productivity over a certain time period is decomposed into different components. Each component's share in total labor productivity change is then multiplied with the compound annual growth rate (CAGR) of average labor productivity over a certain time period. Labor productivity is calculated as average labor productivity by dividing value added output, noted in Purchasing Power Parities (PPPs), by the number of employed workers.

I start with the same decomposition method as in McMillan et al. (2014). Labor productivity change is decomposed into two components:

$$\Delta P = \Delta PW + \Delta PS$$

where $\Delta PW$ is a change in aggregate labor productivity that results from productivity growth *within* individual sectors. The second term, $\Delta PS$, is the structural change effect, which measures productivity changes that result from a shift of employers between sectors. In more detail, we can decompose $\Delta P$ into

$$\Delta P = \sum_i (P_i^T - P_i^0) * S_i^0 + \sum_i (S_i^T - S_i^0) * P_i^T \tag{1}$$

where $Si$ is the share of sector $i$ in overall employment, $Pi$ is the labor productivity level of sector $i$, and superscript 0 and $T$ refer to the first and last year of a time interval.[5] Growth-enhancing structural change results when labor moves into those sectors whose productivity is either higher or growing. To what extend gains from a shift into higher productivity *level* sectors contribute to gains from structural change compared to gains resulting from a reallocation into sectors with higher productivity *growth*, can be estimated by using a second modified decomposition. Labor productivity change can be split into

$$\Delta P = PW + \Delta PSstatic + \Delta PSdynamic$$

where $PW$ is again the within sector component. Following de Vries et al. (2015), I call the remaining two terms *static component* of structural change effect and *dynamic component* of structural change effect. In detail,

$$\Delta P = \sum_i (P_i^T - P_i^0) * S_i^0 + \sum_i (S_i^T - S_i^0) * P_i^0 + \sum_i (P_i^T - P_i^0) * (S_i^T - S_i^0) \tag{2}$$

What do the two latter terms exactly measure and why might this division be informative? Note that the static component represents the sum of changes in employment share weighted by the initial productivity level, opposed to the productivity level of the final period considered in the total component of equation 1. This modification enables to differentiate between two sources of productivity-enhancing structural change. First, gains that result from workers shifting to sectors with above-average productivity levels, captured in the static component. Aside from this, the reallocation of workers can also contribute positively to productivity changes if labor shifts, overall, to sectors with above-average productivity growth. The change in productivity resulting from the joint effect of changes in employment shares and sectoral productivity is captured in the dynamic component.

[5] A different approach to decompose productivity growth would be to consider period averages instead of the initial share in employment and final productivity level of a sector. I prefer the decomposition based on equation 1 as it allows to further decompose the structural change component. However, the terms obtained by equation 1 and the one with period averages are highly correlated (>0.97). To check the robustness of the results nonetheless, I run a regression where the dependent variable is calculated based on period averages. The estimation results do not change in any meaningful way and are available upon request.

It should be noted that the decomposition methods above likely underestimate the real growth contribution from structural change for several reasons. As pointed out by Timmer and de Vries (2009), the decomposition of labor productivity growth based on equation 1 is linked to the problematic assumption that sectoral labor productivity growth is independent of changes in employment. For this to hold, however, marginal and average labor productivity in a sector need to be equal, which stands in contrast to the idea of surplus labor in the agricultural sector, a typical phenomenon in many countries in early stages of development. As long as marginal productivity is below average productivity, a decline in the number of agricultural workers will by definition raise the average labor productivity level in agriculture. Although caused by a reallocation of work across sectors, this increase in labor productivity will be captured by the within component instead of the structural change term. Besides this, when lower mobility costs allow workers to better allocate their time to the sector in which their idiosyncratic productivity is highest, aggregate productivity raises as a consequence of a reallocation of workers. However, since it can lead to flows of workers in both directions, the effect on sectoral employment shares is potentially small. Hence, it will not be recorded as gains from structural change, but within sector productivity growth in the above decomposition.[6] Finally, the extend of labor reallocation across sectors captured by the decompositions crucially depend on the number of sectors in the economy considered. As new findings show, there is substantial heterogeneity within services in particular when it comes to employment and productivity levels as well as their respective changes (Jorgenson and Timmer, 2011). A higher level of disaggregation allows to capture shifts in employment between sectors, which would otherwise be regarded as within sector movement. Hence, the real gains from reallocation are therefore measured more precisely and likely found to be larger, the finer the economy is disaggregated. This emphasizes the importance to go beyond the standard three-sector-classification.

## 3.2 Data

### 3.2.1 *Data on employment and value added*

Data on employment and value added comes from the Groningen Growth and Development Centre 10-Sector (GGDC10) database by Timmer et al. (2014). The main argument for this choice is the fact that the GGDC10 comprises high-quality employment and value added data disaggregated for ten sectors, which cover the total economy. A finer disaggregation level has often major limitations in terms of data availability and consistency. The GGDC10 addresses these issues explicitly. The data ranges from 1950 (for selected countries) to 2010.

[6] This issue is also raised by Lee and Wolpin (2006).

Regarding the quality of the data set, as reported in Timmer and de Vries (2009) and Timmer et al. (2014), substantial effort has been undertaken to reduce gaps and inconsistencies found in other data sets.[7]

However, to be able to examine the comparative performances on structural change and productivity growth, some adjustments have to be made to the original data. First, for a number of countries the data set did not distinguish between value added or employment (or both) for Government Services and Personal Services. I follow McMillan et al. (2014) and increase the level of aggregation by combining the data for the two sectors into a single one. This results in the nine sectors listed in table 5 in the appendix. To maximize the number of countries, while keeping an adequate time period, I select the time period 1970-2010 for which data is available for 25 countries without gaps.[8] The earliest available data on employment for the Philippines and Indonesia is 1971. I account for these differences in the calculation of the CAGR of average labor productivity. More problematic are the cases Hong Kong and Malaysia. Here employment data is only available starting from 1974 and 1975 respectively. Due to this problem, I drop the period 1970-1975 for both countries in the 5-year specification. For the 10-year interval case, I account for the shorter period length in the calculation of the CAGR of average labor productivity for the respective countries. Overall, the sample includes 29 countries, which are listed in table 6 in the appendix, including nine from Latin America, ten from Asia, nine African countries, and the United States of America. In a last step, using conversion factors from PWT 8.0 data by Feenstra et al. (2015), I convert value added data from constant local currencies into PPPs to compare productivity values internationally.[9]

Figure 2 shows the contribution of the different components of structural change to annual labor productivity growth in percentage points for four decades since 1970. The figure illustrates that there is not only variation in the size of the structural change components across countries, but also within countries over time. This variation is further quantified in the summary statistics presented in table 8 in the appendix. Regarding the two channels of growth-enhancing structural change, the two lower bar charts in figure 2 indicate that it rarely occurs that workers shift, on average, into sectors with below-average productivity levels. Opposite to this, dynamic losses resulting from a shift of workers into sectors with below-average

