Economic growth in the face of changes

Doctoral thesis

ECONOMIC GROWTH IN THE FACE OF CHANGES

Ming Li

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Economic Growth in the Face of Changes

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Ming Li

Supervisors:

Prof. dr. Jaap W.B. Bos
Prof. dr. Pierre Mohnen

Assessment Committee:

Dr. Stefan Straetmans (Chair)
Prof. dr. Mette Asmild, University of Copenhagen
Prof. dr. Rob Bauer
Dr. Tommaso Ciarli
Dr. Christopher Parmeter, University of Miami

To my parents

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Ming Li
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1
Introduction

Economic growth is the engine of great prosperity. It is critical for reducing poverty and improving living standards. In an ideal situation, continuing growth would lead everyone to a better life. Unfortunately, this seems overpromising because not all of the population can benefit from economic growth. The unequal distribution of resources and income among the population leads to rising levels of inequality (Mdingi & Ho, 2021). Economic growth is usually accompanied by economic inequality. The association between inequality and economic growth has long been the center of macroeconomics, development economics, and labor economics [1].

Inequality involves the disproportionate distribution of resources, wealth, and income, arising between countries, industries, and essentially individuals. For individuals, inequality happens in many dimensions, for example, income, education, and other opportunities. In particular, income inequality keeps rising in many advanced and emerging economies. It has increased in most OECD member countries during the past three decades (OECD, 2015). High-income groups may have profited more from economic growth, if any, than lower-income ones. A growing body of research suggests that the rise of inequality hampers economic growth, especially in less developed countries (Barro, 2001; Berg et al., 2018; Cingano, 2014; Neves et al., 2016). The analysis of OECD (2015) indicates that between 1985 and 2005, the average increase in income inequality was more than 2 Gini points across

[1] The literature is vast, ever since Kuznets proposed the Kuznets curve, an inverted U-shape, which hypothesizes inequality increases during the early stage of economic development and decreases during later stages (Kuznets, 1955). Some studies find a positive relationship (Forbes, 2000; Li & Zou, 1998; Scholl & Klasen, 2018), while other studies find a negative relationship (Braun et al., 2019; Perotti, 1996; Persson & Tabellini, 1994; Royuela et al., 2019)

19 OECD countries, estimated to have dragged down cumulative growth by 4.7 percentage points between 1990 and 2010. It also shows that in many countries, there has been a widening gap between the bottom 40% of the income distribution and the rest, which can hurt the entire economy. Besides the impairment of economic growth, the widening gap between the rich and the poor worries people considerably, particularly social and political egalitarians. Policymakers play vital roles in the redistribution of income and resources among the population and inequality sits at the center of their agenda. In consequence, reducing inequality is key to not only sustaining long-term growth but also ensuring social stability.

Inequality is the product of various factors, consisting of, but not limited to, technology, education, labor markets, policies, gender, racism, and so on. Within modern economies, technology has been developing immensely fast and thus unavoidably becomes one of the crucial drivers of economic growth and inequality. Technology is a two-sided coin, boosting economic growth while causing disparities between individuals, sectors, and countries (see, for example, Aghion et al. (2002) and Galor and Tsiddon (1997). Firms or economies adjust to new technologies and therefore adjust to demand in factors in response to technological change. More often than not, they incur adjustment costs that are immanent in the act of changing the amount of the inputs (Hamermesh & Pfann, 1996). For example, companies may face high adjustment costs in the form of retraining employees or investing in new equipment because of shifts in technology. Similarly, workers whose skills become outdated need to find new job opportunities, which can be costly. Because firms and workers may be reluctant to change due to adjustment costs, economic growth can be impeded. Kiley (1999) finds that large adjustment costs impair the contribution of computers to economic growth and may lower productivity growth. Adjustment costs can induce efficiency loss (Chapter 2), impede the labor market adjustments to technology shocks (Chapter 3), and thus hinder technological development. Moreover, the labor market may face higher adjustment costs induced by labor market institutions and policies (Serfling, 2016). Pierre and Scarpetta (2013) and Haltiwanger et al. (2014) find that stringent hiring and firing regulations can slow down the pace of job reallocation, implying high labor adjustment costs. Policymakers endeavor to find effective approaches to reduce inequality and protect people with lower income, but they may produce more adjustment costs nevertheless. This type of adjustment costs may mitigate inequality but slow economic growth (Chapter 4). Concerning policy-making, we often face painful trade-offs between benefits and costs. It is ultimately about how to balance the pros and cons and what is best for people and society. Therefore, policymakers can not afford to ignore adjustment costs. Otherwise, biases can flow into policies.

This dissertation focuses on the analysis of adjustment costs of labor markets. In order to adapt to currently fast-changing technological progress, labor markets need to adjust the skill composition of the workforce, reallocate labor across sectors, and further enhance human capital. However, the adjustments of labor markets do not come for free. Firms incur adjustment costs when changing the amount of labor input used, for example, the cost of hiring and firing and the cost of adjusting employment (Hamermesh, 1995; Hamermesh & Pfann, 1996). It is widely recognized that there are adjustment costs associated with specific human capital, inter-industry mobility, and labor market policies. The first two chapters focus on the labor market adjustments to technology shocks, especially when technology favors a specific type of labor. Both chapters incorporate the costs of adjusting employment shares for workers with different skill levels in the production function. Chapter 2 theoretically and empirically investigates the adjustment costs of the change in the skill composition of the workforce, especially how the different costs of adjusting inputs of different skill levels influence productivity changes and wage differentials. Subsequently, Chapter 3 extends Chapter 2 to theoretically model the cost of reallocation of labor of different skills and study in more detail the relation between productivity changes and wage dynamics across sectors. Apart from the adjustments to technology shocks, Chapter 4 examines the adjustment costs induced by labor market institutions. It uses a similar empirical framework as Chapter 2 to study if labor market institutions can explain the distance from the best practice frontier of minimizing inflation and unemployment. In the remainder of this Chapter, I will provide a brief overview of each paper.

1.1 Changes in Skill Composition

This dissertation examines how labor adjustment costs influence economic growth and inequality and it sheds light on relevant policy-making. First, I focus on adjustment costs from adapting to skill-biased technical change (SBTC). Technical change (TC) includes technological change and any other changes that can increase the amount of output without changing the amount of input. More often than not, TC is skilled-biased. SBTC complements the productivity of high-skilled relatively to low-skilled labor and thus increases the relative demand for high-skilled labor. There is evidence that job polarization and structural change are attributed to skill-biased technological progress, which has important implications for the labor market (e.g., Adermon & Gustavsson, 2015; Goos et al., 2014). SBTC is commonly considered the major cause of the widening wage differential between high-skilled and low-skilled labor, which results in high inequality between different types of workers. This reasoning puts SBTC at the center of the income inequality debate. The labor market reacts by changing the skill composition of the labor force. These changes bring about costs if there are differences in the ease with which labor of different skill levels becomes efficient at the job. The essential question to answer is how adjustments to the skill composition of workers can affect SBTC and wage differentials.

In Chapter 2, I explore the impact of short-term labor market adjustments on skill-biased technical change. Technical change is biased towards specific inputs of production in the sense that the marginal productivities of those inputs do not increase at the same rate over time. If TC is characterized by a skill bias, the adjustments in the skill composition of the labor employed in production contribute to growth. This contribution changes further if workers of different skill levels differ in their ability to learn on the job and become efficient. As the skill composition changes, newly hired workers adapt to their new job and are temporarily less efficient at their job, which causes adjustment costs. This chapter focuses on this often ignored aspect, although there is extensive literature on technical change. Katz and Murphy (1992) capture the effects of skill-biased technical change by estimating a wage equation. Acemoglu (2002b), Greiner et al. (2004), and numerous studies follow the same approach, treating skill-biased wage differentials as an indicator of high demand for high-skilled relative to low-skilled labor. The more recent study by Jones and Yang (2016) uses higher education costs as an indicator for SBTC. I try to disentangle the adjustment costs of changes in labor at a specific skill level from the productivity growth of that skill level and study how adjustments in skill compositions affect SBTC. I argue that, in particular, slower learning on the job, resulting in higher efficiency losses, by high-skilled labor means that we underestimate the skill bias in technical change. This underestimation is crucial because SBTC leads to increases in wage inequality, and if we underestimate SBTC, we also underestimate its effect on wage inequality.

To account for adjustment costs for each type of labor, I build a simple model that can explain how changes in the skill composition can affect technical change and efficiency change. Next, I take that model to industry-level data for 40 countries and 31 industries over the period between 1995 and 2009 and provide estimates of the bias in traditional measures of skill-biased technical change. Finally, I then use the results to explain how this bias may have contributed to the gap between the marginal rate of technical substitution of labor with different skill levels and the relative wages. I find that adjustment costs can offset some benefits TC brings. The results present vital implications for education policies. If new technology favors high-skilled labor and thus increases wage inequality, it will hurt low-skilled labor and further increase inequality. The reason is that rising inequality can depress the skill development of individuals with a lower parental education background, both in terms of the quantity of education attained and the quality (i.e., skill proficiency), and then prevent lower-income people from realizing their human capital potential (Cingano, 2014). It calls for well-suited policies to help low-wage workers obtain a better education.

1.2 Inter-Sector Reallocation of Skills

In recent decades, there have been considerable changes in employment at the industry level as well (Bárány & Siegel, 2018, 2020; Goos et al., 2014). Developed economies have experienced extensive reallocation from goods to the service sector. Since some industries are centered around innovation more than others, they have seen more rapid technological developments and more changes in employment than others. How difficult it is to reallocate labor across industries can have an effect on growth and inequality. Hence, in the presence of mobility costs, how the labor market responds to industry-specific technology shocks will provide us with important implications for industry and labor market policies.

Skill-biased technical change influences not only individual workers but also sector developments. SBTC can have the attribute of a sector bias if it is concentrated in skill-intensive sectors (Haskel & Slaughter, 2002). The sector bias of SBTC leads to a reallocation of labor forces and intensive skill upgrading in relative sectors. However, sectoral or inter-industry labor mobility encounters obstacles since individuals face the costs of switching jobs. Following the same vein as Chapter 2, Chapter 3 theoretically explores how the labor market adjusts to industry-specific technology shocks, with and without adjustment costs. I pay close attention to adjustment costs from labor reallocation across industries. Therefore, I construct a two-industry model incorporated with SBTC and compare the outcomes with perfect and imperfect inter-industry labor mobility.