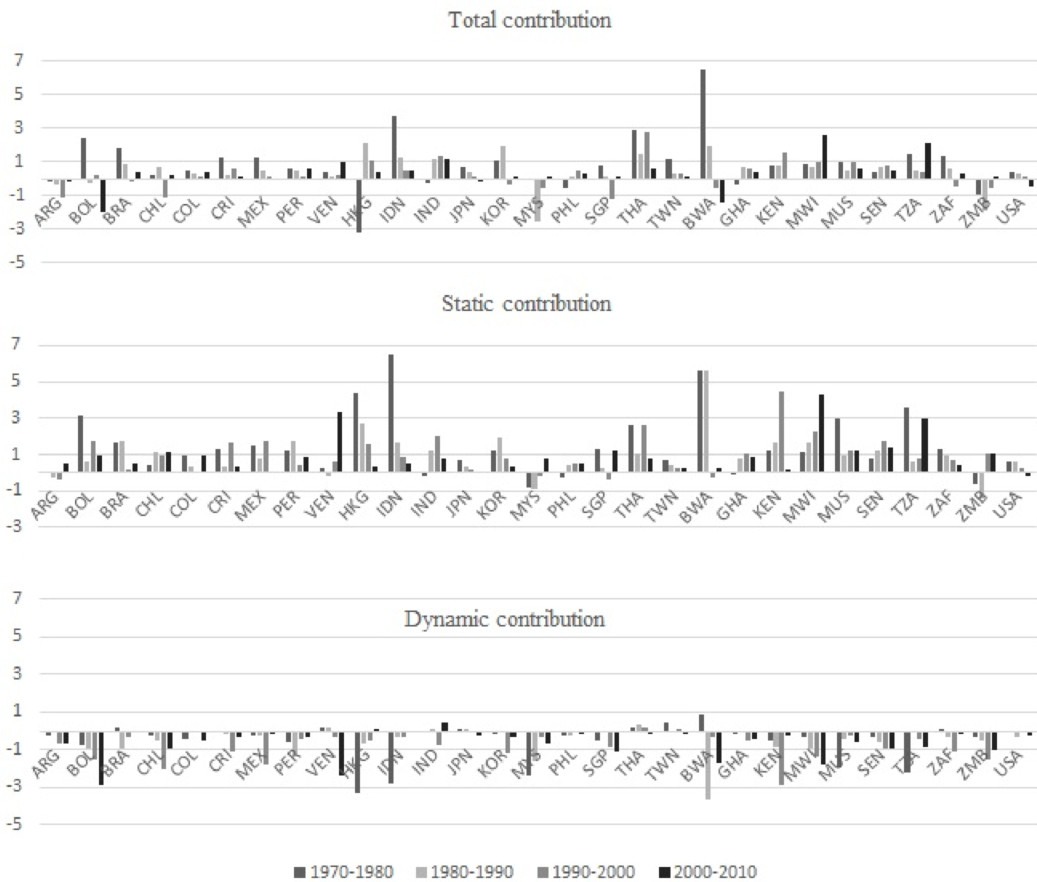
[7] To cite Timmer and de Vries (2009, p.8): "Various international organizations such as the World Bank, the United Nations, the Asian Development Bank, and also the Oxford Latin American Economic History Database collect sectoral data for developing countries and make it publicly available. But series are often short (starting only in the 1980s or 1990s), not consistent over time and across countries, and the series have little sectoral detail."

[8] At the final stages of this study, the GGDC10 has been extended in terms of country coverage, particularly in terms of advanced countries. The data used in this paper originates from an older version of the GGDC10.

[9] The conversion factors differ from those used in McMillan et al. (2014) in that mine account for relative prices of exports and imports to determine the true production capacity more precisely (Feenstra et al., 2015).

growth rates occurs frequently and a look at the magnitudes of the contribution shows that dynamic losses can drag down productivity growth severely. This empirical finding further motivates to not only examine drivers of the overall gains from structural change, but also to extend the analysis to the distinction between the static and dynamic component.

Figure 2: Total Structural Change Contribution (10-year Intervals, in percentage points)




*Note:* Author's calculation based on equations 1 and 2. Shown are the total, static, and dynamic contribution of structural change to the compound annual growth rate in labor productivity (in percentage points).

### 3.2.2 *Data on barriers to labor mobility*

This section discusses the labor mobility variables selected in more detail. There are different potential educational variables to proxy the skill endowment of the workforce. As common in the literature, I use the average years of schooling for the population to proxy the overall education level of the population based on data from Barro and Lee (2013). I focus on the population 25+ because I am interested in capturing the human capital of the labor force that potentially changes its sector of work within short term intervals of 5- and 10-years.[10]

To measure gender gaps in education, I follow Klasen (2002) as well as Klasen and Lamanna (2009) and use the male-to-female ratio in education, short *RED*. The ratio is calculated by dividing the average years of schooling of the male population by the average years of schooling of the female population. Including *RED* next to the average years of schooling implies that I assume that any increase in female education is related to an equal-sized reduction in the education level of males. Whether this assumption is reasonable can be questioned. Therefore, I replace the level of education of the total population with the educational attainment of the male population in a different regression. By doing so, I estimate the effect of changes in *RED*, while holding the male education level constant. The underlying assumption thus changes, as sending more girls to school does now not come at the expense of education for boys.

To investigate whether gender bias in education or rather inequality in education within the society per se matters, I calculate a variable *(Gini_schooling)* using a Gini-like formula taken from Castelló-Climent and Doménech (2012) and defined as

$$Gini_{schooling} = n_0 + \frac{n_1(n_2x_2+n_3(x_2+x_3))+n_2n_3x_3}{\bar{H}}$$

where $\bar{H}$ are the average years of schooling in the population, $x_i$ refers to the cumulative average years of schooling of each level of education, and $n_j$ are the share of population with a given level of education: no schooling (0), primary (1), secondary (2) and tertiary (3) education.

Finally, to capture changes in the degree of labor market rigidity in countries since 1970, I use an de-jure index constructed by Campos and Nugent (2012). The authors construct a single comprehensive measure of labor market rigidity based on the comparisons of labor laws across countries and over time. In more detail, the index captures information for the following criteria: conditions of work, employment security, termination of employment, conditions of employment, general provisions, cost of increasing hours worked, cost of firing workers, dismissal procedures, and alternative employment contracts. A country's index score is related to a period rather than a single year. As an example, I use a country's score for the years 1990 to 1994, captured in one observation, as determinant of the magnitude of growth-affecting structural change in the period 1990 to 1995. Unfortunately, data is only available until 2005. This results in the loss of one cross-section in the 5-year regressions. Table 9 in the appendix presents descriptive statistics on the main labor mobility variables.