In particular, I analyze to what extent SBTC and human capital specificity can affect the labor market‘s responses to technology shocks in a specific industry. Following the same logic as in Chapter 2, I suppose that workers of different skill levels have various rates of specific human capital. Specific human capital can come from specific on-the-job learning or work experience. Since on-the-job learning plays a crucial role in productivity growth and the acquired skills from work are not fully transferable between industries, workers can not easily switch jobs. Thus, inter-industry labor mobility has an adjustment cost in the form of the destruction of specific human capital. My model can show how workers of different skill levels have distinct human capital specificity and how the loss of specific human capital affects labor mobility, skill premiums, and skill upgrading. I consider those effects under different circumstances, for example, the partial or general equilibrium with wage compression or without it. I try to answer several related questions: Does human capital specificity constrain the inter-industry reallocation of labor from a contracting to an expanding industry? How does the specificity of human capital influence skill upgrading? And who should pay for skill upgrading? The model suggests that wage compression plays a vital role in skill upgrading and wage inequality. More importantly, I put forward implications for the labor market and education policies. I show that policymakers should consider four factors: the competitiveness of product markets, the specificity of human capital, the bargaining power of firms, and education costs.

1.3 Labor Market Institutions

Labor market institutions play a crucial role in labor market adjustments by increasing or decreasing frictions and costs. They aim to improve equity among individuals and meet the requests of specific interest groups (Boeri & van Ours, 2013). However, they can also make the labor market inflexible to adjust and therefore affect economic performance. Policy-making is far from easy, especially when we cannot achieve one goal without hurting the other. With the existence of adjustment costs, effective policy-making is essential to reach optimal economic goals.

Policy-making is challenging and complicated. Although policymakers try hard to achieve their goals, there are inevitable gains and losses. In Chapter 4, I examine the influence of different labor market policies on growth and inequality between countries. I focus on one crucial topic on many policymakers‘ recurring agenda: controlling inflation and curbing unemployment. Phillips (1958) observed a negative correlation between the unemployment rate and nominal wages in the UK. It has been the starting point for many policymakers ever since, in particular for many central banks (Mavroeidis et al., 2014). Although the downward slope of the Phillips curve has flattened in advanced economies, minimizing inflation and unemployment remains very important. Even though Labor market policies have the advantage of reducing inequality, they create labor market frictions and adjustment costs. The key consequence is that they result in downward nominal wage rigidities (e.g., Daly and Hobijn (2014)). The pervasive downward nominal wage rigidities will lead to higher unemployment.

In Chapter 4, I benchmark the extent to which countries are able to minimize inflation and unemployment. By doing so, I first build a global best practice frontier, that describes the optimal attainable combinations of low unemployment and inflation, given the data at hand. I separate the *optimal* trade-off between maintaining low inflation and low unemployment from suboptimal, inefficient drifts from the best practice frontier. Second, in estimating the best practice frontier, I distinguish inefficiency (the deviations from the frontier) from uncertainty and allow both to vary depending on the mix of inflation and unemployment. Third, I then explore how to diminish inefficiency. I relate those deviations to labor market policies, in particular to minimum wage, trade union density, and collective bargaining coverage. Last but not least, I test whether inefficient countries can move closer to the best-performing countries over time (convergence). The results indicate that there is a significantly negative relationship between inflation and unemployment. In a low inflationary environment, it is hard to fight against inefficient unemployment. In addition, I find that labor market frictions can drive the gap between optimal and inefficient combinations. Finally, the findings suggest that high labor market frictions could hinder the improvement of economic performance.

In summary, this dissertation studies how adjustment costs influence aggregate dynamics and policy-making. On the individual level, I find that adjustment costs can cut down the benefits of technological developments, especially for high-skilled labor, since high-skilled labor has higher adjustment costs. On the industry level, adjustment costs can depress inter-industry labor mobility but encourage skill upgrading. When high-skilled labor has more specific human capital than low-skilled labor, the wage differentials between the two types of workers will be higher in the expanding industry than in the contracting one. On the country level, it shows that the gap between efficient and inefficient countries can be driven by labor market frictions (adjustment costs) and those frictions can influence the average level of inefficiency distinctly. The findings also show that inefficient countries can move closer to the best-performing countries over time (convergence). Those findings provide potential options for how to develop research-informed programs and policies.

2

How Biased is Skill-Biased Technical Change?

This chapter is co-authored with Jaap Bos (Maastricht University).

2.1 Introduction

Technical change (TC) changes everything ... especially if it is skill-biased. It is a prime source of increases in productivity (Solow, 1957), In its neutral form, it means that we can produce more today than we could yesterday, through the adoption of better production technology. In its less simple form, technical change is not factor neutral but dependent on changes in the mix of inputs employed. Its most poignant form is skill-biased technical change (SBTC). Skill-biased technical change refers to the type of technical change that increases the demand for high-skilled labor relative to lower-skilled labor. SBTC favors high-skilled labor over low-skilled labor by increasing high-skilled labor's relative productivity and thus relative demand. The underlying reasoning is that technological progress favors workers who possess certain types of skills, such as problem-solving, critical thinking, and advanced computer skills (Nelson & Phelps, 1966). With the development of technology, more high-skilled workers will be needed to replace low-skilled workers. The result is an increase in the skill premium, the ratio of the wages of skilled to unskilled workers, leading to increased wage inequality (Autor et al., 1998; Galor & Moav, 2000; Hornstein et al., 2005; Katz & Autor, 1999; Katz & Murphy, 1992).

SBTC can have a significant impact on labor markets (Acemoglu, 2002a). It will increase the ratio of the marginal product of high-skilled over low-skilled labor, the marginal rate of technical substitution (MRTS). As a result, it changes how many low-skilled workers need to be replaced by one extra high-skilled worker, for firms to produce the same output. In a perfectly competitive labor market, the MRTS equals the relative price of inputs, in this case, the wage ratio of high-skilled over low-skilled labor. SBTC changes the MRTS and thereby also affects the wage differential between high-skilled and low-skilled labor. Indeed, the wage gap, favoring high-skilled labor, has widened in many countries over the past decades (Katz & Autor, 1999). At the same time, labor-saving technical change is the leading explanation for the shift in demand away from unskilled and toward skilled labor in U.S. manufacturing during the 1980s (Berman et al., 1994).

One of the aspects of SBTC that is less well understood is learning on the job. The quality of labor forces depends not only on education attainments but also on working experience. Learning on the job plays a crucial role in improving productivity. The learning process and the effectiveness of on-the-job learning may vary across different skill levels. This leads to differences in the ease with which labor of specific skill levels increases productivity. As the labor composition changes, newly hired labor adjusts to its new job and is - at least temporarily - less efficient at its job than the labor it replaced. The effects of this adjustment would interact with the effects of SBTC. Black and Lynch (1996) find that there are adjustment costs related to introducing new skills, so the current training at the workplace will lower productivity in the short run and improve it after some time. We incorporate learning on the job for the labor of different skill levels in a production model aimed at estimating technical change, including SBTC. Hiring and training new workers is not costless and hence involves a loss in efficiency. Newly-hired workers do not reach their full productivity as soon as they enter the labor market, but rather their productivity can stay temporarily below the productivity of experienced workers (Blatter et al., 2012). More importantly, previous studies show both theoretically and empirically that high-skilled workers are more costly to hire and replace and therefore have higher adjustment costs than low-skilled workers (e.g., Belo et al., 2017; Blatter et al., 2012; Ghaly et al., 2017; Golden et al., 2020; Hamermesh & Pfann, 1996; Oi, 1962). If newly-hired labor has to learn on the job, some of the gains of replacing low-skilled workers for workers of another, better skill level, are - at least in the medium run - reduced by a loss in the efficiency with which each unit of labor contributes to producing output. We build a simple model that explains how changes in the composition of the labor force, the mix of high-, medium- and low-skilled labor, affect the efficiency of production. The key finding of our paper is that we end up with a biased estimate of SBTC if learning on the job leads to (temporary) efficiency losses that differ between skill levels. We demonstrate how important this bias is in explaining the wage gaps between the labor of different skill levels as they have developed over a period of 15 years.

We contribute to the literature on SBTC in three ways. First, we derive the bias in the measurement of technical change in a simple production model with learning on the job that can easily be extended to accommodate many of the existing manners of measuring SBTC. Second, we use a rich data set covering 40 countries and 31 industries over the period 1995-2009, to empirically measure the bias in skill-biased technical change. Third, we provide further evidence of how the bias in the measurement of SBTC can help explain the widening wage gap.

We are not the first to tackle the measurement of SBTC. Although the literature on technical change is vast, most of it ignores the role of efficiency change. Baltagi and Griffin (1988) propose a procedure for calculating a general index of technical change, which replaces the time trend with time-specific dummies and can be both neutral and scale augmenting. Their approach can offer salient advantages over the traditional time trend representation of technical change and contribute to the analysis of the determinants of technical change. Baltagi and Rich (2005) apply this general index approach to technical change between production and non-production labor in U.S. manufacturing industries over the 1959-1996 period. They find that SBTC is significant and evident prior to 1983, predating the diffusion of personal computer technologies in the workplace and the dramatic changes in the wage structure in the 1980s. However, they assume that all firms operate efficiently.

Katz and Murphy (1992) capture the effects of skill-biased technical change by estimating a wage equation. Acemoglu (2002b), Greiner et al. (2004), and numerous studies follow the same approach, treating skill-biased wage differentials as an indicator of high demand for high-skilled relative to low-skilled labor. The more recent study by Jones and Yang (2016) uses higher education costs as an indicator for SBTC. Other research tries to use computerization as a proxy for technical change. For example, Autor et al. (1998) measure the fraction of workers who use a computer keyboard, Autor et al. (2003) use the percentage of computer usage, Machin and Van Reenen (1998) measure technical change by R&D intensity, Michaels et al. (2014) test the role of information and communication technologies (ICT) capital, etc. All of the above measures are incomplete. Contrary to our approach, however, they disregard the existence of technical inefficiencies in production. Therefore, we adopt the traditional measure of economy-wide technological change and incorporate skill biases and efficiency change.

In Section 2.2, we introduce a model that explains how inefficiencies from learning on the job by the labor of different skill levels can bias the measurement of technical change. Section 2.3 explains how we can test this model empirically. In Section 2.4, we present results from simulating and estimating our model, respectively. To demonstrate the policy relevance of our results, we demonstrate their contribution to the debate on wage inequality in Section 2.5. Some conclusions are drawn in Section 2.6.

2.2 Theoretical Model

Our objective is to analyze how SBTC is affected by differences in the manner in which labor of different skill levels becomes efficient. [1]

In this section, we theoretically derive the bias in the measurement of technical change, especially skill-biased technical change. Before we show omitted variable bias in a production function parametrically in Section 2.2.2, we first developed a non-parametric model to distinguish the growth of output attributed to technical change and efficiency change. We demonstrate how changes in the efficiency of labor of different skill levels play a role in productivity change and how they affect SBTC.