[10]Since in developing countries a significant share of the 16-24 year-old population is already active in the labor force, the average years of schooling for the population 16+ is included in an alternative regression.

### 3.2.3 *The convergence term and other determinants*

The variable definitions and data sources of included control variables can be found in table 7. Aside from the three variables elaborated on above, the most important variable to be considered in my regression is a proxy for the convergence term. I decided to follow McMillan et al. (2014) and use the employment share in agriculture as my main proxy. This has two primary reasons. First, the variables is readily to interpret economically. Second, it makes my results comparable to McMillan et al. (2014). Nonetheless, to test the robustness of my findings, I will consider a measure for the overall labor productivity variation as an alternative convergence term, computed as the coefficient of variation (standard deviation divided by the mean) of the average labor productivity across all sectors. This second convergence term thus also accounts for the potential gains from reallocating workers across the non-agricultural sectors.[11] As noted, the economic rationale for the inclusion of additional macroeconomic variables is to account for potential changes in the economic environment that might impact the expansion of employment in more productive sectors by providing (dis)incentives to hire additional labor. That is, they potentially affect the country's state of efficient allocation.[12] Descriptive statistics are reported in table 10 in the appendix.

## 3.3 Econometric specification

I now present the empirical approach that I apply to estimate the determinants of the magnitude of growth-enhancing structural change. I start with a regression equation in the form

$$total_{it} = \beta_o + \beta_1 Conv_{it} + \beta_2 X_{it} + \beta_3 Z_{it} + \delta_t + \theta_i + u_{it} \tag{3}$$

where $total_{it}$ is the total contribution of structural change to the CAGR of average labor productivity in country $i$ for a certain time interval $t$, $\beta_o$ is a constant, $Conv_{it}$is the domestic convergence term, $X_{it}$ are the explanatory variables of interest, $Z_{it}$ are control variables, $\delta_t$ are period dummies, $\theta_i$ are country-fixed effects, and $u_{it}$ are idiosyncratic error terms. Accounting for country-characteristics allows me to, at least partially, control for unobserved heterogeneity. This removes a potential source of omitted variable bias. Moreover, it narrows the analysis down to an examination of the within country variation. To verify a fixed-effects estimation strategy, I run a F-test on the joint significance of all country-characteristics as

[11]Unfortunately, since this papers underlying data set does not provide information on sectoral labor shares, the convergence term, *cov*, captures variation in average labor productivity oppose to productivity at the margin which would be the preferable measure for potential gains from structural change.

[12]These factors can thus be compared to as the ad hoc specifications used in growth regression to proxy for variation in the technological shift parameter of the production function. In fact, many of the variables considered in my regression also appear in standard growth regressions.

well as a cluster-robust version of the Hausman test as proposed by Wooldridge (2010). Moreover, the regression includes initial values oppose to growth variables to remove an additional source of potential simultaneity coming from reversed causality.[13] Finally, time dummies account for global shifts in demand or global technological innovation that impact structural change within countries.

In a second step, I test the hypothesis that a significant effect of a change in either an education-related or the labor market rigidity variable is conditional on the other dimension not representing a constraining factor. To do so, I split my sample into two subgroups of countries according to the following characteristics. First, whether a country belongs to the group of countries with a rigid or flexible labor market. Second, whether the country's level of education is high or low. Third, whether educational inequality is high or low. Fourth, whether gender gaps in education are high or low. The decision criterion in each case is whether the country's mean value in one of the four characteristics is above or below the median average of all countries. Hence, I assume that if a country's mean *labormarket* score is below the median mean score of all countries, then labor market rigidity does not represent a constraining factor in that country. Therefore, improvements along the education-related variables are expected to promote growth-enhancing structural change. I do not expect this relationship to hold in country where mean *labormarket* score is above the median mean score of all countries, since this indicates that the rigidness of the labor market represents a major impediment that constraints the reallocation of workers despite an increase in the pool of sufficiently educated workers. Empirically, I extend the regression framework to equation 4:

$$total_{it} = \beta_o + \beta_1 Conv_{it} + \lambda_1 X^*_{it} D_{low} + \lambda_2 X^*_{it} D_{high} + \beta Z_{it} + \delta_t + \theta_i + u_{it}. \tag{4}$$

The important addition in equation 4 is the inclusion of the two dummy variables $D_{low}$ and $D_{high}$. The two dummies represent the two subgroups based on either of the four character-

[13] A remark has to be made regarding the variable *invest*, which is defined as the average investment rate over the respective interval. This definition displays a potential simultaneity problem. For instance, if we consider a 5-year period, an agents' decision to invest in year 3 of that period could be influenced by growth-enhancing structural change that took place in the previous two years. This problem would be avoided if I considered only the initial investment rate at the beginning of the period. I decided to use average rates nonetheless, for two reasons. First, there is substantial year to year variation in the investment rate of a country. Only using the investment rate at the beginning of a period would then be a unsatisfactory proxy for the actual rate of investments conducted in that period. Second, given the considerable year-to-year fluctuation in the data, it seems unlikely that these variation are driven by annual growth-enhancing structural change. Despite the variation in the dependent variable within countries over time highlighted in this study, these are still based on 5-year intervals. This is arguably the shortest reasonable time period in which to relate sectoral shifts in employment to productivity changes on an economy level. Finally, also *lamrig* and *lamrig2* cover the degree of labor market flexibility over a period instead of a single point of time. However, in this case, I am convinced that the causal linkage runs from *lamrig* to growth-enhancing structural change and not the other way around.

istics. For instance, consider a country that has an average labor market rigidity score that is below the median average labor market rigidity score across all countries. In this case, the variable $D_{low}$ takes the value 1, while $D_{high}$ takes the value 0. Hence, equation 4 allows the effect of our variables of interest, $X^*$, to be heterogeneous between the two groups of countries defined by one of the four characteristic. Using two dummy variables, instead of just one, has the advantage that the estimated coefficients can be directly interpreted in terms of statistical and economic significance independently for both groups of countries.

Finally, in a third step, I replace the total contribution of structural change with its sub-components as shown in equation 5 and 6. By doing so, I get information on the two distinct channels through which the determinants effect the total contribution of structural change to labor productivity growth, that is, a shift into sectors with above average productivity *levels* (static) or productivity *growth* (dynamic).

$$static_{it} = \beta_o + \beta_1 Conv_{it} + \lambda_1 X^*_{it} D_{low} + \lambda_2 X^*_{it} D_{high} + \beta_3 Z_{it} + \delta_t + \theta_i + u_{it} \tag{5}$$

$$dynamic_{it} = \beta_o + \beta_1 Conv_{it} + \lambda_1 X^*_{it} D_{low} + \lambda_2 X^*_{it} D_{high} + \beta_3 Z_{it} + \delta_t + \theta_i + u_{it} \tag{6}$$

# 4 Empirical Results and Discussion

## 4.1 Baseline results

The baseline regressions for equation 3 are shown in table 1. In all cases, the F-test and the cluster-robust version of the Hausman test supports a fixed-effects estimation specification on at least a 0.05 significance level, and in most cases on a 0.01 level. The first empirical finding of this paper is thus that there is a rational for a second pass through the data in a within-country setting as a complement to the cross-section approach of McMillan et al. (2014).