[1] In Appendix 2.7.1, we reacquaint ourselves with the way we tend to measure and decompose total factor productivity (TFP) and its growth.

2.2.1 Derivation of the Growth Equation

We start with a non-parametric model to illustrate how efficiency change plays a role in productivity change. With such a model, we do not need a specific parametric production function for an illustrative purpose. Sequentially, we will show that omitted efficiency change could bias estimations in a parametric function in Section 2.2.2. Based on Hulten (1986)'s model, we adopt a traditional production model to a production frontier model. In a one output-multiple input setting, the general form of the aggregate production function is $Y_t = F(X_t, A_t)$, where Y_t is the scalar output at time t, X_t is a vector of input quantities used at time t, and A_t is a factor for technology. If not all outputs, given inputs, attain the maximum possible output level, we incorporate the efficiency term and form the production frontier as:

$$Y_t = F(X_t, A_t) \cdot TE_t, \tag{2.1}$$

where TE_t is technical efficiency at time t. Output Y_t achieves maximum output $F(X_t, A_t)$ when $TE_t = 1$.

In an attempt to introduce SBTC, we consider three inputs: capital K_t, high-skilled labor H_t, and low-skilled labor L_t, so the production frontier will be

$$Y_t = f(K_t, A_H H_t, A_L L_t, A_t) \cdot TE_t, \tag{2.2}$$

where A_H and A_L capture the factor-specific productivity of high- and low-skilled labor. A change in the ratio A_H/A_L is factor-biased technical change. Particularly, technical change is skill-biased if A_H/A_L increases.

Firstly, we show how neutral technical change is influenced by efficiency change. In order to account for output growth, we logarithmically differentiate equation (2.2)) and obtain

$$\frac{\dot{Y}}{Y} = E_K \frac{\dot{K}}{K} + E_H \left[\frac{\dot{A_H}}{A_H} + \frac{\dot{H}}{H} \right] + E_L \left[\frac{\dot{A_L}}{A_L} + \frac{\dot{L}}{L} \right] + \frac{\dot{A}}{A} + \frac{\dot{TE}}{TE}, \tag{2.3}$$

where the dotted variables denote derivatives with respect to time, and the fractions, for example, $\dot{Y}/Y$, indicate the growth rate (relative changes) of variables over time. E_K, E_H, and E_L are calculated as

$$E_K = \frac{\partial Y}{\partial K} \frac{K}{Y}, \quad E_H = \frac{\partial Y}{\partial H} \frac{H}{Y}, \quad \text{and} \quad E_L = \frac{\partial Y}{\partial L} \frac{L}{Y},$$

which demonstrate output elasticities with respect to each input. We assume that inputs are paid the value of their marginal product, so output elasticities are equal to the income shares of each input.

As a result, technical change can be measured as

$$\frac{\dot{Y}}{Y} - W_K \frac{\dot{K}}{K} - W_H \frac{\dot{H}}{H} - W_L \frac{\dot{L}}{L} - \frac{\dot{TE}}{TE},$$

where W_K, W_H, and W_L are the income shares of capital, high-skilled labor, and low-skilled labor respectively. In the absence of technical efficiency change, it is equal to the sum of neutral and non-neutral technical change:

$$\frac{\dot{A}}{A} + W_H \frac{\dot{A_H}}{A_H} + W_L \frac{\dot{A_L}}{A_L},$$

where $\dot{A}/A$ is neutral technical change, and $\dot{A_H}/A_H$ and $\dot{A_L}/A_L$ are factor-augmenting technical change. If technical efficiency does not change over time, $\dot{TE}/TE$ will be eliminated. Otherwise, not accounting for efficiency change, technical change will be equal to the sum of real technical change and efficiency change. Moreover, technical change is skill-biased if

$$\frac{\dot{A_H}}{A_H} > \frac{\dot{A_L}}{A_L}.$$

It suggests that the growth rate of productivity of high-skilled workers is higher than that of low-skilled workers. The rate of SBTC between high- and low-skilled labor (S) is calculated as

$$S = \frac{\dot{A_H}}{A_H} - \frac{\dot{A_L}}{A_L}. \tag{2.4}$$

The further step is to illustrate how effective labor affects SBTC. In our assumption, due to learning on the job, newly hired workers, the entrants, would have lower productivity than old experienced workers. In turn, new workers are less efficient and could influence output changes. As a consequence, efficiency changes over time, and it is correlated with the changes in labor inputs. There is a negative correlation between efficiency and the growth of new workers.

Based on our assumption, we denote the effective rates of high-skilled and low-skilled labor as

$$\eta_H = \frac{H_e}{H} \quad \text{and} \quad \eta_L = \frac{L_e}{L},$$

where H_e and L_e are effective corresponding labor inputs, and they vary with the increase of newly hired labor. The more newly hired labor, the less effective. The effective rates of high-skilled and low-skilled labor are different from each other, depending on the percentage of newly hired workers with respect to their skill levels and different learning processes. In addition, we assume that the change of efficiency ($\dot{TE}/TE$) only comes from the effectiveness of labor inputs, so TE is input-oriented technical efficiency. Taking into account the efficiency change of labor, we expect technical change to be

$$\frac{\dot{Y}}{Y} - W_K \frac{\dot{K}}{K} - W_H \left[\frac{\dot{\eta_H}}{\eta_H} + \frac{\dot{H}}{H} \right] - W_L \left[\frac{\dot{\eta_L}}{\eta_L} + \frac{\dot{L}}{L} \right],$$

where the effective rates, η_H and η_L, fluctuate with time and they are unobservable. Accordingly, the change in technical efficiency is considered as the weighted sum of the efficiency change of different workers:

$$\frac{\dot{TE}}{TE} = W_H \frac{\dot{\eta_H}}{\eta_H} + W_L \frac{\dot{\eta_L}}{\eta_L}. \tag{2.5}$$

It is worth noting that to focus on labor changes, we suppose the efficiency of capital remains constant and does not influence efficiency change. Therefore, ignoring efficiency change will result in

$$\frac{\dot{A'_H}}{A'_H} = \left[\frac{\dot{A_H}}{A_H} + \frac{\dot{\eta_H}}{\eta_H} \right] \quad \text{and} \quad \frac{\dot{A'_L}}{A'_L} = \left[\frac{\dot{A_L}}{A_L} + \frac{\dot{\eta_L}}{\eta_L} \right],$$

where $\dot{A'_H}/A'_H$ and $\dot{A'_L}/A'_L$ are estimated factor-augmenting technical change. Factor-augmenting technical change is biased by changes in efficiency attributed to inefficient new hires. The biased rate of SBTC (S')will be

$$S' = \frac{\dot{A'_H}}{A'_H} - \frac{\dot{A'_L}}{A'_L} = S + \frac{\dot{\eta_H}}{\eta_H} - \frac{\dot{\eta_L}}{\eta_L}. \tag{2.6}$$

If $\dot{\eta_H}/\eta_H > \dot{\eta_L}/\eta_L$, for example, the effective rate of high-skilled labor increases larger than that of low-skilled labor, SBTC is overestimated. On the contrary, if $\dot{\eta_H}/\eta_H < \dot{\eta_L}/\eta_L$, SBTC is underestimated.

We have established that learning on the job and the resulting inefficiency loss can affect SBTC. To assess whether the bias in SBTC is indeed observed empirically, we turn to a parametric setting. Therefore, we can then treat the bias as an omitted variable bias, which we can measure in our subsequent empirical setting.

2.2.2 Omitted Variable Bias

In the previous section, the non-parametric decomposition of the growth of output provides a convenient explanation of how efficiency change influences the measure of technical change. Although the non-parametric model can avoid any necessity to specify the production function, it has some restrictive assumptions and limitations, for example, perfect competition in the input market is required. Therefore, in some situations, econometric estimations cannot be avoided. For instance, estimates of the underlying substitution elasticities and return-to-scale parameters are of great importance in their own right. Similarly, in the estimation of a parametric production function, omitted variable bias will arise if we leave out inefficiency. In this section, we illustrate the omitted variable bias in a translog production function, since it is flexible and can approximate the non-parametric model. Furthermore, we use Baltagi and Griffin (1988)'s general index method to measure technical change. We begin with a simple two-firm setting and then generalize our model to show how inefficient labor can contribute to a biased measurement of non-neutral (skill-biased) technical change.

A Two-Firm Model

For simplicity, we consider a two-firm model with two inputs and one output. In this scenario, we define two firms as firm A and firm B and suppose that they have different efficiency rates. Both of them have the same quantity of each input but different outputs. We assume that firm A is efficient and firm B is inefficient, which means that with the same quantities of inputs, the output of firm A is larger than that of firm B. Our assumptions can be expressed as $H_A = H_B$, $L_A = L_B$, and $Y_A > Y_B$, where H_A and H_B are high-skilled labor inputs, L_A and L_B are low-skilled labor inputs, and Y_A and Y_B are outputs for firm firms A and B respectively. Y_A^* and Y_B^* are the maximum feasible outputs for firm A and firm B separately, and they are equal in our setting because the inputs of high- and low-skilled labor are the same for the two firms. Since firm A is efficient, the output of firm A, Y_A, is equal to the maximum feasible output Y_A^*. All the inputs and outputs are specified in natural logarithms, so the inefficiency term u equals $Y_B^* - Y_B$.

The production function for firm A is specified as

$$\begin{aligned} Y_A =& b_A + \sum \theta_{At} D_{At} + b_{AH} H_A + b_{AL} L_A + \frac{1}{2} b_{AHH} (H_A)^2 \\ &+ \frac{1}{2} b_{ALL} (L_A)^2 + b_{AHL} H_A L_A + \sum b_{AHt} D_{At} H_A + \sum b_{ALt} D_{At} L_A, \end{aligned} \tag{2.7}$$

where b_A is a constant term, and D_{At}s are the time dummy variables year, capturing the effects of technical change. The effects of non-neutral technical change (b_{AHt} and b_{ALt}) are also included in this specification. The compact form is $Y_A = \boldsymbol{X}_A \beta_A$, where $\boldsymbol{X}_A$ is the vector of input factors.