Switching to the estimated coefficients, the results indicate that there is conditional domestic convergence. The coefficient of *agriculture* is positive and statistically significant in all six regressions in table 1. Moreover, the coefficient size suggests that changes in the agricultural employment share have economic meaningful implications for growth-enhancing structural change. Taking the smallest coefficient from regression 6 that includes the full set of possible determinants, the estimate indicates that a lower agricultural employment share of 7.8 percent (one within standard deviation) is associated with smaller gains from structural change of 0.4 percentage points per annum.[14] Comparing the coefficient to the cross-country estimates in McMillan et al. (2014) (range of coefficient lays between 0.013 and 0.027) shows that the coefficients in the fixed-effects estimates are considerably larger. This is in line with the findings in the cross-section and panel growth literature (Mankiw et al., 1992; Islam, 1995). In column 7, I replace *agriculture* with the alternative convergence term *cov*. The variable enters the specification on a 0.1 significance level.

From column 2 onwards, the regressions include the variable *schooling*. Somewhat surprisingly, the variable is insignificant and even has a negative sign in each specification. This result holds, if I replace *schooling* with different proxies.[15] This finding suggests that improvements in formal education do not promote gains from structural change. However, it is well known that the available macroeconomic education variables are quite imperfect measures of the actual "practical knowledge" of a society. For instance, the proxies do not account for differences in the returns to experience, the quality of schooling, or the distribution of education within the society.

[14] This and all following interpretations state the average correlation and are made based on the ceteris paribus assumption.

[15] Aside from years of schooling, I also consider an index of human capital per worker, which I take from Feenstra et al. (2015). The index not only considers the average years of schooling of the population, but assumes a rate of return for primary, secondary and tertiary education. I further run regressions where I replace the schooling variable with 1) the share of population 25+ with no schooling 2) the share of population 25+ with tertiary schooling received 3) average years of schooling attained by the population of age 16 years and older. The coefficients are in all cases negative and statistically insignificant.

Table 1: Regression results I: Baseline estimations

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Convergence term:* | | | | | | | |
| agriculture | 0.083** | 0.081*** | 0.075*** | 0.075*** | 0.081*** | 0.052* | |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | |
| cov | | | | | | | 0.180* |
| | | | | | | | (0.10) |
| *Mobility variables:* | | | | | | | |
| schooling | | –0.057 | –0.110 | | –0.038 | –0.039 | –0.158 |
| | | (0.18) | (0.23) | | (0.23) | (0.19) | (0.18) |
| male_schooling | | | | –0.117 | | | |
| | | | | (0.21) | | | |
| RED | | | –0.930** | –0.928** | | –0.644 | –0.754* |
| | | | (0.44) | (0.44) | | (0.43) | (0.44) |
| Gini_schooling | | | | | 0.129 | | |
| | | | | | (2.13) | | |
| labormarket | | | –0.803 | –0.787 | –0.790 | –0.881 | –0.330 |
| | | | (0.71) | (0.69) | (0.79) | (0.77) | (0.84) |
| *Other determinants:* | | | | | | | |
| income | | | | | | –1.134** | –1.346*** |
| | | | | | | (0.51) | (0.42) |
| invest | | | | | | 0.048* | 0.040 |
| | | | | | | (0.03) | (0.03) |
| popgrowth | | | | | | –0.335 | 0.883 |
| | | | | | | (5.08) | (3.90) |
| mining | | | | | | 0.005 | –0.017 |
| | | | | | | (0.03) | (0.03) |
| FDIflow | | | | | | –0.453 | –0.216 |
| | | | | | | (0.48) | (0.45) |
| openness | | | | | | 0.007 | 0.009** |
| | | | | | | (0.01) | (0.00) |
| caopen | | | | | | –0.082 | 0.029 |
| | | | | | | (0.10) | (0.11) |
| reer | | | | | | 0.001 | 0.001 |
| | | | | | | (0.00) | (0.00) |
| Country effects | yes | yes | yes | yes | yes | yes | yes |
| Time effects | yes | yes | yes | yes | yes | yes | yes |
| Observations | 230 | 230 | 201 | 201 | 201 | 194 | 194 |
| Prob > F | 0.02 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 |
| $R^2$ within | 0.21 | 0.22 | 0.25 | 0.25 | 0.22 | 0.33 | 0.34 |

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.

*Note:* The dependent variable is the total contribution of structural change to labor productivity growth over 5-year intervals from 1970-2010. The period 1970-1975 has been dropped for Malaysia and Hong Kong. No data is available on labormarket for the period 2005-2010. No data is available on caopen for Taiwan

At least the variation in the latter, we can capture through the inclusion of the *Gini_schooling* variable or the *RED* variable. The *RED* variable enters the regression at a 0.05 significant level, although it drops slightly out of the conventional significance range in the specification including all potential determinants with a p-value of 0.15.[16] The coefficient has the expected negative sign and even the smaller coefficient of -0.64 points to an economically important relationship between gender inequality in education and growth-enhancing structural change. To put the magnitude into perspective, the estimate suggests that a reduction in the gender gap in education of one standard deviation change is associated with an increase in growth-enhancing structural change of roughly 0.2 percentage points per annum. Aside from this, the virtual equality of the coefficients in columns 3 and 4 shows that the underlying assumption how gender equality is achieved does not matter (that is, sending more girls to school does (not) come at the expense of education for boys).

Although *gender* inequality in education appears to play an important role, *overall* inequality in education seems not. The variable *Gini_schooling* is statistically insignificant.[17] The same seems to hold true for the *labormarket* variable. The coefficient has the expected sign, indicating that labor market rigidity limits gains from reallocation, but is statistically insignificant with a p-value of 0.26 in the regression of column 6. Finally, turning to the set of potential determinants, the regression in column 6 indicates that the gains from structural change are negatively related to the income level per capita and potentially positively to the investment rate as well as the share of trade in GDP. On the contrary, changes in the population growth rate, the ratio of inward FDI to GDP, mining share in value added, the exchange rate, as well as capital openness appear to be not closely linked to changes in the magnitude of growth-enhancing structural change. I will leave the close examination on the relationship between the set of potential determinants and growth-enhancing structural change to future research. In the remaining regressions presented in this paper they will merely function as controls, and therefore, appear in the regressions labeled as such.[18]

To summarize the results so far, we find evidence for growth-enhancing structural change to be the outcome of a conditional domestic convergence process and that controlling for unobserved time-invariant country-characteristics which determine each country's state of efficient allocation increases the estimated speed of domestic convergence. Further, aside from *RED*, the variables considered to determine the labor mobility of a country's population appear not to be related to growth-enhancing structural change in a statistically significant way.