For firm B, the production function is similar to that of firm A, $Y_B = \boldsymbol{X}_B \beta_B - u$. If firm B is also efficient, which means that $u = 0$, then the coefficients must be the same for firm A and B, so the pooled OLS (POLS) estimator for panel data will be the same as the OLS estimator for each firm: $\hat{\beta}^*_{POLS} = \hat{\beta}_A = \hat{\beta}^*_B$, where $\hat{\beta}^*_{POLS}$ is the POLS estimator $\hat{\beta}_A$ is the estimator for the efficient firm A, and $\hat{\beta}^*_B$ is the estimator for the efficient firm B. However, since firm B is inefficient, the estimator of coefficients should be different and can be expressed as:

$$\hat{\beta}_B = (\boldsymbol{X}'_B \boldsymbol{X}_B)^{-1} \boldsymbol{X}'_B Y^*_B - (\boldsymbol{X}'_B \boldsymbol{X}_B)^{-1} \boldsymbol{X}'_B u. \tag{2.8}$$

As long as $\mathrm{E}(X'_B u) \neq 0$, which is inevitable since $u \neq 0$ for firm B, $\hat{\beta}_B$ is different from $\hat{\beta}^*_B$. As is shown previously, $\hat{\beta}_B$ will be smaller than $\hat{\beta}^*_B$, if $\mathrm{E}(X'_B u) > 0$, and otherwise $\hat{\beta}_B$ will be larger.

When the model is estimated with panel data for firms A and B, the POLS estimator $\hat{\beta}_{POLS}$ is also deviated from $\hat{\beta}^*_{POLS}$,

$$\hat{\beta}_{POLS} = \hat{\beta}^*_{POLS} - \frac{1}{2} (\boldsymbol{X}'_A \boldsymbol{X}_A)^{-1} \boldsymbol{X}'_A u. \tag{2.9}$$

The true coefficients $\hat{\beta}^*_{POLS}$ will be biased by $\frac{1}{2}(X'_A X_A)^{-1} X'_A u$. Whether the coefficients are overestimated or underestimated depends on the correlation between input X_B and inefficiency u. If X_B and u are positively correlated, the coefficients are underestimated. On the other hand, if X_B and u are negatively correlated, the coefficients are overestimated. Note that inefficiency u is time-varying, otherwise, it would be absorbed in the firm-specific characteristics b_A or b_B.

In a similar case, all the conditions are the same, except firm A has inefficiency u_1 and firm B has inefficiency u_2. The POLS estimator of the panel data has become:

$$\hat{\beta}_{POLS} = (\boldsymbol{X}'_A \boldsymbol{X}_A)^{-1} \boldsymbol{X}'_A Y^*_A - \frac{1}{2} (\boldsymbol{X}'_A \boldsymbol{X}_A)^{-1} \boldsymbol{X}'_A (u_1 + u_2). \tag{2.10}$$

This result is analogous to the previous one: the existence of inefficiency can bias the calculation of the parameters by $\frac{1}{2}(\boldsymbol{X}'_A \boldsymbol{X}_A)^{-1} \boldsymbol{X}'_A (u_1 + u_2)$. The larger the inefficiency of both firms, the larger the estimation bias.

Given the estimation of the parameters in equations (2.9) and (2.10), it is possible to compute the rate of technical change for the pooled data as

$$\dot{T}_t = \theta_t - \theta_{t-1} + (b_{Ht} - b_{Ht-1})H + (b_{Lt} - b_{Lt-1})L. \tag{2.11}$$

If the estimation above is biased by ignoring inefficiency, the estimates of technical change would be largely biased. To determine the biases in technical change, we need to calculate the subsets of variables. In the first case, when only firm B is inefficient, $\hat{\beta}_{POLS}$ is a $(3T+3)\times 1$ matrix,

$$\hat{\beta}'_{POLS} = (\hat{b}_0, \hat{\theta}_2, \cdots, \hat{\theta}_T, \hat{b}_H, \hat{b}_L, \hat{b}_{HH}, \hat{b}_{LL}, \hat{b}_{HL}, \hat{b}_{H2}, \cdots, \hat{b}_{HT}, \hat{b}_{L2}, \cdots, \hat{b}_{LT}),$$

and X_A is a $T \times (3T+3)$ matrix. $(X'_A X_A)^{-1} X'_A$ is denoted as a $(3T+3)\times T$ matrix Z. For the period from $t-1$ to t, the estimated parameters are calculated as

$$\begin{aligned}
\hat{\theta}_{t-1} &= \theta_{t-1} - \frac{1}{2} Z_{row(t-1)} u, \\
\hat{\theta}_t &= \theta_t - \frac{1}{2} Z_{rowt} u, \\
\hat{b}_{Ht-1} &= b_{Ht-1} - \frac{1}{2} Z_{row(T+3+t)} u, \\
\hat{b}_{Ht} &= b_{Ht} - \frac{1}{2} Z_{row(T+4+t)} u, \\
\hat{b}_{Lt-1} &= b_{Lt-1} - \frac{1}{2} Z_{row(2T+2+t)} u, \\
\hat{b}_{Lt} &= b_{Lt} - \frac{1}{2} Z_{row(2T+3+t)} u.
\end{aligned} \tag{2.12}$$

The biased estimate of technical change will be

$$\begin{aligned}
\dot{T}_t =& \theta_t - \theta_{t-1} - \frac{1}{2}(Z_{rowt} - Z_{row(t-1)})u + (b_{Ht} - b_{Ht-1})H \\
& - \frac{1}{2}(Z_{row(T+4+t)} - Z_{row(T+3+t)})uH + (b_{Lt} - b_{Lt-1})L \\
& - \frac{1}{2}(Z_{row(2T+3+t)} - Z_{row(2T+2+t)})uL.
\end{aligned} \tag{2.13}$$

The direction of the bias depends on $(Z_{rowt} - Z_{row(t-1)})$, $(Z_{row(T+4+t)} - Z_{row(T+3+t)})$, and $(Z_{row(2T+3+t)} - Z_{row(2T+2+t)})$.