[16] I checked whether any sizable change in the coefficients needs to be attributed to the change in the sample. This is not the case.

[17] Contrary to what was expected, the coefficient size is positive. However, the coefficient size suggests a small economic effect. Moreover, the standard error of the estimate is very large.

[18] I decided to exclude the proxy for capital openness, *caopen*, in the coming regressions to keep Taiwan in the sample.

However, as hypothesized earlier, improving one dimension (pool of sufficiently educated people or labor market rigidities) might not pay-off in terms of gains from labor reallocation, if the other dimension is a potentially constraining factor.

## 4.2 Digging more deeply: Alternative specifications

### 4.2.1 *Group regressions*

The regressions in table 2 allow a certain level of parameter heterogeneity. More precisely, for each of the education-related variables, the effect is measured separately for two groups of countries classified according to their absolute level of *labormarket*. Likewise, the relationship between labor market flexibilization and growth-enhancing structural change is measured separately for two groups of countries defined by either the absolute level of either *schooling*, *Gini_schooling*, or *RED*. Starting with the estimated coefficients of *schooling*, the results emphasize the previous finding, with no sizable sign of parameter heterogeneity. Improvements in overall education are unrelated to changes in the magnitude of growth-enhancing structural change. The variable *Gini_schooling* remains statistically insignificant as well, while a heterogeneous effect is indicated. Opposite to this, the estimated effect for *RED* is very different within the two groups of countries. While there seems to be no significant relationship between improvements in gender equality in education and gains from structural change in the group of countries characterized by rather rigid labor markets, the correlation is highly significant in a statistical and economical sense within countries with more flexible labor markets. Parameter heterogeneity is also visible in the case of the *labormarket* variable. The estimates show a statistically significant relationship within countries with lower levels of inequality in education (overall and gender) suggesting that labor market flexibility promotes growth-enhancing structural change. For countries marked by a more unequal distribution of education in the population, the estimated coefficient has the opposite sign and is statistically insignificant. It might seem odd to the reader that, although both variables condition the effect of *labormarket*, changes in *RED* are found themselves to be significantly correlated with growth-enhancing structural change, while changes in *Gini_schooling* are not. These results can, however, be statistical explained from the fact that the correlation of *RE*D and *Gini_schooling* is quite high (0.84), but the correlation in the within-country variation of both variables is rather low (0.39).

The group-specific coefficients inform us about the respective relationship between the variable of interest and the dependent variables within both groups of countries. This is the primary interest of the present study. However, it might also be interesting to assess whether the estimated effects of a variable of interest are statistically significantly different in the two groups of countries or whether the inclusion of parameter heterogeneity significantly improves the overall fit of the model. While the former can be tested by applying a T-test for parameter equality, the latter can be tested by applying a likelihood ratio (LR) test. Focusing on *RED* and *labormarket*, the tests give the following results: First, regarding *RED*, the null-hypothesis of parameter equality gets rejected on a 0.1 level. Second, regarding *labormarket,* the null-hypothesis of parameter equality can neither be rejected conditional on *Gini_schooling* nor conditional on *RED*. This is not too surprising in light of the large standard errors linked to the *labormarket* coefficient for the respective groups of countries with large (gender) inequality in education. Third, the null-hypothesis that the model which does not allow for parameter heterogeneity in *RED* provides the same fit as the extended model is rejected on the 0.05 level. Fourth, the null-hypothesis gets also rejected on a 0.1 level in the case of parameter heterogeneity of *labormarket* conditional on *Gini_schooling*, but not conditional on *RED*. Finally, the LR test also rules in favor of the model that allows for parameter heterogeneity in *RED* and *labormarket* on a 0.05 level. In sum, the group specifications provide evidence for the hypothesis that the effect of changes in either gender inequality in education or labor market rigidities on growth-enhancing structural change is not unconditional. In order for labor market flexibilization to be correlated with larger gains from structural change, low (gender) inequality seems to be a precondition. Similar, the positive link between lower gender gaps in education and the growth-enhancing reallocation of workers is impeded by strong labor market rigidities.

Table 2: Regression results II: Country groups specifications

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Convergence term:* | | | | | | | |
| agriculture | 0.048<br>(0.03) | 0.050<br>(0.03) | 0.046<br>(0.03) | 0.049<br>(0.03) | 0.043<br>(0.03) | 0.051<br>(0.03) | 0.047<br>(0.03) |
| *Schooling in group of countries:* | | | | | | | |
| with flexible labormarkets | –0.022<br>(0.20) | | | | | | |
| with rigid labormarkets | –0.100<br>(0.20) | | | | | | |
| *RED in group of countries:* | | | | | | | |
| with flexible labormarkets | | | –1.092***<br>(0.38) | | | | –0.986**<br>(0.45) |
| with rigid labormarkets | | | 0.048<br>(0.58) | | | | 0.108<br>(0.62) |
| *Gini_schooling in group of countries:* | | | | | | | |
| with flexible labormarkets | | | | | –0.034<br>(2.52) | | |
| with rigid labormarkets | | | | | 2.628<br>(3.23) | | |
| *labormarket in group of countries:* | | | | | | | |
| with high education attainment | | –0.703<br>(0.90) | | | | | |
| with low education attainment | | –0.880<br>(1.02) | | | | | |
| with low RED | | | | –1.165**<br>(0.49) | | | |
| with high RED | | | | 0.502<br>(2.08) | | | |
| with low Gini_schooling | | | | | | –1.421**<br>(0.62) | –1.315**<br>(0.55) |
| with high Gini_schooling | | | | | | 0.696<br>(1.58) | 0.063<br>(1.60) |
| Controls | yes | yes | yes | yes | yes | yes | yes |
| Country effects | yes | yes | yes | yes | yes | yes | yes |
| Time effects | yes | yes | yes | yes | yes | yes | yes |
| Observations | 201 | 201 | 201 | 201 | 201 | 201 | 201 |
| Prob > F | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $R^2$ within | 0.32 | 0.32 | 0.34 | 0.32 | 0.31 | 0.31 | 0.34 |

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.

*Note:* The dependent variable is the total contribution of structural change to labor productivity growth over 5-year intervals from 1970-2005. The period 1970-1975 has been dropped for Malaysia and Hong Kong. The set of controls include the remaining labor mobility variables as well as income, invest, popgrowth, mining, FDIflow, openness, and reer.

### 4.2.2 *Channel regressions*

The regressions in table 3 allow to examine the channels through which *agriculture, RED,* and *labormarket* affect growth-enhancing structural change. The channel regressions suggests that domestic convergence proxied by the employment share of agriculture contributes exclusively through static gains, that is, through a shift of workers into sectors with *above*-average productivity *levels*. Contrary to this, changes in the *labormarket* variable seem to affect the dependent variable through both the static and the dynamic channel, although in completely different ways. In more detail, a flexibilization of the labor market is correlated with static gains. This relationship is found to be particularly strong and statistically significant in the group of countries with lower inequality in education. However, flexibilization also leads, on average, to a shift of workers into sectors with *below*-average labor productivity *growth*, which indicates that workers enter new sectors with lower marginal productivity. This feature is particularly pronounced in the group of countries with larger inequality in education. Finally, turning to the variable *RED*, the channel specifications reveal a potential explanation for the previous finding of a heterogeneous effect related to *RED* in the two groups of countries with rigid/flexible labor markets. That is, while smaller gender gaps are positively associated to static gains in the group of countries characterized by more flexible labor markets, this relationship is negative in the group with rigid labor markets. Regarding the dynamic channel, the relationship is negative in both groups. However, the variable is not significant in all channel specifications. Overall, the findings seem economically plausible.

## 4.3 Robustness specifications

### 4.3.1 *Replacing the convergence term*

Although the size of the coefficient remains similar to the baseline regressions in table 1, *agriculture* falls slightly out of the 0.1 level of statistical significance in the group specification of table 2. To test whether robustness of the previous finding of a conditional domestic convergence process, I replace the variable *agriculture* by *cov* as the convergence term in columns 5 to 7 of table 3. The variable is significant on a 0.05 level. Besides this, the substitution has a sizable effect on the other coefficients. The coefficient of *RED* in the group of countries with more flexible labor markets is larger in absolute terms (–1.28 compared to –0.99) and now statistically significant at a 0.01 level in the regression with the total contribution of structural change as the dependent variable. For the same group of countries, the channel specifications further show a larger positive correlation between smaller gender gaps in education and static gains from structural change, which is statistically significant on a 0.05 level. Regarding *labormarket*, not only the magnitudes are considerably altered, but the variable is also no longer significantly correlated with both the overall and static contribution of structural change in the group of countries with lower overall inequality in education.[19] How can we interpret this finding? Note that by substituting *agriculture* with *cov* we now also account for the variation in labor productivity among non-agricultural sectors. The changes in the *labormarket* coefficient might thus indicate that the strong relationship between labor market flexibilization and the shift of workers into sectors with *above*-average productivity *levels* is largely due to the reallocation between the non-agricultural sectors. Opposite to this, the negative relationship between labor market rigidity and dynamic losses in the group of countries with large inequality in education is confirmed, roughly of same magnitude, and now even statistically significant at a 0.05 level. This is plausible, since replacing *agriculture* by *cov* should only affect the extend of labor misallocation (that is, the potential for static gains) captured in the convergence term.

#### 4.3.2 *Different interval length*

Table 4 presents the results of the ten-year-interval estimations. Several issues are notable. First, the share of within-variation explained by the specifications increases by around 10 percentage points. Second, while *agriculture* is significantly correlated with the dependent variable on a 0.05 level, *cov* enters the regression in column 4 insignificantly with a coefficient of close to zero. This indicates that, in the medium-term, convergence towards the state of efficient allocation occurs through the shift of workers out of the agricultural sector oppose to a more efficient allocation of workers across the non-agricultural sectors. Third, *RED* and *labormarket* enter the regression on a 0.01 and 0.05 significance level, respectively. Fourth, while the proxy for gender gaps in education is significant on a 0.01 level in countries with more flexible labor markets, it is insignificant in countries with more rigid labor markets. Moreover, the difference between the coefficient between the two groups is statistically significant at a 0.05 level and the LR test indicates the superior model fit of the specification that allows for parameter heterogeneity in *RED* (p-value 0.01). Fifth, although flexibilization is now found to be positively correlated with growth-enhancing structural change in both groups of countries, the effect is still only statistically significant in the two groups of countries with lower (gender) inequality in education.[20] Finally, turning to the channel specification, the

[19] Statistically, this finding is not too surprising in light of the fact that replacing the variable *agriculture* by *cov* as the convergence term had already a notable effect on the *labormarket* coefficient in the baseline specifications (see column 7 in table 1).

[20] Interestingly, the *labormarket* coefficient for the countries with larger inequality in education is now almost of equal size, however, the standard error is significantly larger. This can explain why the variable is not statistically in that group of countries, but overall, a significant correlation between *labormarket* and the total contribution of structural change is found in column 1. Also, it is worth pointing out that the coefficient of *labormarket* for the group with lower inequality in education remains significant despite the inclusion of *cov*.

relationship between lower gender gaps in education and gains from structural change in countries with more flexible labor markets is estimated to be statistically significant at the 0.1 level in the medium-term. This finding points once more to the growth-enhancing effect of improvements in gender equality in education as it indicates that lower educational gender gaps are associated with workers entering new sectors with higher marginal productivity. All in all, the 10-year interval regressions support the previous short-term findings.

Table 3: Regression results III: Channel specifications

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Convergence term:* | | | | | | | |
| agriculture | 0.066** | –0.015 | 0.061** | –0.013 | | | |
| | (0.03) | (0.02) | (0.03) | (0.02) | | | |
| COV | | | | | 0.203** | 0.255** | –0.052 |
| | | | | | (0.10) | (0.10) | (0.05) |
| *Mobility variables:* | | | | | | | |
| RED | –0.344 | –0.352 | | | | | |
| | (0.59) | (0.25) | | | | | |
| labormarket | –1.324* | 0.564* | | | | | |
| | (0.73) | (0.32) | | | | | |
| *RED in group of countries:* | | | | | | | |
| with flexible labormarkets | | | –0.804 | –0.182 | –1.280*** | –1.175** | –0.105 |
| | | | (0.52) | (0.22) | (0.42) | (0.47) | (0.21) |
| with rigid labormarkets | | | 0.668 | –0.560 | 0.162 | 0.737 | –0.576* |
| | | | (0.89) | (0.37) | (0.50) | (0.74) | (0.34) |
| *labormarket in group of countries:* | | | | | | | |
| with low Gini_schooling | | | –1.725*** | 0.411 | –0.603 | –0.827 | 0.224 |
| | | | (0.52) | (0.35) | (0.60) | (0.56) | (0.33) |
| with high Gini_schooling | | | –0.929 | 0.992* | –0.077 | –1.107 | 1.030** |
| | | | (1.70) | (0.49) | (1.61) | (1.68) | (0.46) |
| Controls | yes | yes | yes | yes | yes | yes | yes |
| Country effects | yes | yes | yes | yes | yes | yes | yes |
| Time effects | yes | yes | yes | yes | yes | yes | yes |
| Observations | 201 | 201 | 201 | 201 | 201 | 201 | 201 |
| Prob > F | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $R^2$ within | 0.33 | 0.18 | 0.35 | 0.19 | 0.36 | 0.38 | 0.19 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

*Note:* The dependent variable in columns 1, 3, and 6 is the static contribution of structural change to labor productivity growth over 5-year intervals from 1970-2005. In columns 2, 4, and 7 the dependent variable is the dynamic contribution. In column 5 the dependent variable is the total contribution. The period 1970-1975 has been dropped for Malaysia and Hong Kong. The set of controls include the remaining labor mobility variables as well as income, invest, popgrowth, mining, FDIflow, openness, and reer.

This was not the case in the short-term estimations.

Table 4: Regression results IV: Ten-year interval specification

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Convergence term:* | | | | | | |
| agriculture | 0.067** | 0.063** | 0.065** | | 0.053 | 0.012 |
| | (0.03) | (0.03) | (0.03) | | (0.03) | (0.02) |
| COV | | | | –0.002 | | |
| | | | | (0.09) | | |
| *Mobility variables:* | | | | | | |
| RED | –0.860*** | | | | | |
| | (0.29) | | | | | |
| labormarket | –1.071** | | | | | |
| | (0.45) | | | | | |
| *RED in group of countries:* | | | | | | |
| with flexible labormarkets | | –1.144*** | –1.177*** | –1.241*** | –0.640 | –0.537 |
| | | (0.33) | (0.33) | (0.31) | (0.48) | (0.34) |
| with rigid labormarkets | | –0.189 | –0.213 | –0.086 | 0.680 | –0.892* |
| | | (0.42) | (0.43) | (0.44) | (0.78) | (0.46) |
| *labormarket in group of countries:* | | | | | | |
| with low RED | | –1.464*** | | | | |
| | | (0.32) | | | | |
| with high RED | | –0.564 | | | | |
| | | (1.03) | | | | |
| with low Gini_schooling | | | –1.428*** | –1.126** | –1.645** | 0.217 |
| | | | (0.40) | (0.48) | (0.74) | (0.69) |
| with high Gini_schooling | | | –0.728 | –1.171 | –2.323 | 1.594* |
| | | | (1.02) | (1.31) | (1.60) | (0.94) |
| Controls | yes | yes | yes | yes | yes | yes |
| Country effects | yes | yes | yes | yes | yes | yes |
| Time effects | yes | yes | yes | yes | yes | yes |
| Observations | 114 | 114 | 114 | 114 | 114 | 114 |
| Prob > F | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $R^2$ within | 0.46 | 0.49 | 0.49 | 0.43 | 0.39 | 0.23 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

*Note:* The dependent variable in columns 1 to 4 is the total contribution of structural change to labor productivity growth over 10-year-intervals from 1970-2010. In column 5 and 6, the dependent variable is the static or dynamic contribution, respectively. The set of controls include the remaining labor mobility variables as well as income, invest, popgrowth, mining, FDIflow, openness, and reer.

# 5 Conclusion and Caveats

Before turning to the conclusion of this paper, I address some potential caveats. First, the definition of a sector's average labor productivity as value added divided by number of works employed in a sector is a second-best approach. It could very well be that productivity differences between sectors are inflated because the actual hours work per employer over a certain time period differ substantially. An improvement would thus be to replace the number of employed workers with the actual hours worked to calculate average labor productivity more precisely. Second, this paper solely focused on inter-sector reallocation. A disaggregation of the economy into nine sectors displays a major innovation compared to the three-sector approach found in many previous studies. However, the growth-enhancing effect from a reallocation across the various sub-industries within sectors is captured in the within component and not the structural change term in this study. Extending the level of aggregation at the costs of a smaller sample of developing and emerging countries can thus represent an interesting complementary approach. The EU KLEMS Database or the recently published World-Input-Output Database with data on various input factors on a highly disaggregated industry level for a set of advanced countries offer potential starting points for such an investigation. Finally, by looking at the relationship between right-hand side variables and the magnitude of growth-enhancing structural change, this paper observes only one channel through which labor productivity growth occurs. This being said, it is the large pool of people working in the agricultural sector that represents a major share of the poor in the world. Growth-enhancing structural change thus represents not only a source of economic growth in general, but also a powerful channel to reduce poverty in particular.

Although it is one of the oldest and most fundamental findings that economic development entails structural change, the lack of data has severely constraint empirical work on the topic. This study's objective was to extend the recent work of McMillan et al. (2014) and provide a "second pass through the data" on the determinants of growth-enhancing structural change by constructing a panel data set of 5- and 10-year intervals ranging from 1970 to 2010 for 29 (mostly developing) countries that goes beyond the standard three-sector disaggregation of the economy. Controlling for a wide range of variables and unobserved heterogeneity, the empirical analysis leads to the following main conclusions. The regressions present evidence for growth-enhancing structural change to be the outcome of a conditional domestic convergence process towards each country's idiosyncratic state of efficient allocation. This is in line with the cross-section findings by McMillan et al. (2014). The estimated coefficient speed is considerably larger in my fixed-effects specifications.

The paper then looks more closely at potential sources of labor mobility barriers that determine a country's steady state of allocative efficiency. Overall, the findings indicate that promoting (gender) equality in education is not a normative policy issue alone (See Klasen (2008) for a survey on the "Efficiency of equity"). It should also be a policy target to promote a more efficient allocation of the workforce across sectors. Both the short- and medium-term regressions point to an economically meaningful and statistical robust correlation between lower gender gaps and productivity gains from structural change. However, the results also show that this relationship does not hold within the group of countries characterized by more rigid labor markets. This supports the hypothesis that improving gender equality in education will only be related to sizable gains from labor reallocation, if the rigidity of the labor market does not represent a constraining factor for structural change. Likewise, also the relationship between labor market flexibilization and growth-enhancing structural change is not unconditional. Although there is empirical support for the theory that labor market flexibilization promotes growth-enhancing structural change, this relationship is not found in countries with larger (gender) inequality in education. Here, flexibilization is linked to workers entering new sectors with lower marginal productivity which drags average labor productivity growth down. This finding emphasizes that an economic environment in which educational equally prevails is a necessary precondition, if a country intends to promote growth-enhancing structural change by reducing labor market rigidities.

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# Appendix

Table 5: Sector Disaggregation

| Abbr | Sector Name | ISIC Rev3.1 description |
|---|---|---|
| Agr | Agriculture | Agriculture, Hunting and Forestry, Fishing |
| Min | Mining | Mining and Quarrying |
| Man | Manufacturing | Manufacturing |
| Pu | Public Utilities | Electricity, Gas and Water supply |
| Con | Construction | Construction |
| Trade | Trade Service | Wholesale and Retail trade, Hotels and Restaurants, Repair of motor vehicles, motorcycles and personal and household goods |
| Transport | Transport Services | Transport, Storage and Communications |
| Business | Business Services | Financial Intermediation, Real Estate, Renting and Business Activities |
| GCSP | Government, Community, Personal and Social Services | Public Administration and Defense, Education, Health and Social work<br>Other Community, Social and Personal service activities<br>Activities of Private Households |

Table 6: Country Sample

| Countryiso | Country | Region | Countryiso | Country | Region |
|---|---|---|---|---|---|
| ARG | Argentina | Latin America | PHL | Philippines | Asia |
| BOL | Bolivia | Latin America | SGP | Singapore | Asia |
| BRA | Brazil | Latin America | THA | Thailand | Asia |
| CHL | Chile | Latin America | TWN | Taiwan | Asia |
| COL | Colombia | Latin America | BWA | Botswana | Africa |
| CRI | Costa Rica | Latin America | GHA | Ghana | Africa |
| MEX | Mexico | Latin America | KEN | Kenya | Africa |
| PER | Peru | Latin America | MWI | Malawi | Africa |
| VEN | Venezuela | Latin America | MUS | Mauritius | Africa |
| HKG | Hong Kong | Asia | SEN | Senegal | Africa |
| IDN | Indonesia | Asia | TZA | Tanzania | Africa |
| IND | India | Asia | ZAF | South Africa | Africa |
| JPN | Japan | Asia | ZMB | Zambia | Africa |
| KOR | Korea, Republic of | Asia | USA | United States | North America |
| MYS | Malaysia | Asia | | | |

Table 7: Data definitions and sources

| Variable Name | Definition | Data Source |
|---|---|---|
| *Mobility Variables* | | |
| HC | Human Capital Index | PWT 8.0 by Feenstra et al. (2015) |
| schooling | Average years of schooling attained by the population 25+ | Barro and Lee (2013) |
| male_schooling | Average years of schooling attained by male population 25+ | Barro and Lee (2013) |
| RED | Male-female ratio of schooling | Calculated based on: Barro and Lee (2013) |
| Gini_schooling | A gini coefficient for education between 0 - 1 | Calculated based on: Barro and Lee (2013) |
| labormarket | Rigidity of employment protection legislation index between 0 to 3.5 over time period | Campos and Nugent (2012) |
| *Control Variables* | | |
| agriculture | Employment share of agriculture | Timmer et al. (2014) |
| agrgap | Gap between employment and value added share of agriculture | Calculated based on: Timmer et al. (2014) |
| cov | Coefficient of variation over sector labor productivity | Calculated based on: Timmer et al. (2014) |
| *Other Determinants* | | |
| income | Natural log of expenditure-side real GDP per capita at chained PPPs | PWT 8.0 by Feenstra et al. (2015) |
| invest | Average investment rate over time period | PWT 7.1 by Heston and Summers (2012) |
| caopen | A de jure measure of financial openness between 2.44 and -1.86 | Chinn and Ito (2006) |
| openness | Exports plus imports as share of GDP | PWT 7.1 by Heston and Summers (2012) |
| reer | CPI based real effective exchange rate against a basket of foreign currencies | Darvas (2012) |
| popgrowth | Population growth in period | PWT 8.0 by Feenstra et al. (2015) |
| FDIflow | Inward flow of Foreign Direct Investment as share of GDPe | UNCTAD |
| mining | Share of mining and quarrying in value added | Timmer et al. (2014) |

*Note:* If not stated otherwise, the variables enter the regression as initial levels.

Table 8: Descriptive statistics of components of growth-enhancing structural change

| Variable | | Mean | | Std. Dev. | Min | Max | Obs |
|---|---|---|---|---|---|---|---|
| | | | overall | 1.26 | -3.36 | 6.54 | |
| Total term | overall | 0.55 | between | 0.65 | -1.18 | 1.95 | 230 |
| | | | within | 1.09 | -2.97 | 5.81 | |
| | | | overall | 1.39 | -2.01 | 9.33 | |
| Static term | overall | 0.95 | between | 0.71 | -0.37 | 2.26 | 230 |
| | | | within | 1.20 | -2.33 | 8.03 | |
| | | | overall | 0.58 | -3.51 | 0.82 | |
| Dynamic term | overall | -0.41 | between | 0.31 | -1.23 | 0.07 | 230 |
| | | | within | 0.59 | -2.69 | 1.41 | |

*Note*: Author's calculation based on 5-year intervals from 1970 to 2010 for 29 countries. The period 1970-1975 has been dropped for Malaysia and Hong Kong. The Min and Max within values are calculated by subtracting the group mean and then add in the overall mean to the series.
*Data source*: See table 7 in the appendix.

Table 9: Descriptive statistics of labor mobility variables

| Variable | Overall Mean | Within Std. Dev. | Difference to Country Mean Min | Max | Obs |
|---|---|---|---|---|---|
| *Education* | | | | | |
| schooling | 5.56 | 1.51 | 2.17 | 9.11 | 232 |
| *Inequality in education* | | | | | |
| RED | 1.46 | 0.29 | 0.62 | 2.68 | 232 |
| Gini_schooling | 0.31 | 0.09 | 0.09 | 0.57 | 232 |
| *Labor market rigidity* | | | | | |
| labormarket | 1.43 | 0.12 | 0.99 | 1.79 | 203 |

*Note*: Author's calculation based on 5-year interval observations. No data on labormarket available for period 2005-2010. The Min and Max within values are calculated by subtracting the group mean and then add in the overall mean to the series. *Source*: See table 7.

Table 10: Descriptive statistics of convergence terms and other determinants

| Variable | Overall Mean | Within Std. Dev. | Difference to Mean Min | Difference to Mean Max | Obs |
|---|---|---|---|---|---|
| *Convergence Terms* | | | | | |
| agriculture | 37.28 | 7.85 | 18.24 | 66.02 | 232 |
| cov | 1.15 | 1.31 | 6.42 | 17.42 | 232 |
| *Control Variables* | | | | | |
| income | 8.41 | 0.41 | 6.86 | 9.53 | 232 |
| invest | 25.10 | 5.18 | 9.22 | 46.24 | 232 |
| popgrowth | 0.09 | 0.02 | 0.01 | 0.18 | 232 |
| caopen | 0.04 | 0.87 | -2.04 | 2.96 | 224 |
| openness | 65.11 | 31.35 | -49.28 | 242.12 | 232 |
| reer | 125.62 | 55.68 | -26.53 | 587.96 | 232 |
| FDIflow | 0.05 | 0.13 | -0.27 | 1.02 | 232 |
| mining | 7.22 | 3.52 | -11.87 | 30.06 | 232 |

*Note*: Author's calculation based on 5-year interval observations. No data on caopen available for Taiwan. The Min and Max within values are calculated by subtracting the group mean and then add in the overall mean to the series. *Source*: See table 7.