A General Model

Based on panel data, the previous two-firm model can be easily generalized to an extensive model of many firms. In this section, we apply a more general model to illustrate the bias in the measurement of technical change due to the omission of inefficiency. If we miss out on an important variable, it is more likely that not only our model is poorly specified, but also the estimated parameters are biased. If there are correlations between explanatory variables and the omitted variable, bias, and inconsistency will occur from the OLS estimates. Intending to determine the effect of an omitted variable on the estimated production function and technical change, we omit the subsets of variables from the model. The true model is supposed to be

$$y_{it} = \alpha_0 + \alpha_1 x_{it} - u_{it} + v_{it} \qquad (i = 1, \cdots, N; \quad t = 1, \cdots, T), \tag{2.14}$$

where u_{it} denotes technical inefficiency, $v_{it} \sim N[0, \sigma_v^2]$ represents the noise term, and they are independent of each other. In the frontier model (Aigner et al., 1977), the joint error term $\varepsilon = v - u$, and v and u are identified by the differences in their distributional assumptions. If we overlook inefficiency and estimate a production function model instead, then the misspecified model will be

$$y_{it} = \beta_0 + \beta_1 x_{it} + \varepsilon_{it}, \tag{2.15}$$

where

$$\varepsilon_{it} = -u_{it} + v_{it}. \tag{2.16}$$

In this case, $\alpha_1 \neq \beta_1$. The omitted variable u_{it} is assumed as a function of explanatory variables x_{it} in a conditional or auxiliary regression

$$u_{it} = \gamma x_{it} + w_{it}. \tag{2.17}$$

After all, if inefficiency changes because the input vector (x_{it}) changes, for example as low-skilled labor is replaced by high-skilled labor, to realize skill-biased technical change, then inefficiency u_{it} is correlated with that same input vector x_{it}. In that case, the OLS estimator $\hat{\beta}_1$ of parameter β_1 is biased and inconsistent. The variance-covariance matrix of x_{it}, denoted by Σ_x (which has dimensions $T \times T$), is the same across individuals but otherwise of general form over time. In vector form, the model becomes

$$y = \beta_0 + \beta_1 x + \varepsilon, \tag{2.18}$$

where

$$v' = (v_{11}, \cdots, v_{N1}, \cdots, v_{1T}, \cdots, v_{NT}),$$

$$u' = (u_{11}, \cdots, u_{N1}, \cdots, u_{1T}, \cdots, u_{NT}).$$

Now consider any matrix P that eliminates the individual effects. P must satisfy $P\iota_T = 0$. An example of such a matrix is $P = I_T - (\iota_T \iota_T' / T)$ and the corresponding estimator is the within estimator. Let $Q = P'P$. Generally, for any Q, the estimator β_1 is given by

$$\begin{aligned} \hat{\beta}_1 =& x'(Q \otimes I_N)y / x'(Q \otimes I_N)x \\ =& \beta_1 + x'(Q \otimes I_N)(v - u) / x'(Q \otimes I_N)x. \end{aligned} \tag{2.19}$$

For a fixed T, taking probability limits as the limit of expectations of the numerator and denominators as $N \to \infty$, we get:

$$\begin{aligned} &\frac{1}{N}[x'(Q \otimes I_N)(v-u)] = -\frac{1}{N}\mathrm{tr}[(Q \otimes I_N)\mathrm{cov}(x'u)] = -\gamma \mathrm{tr}(Q\Sigma_x), \\ &\frac{1}{N}[x'(Q \otimes I_N)x] = \frac{1}{N}\mathrm{tr}[(Q \otimes I_N)(\Sigma_x \otimes I_N)] = \mathrm{tr}(Q\Sigma_x), \end{aligned} \tag{2.20}$$

and

$$\begin{aligned} \mathrm{plim}\hat{\beta}_1 =& \beta_1 - \mathrm{tr}[(Q\mathrm{cov}(x'u)] / \mathrm{tr}(Q\Sigma_x) \\ =& \beta_1 - \gamma[\mathrm{tr}(Q\Sigma_x) / \mathrm{tr}(Q\Sigma_x)] \\ =& \beta_1 - \gamma. \end{aligned} \tag{2.21}$$

The correlation γ between x and u determines the direction of the bias. If $\gamma > 0$, which means they are positively correlated, the bias will be downward. On the contrary, if $\gamma < 0$, the negative correlation will lead to an upward bias. In particular, inefficiency u is time-varying, so the bias in technical change is determined by how inefficiency changes over time.

2.3 Methodology

What remains, is how we can estimate technical change and efficiency change empirically. Some research has decomposed the productivity change into technical change and efficiency change by a non-parametric index approach (Banker et al., 2005; Fare et al., 1994; Maudos et al., 2000), but not often by parametric estimation (Feng & Serletis, 2010). Nevertheless, the non-parametric approach does not provide as much insight into the production technology and individual behaviors as the parametric stochastic frontier analysis (SFA) does. Therefore, the SFA approach is naturally applied to estimate both technical change and efficiency. The general stochastic frontier model with panel data can be written as

$$y_{it} = \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{it} + A(t) + \sum \psi A(t)\boldsymbol{x}_{it} + v_{it} \pm u_{it}, \quad i = 1, \cdots, N, \quad t = 1, \cdots, T, \tag{2.22}$$

where y_{it} is the observed performance of individual i in the period t, and α_i is a vector of dummy variables, which captures any firm or unit-specific characteristics. The vector $\boldsymbol{x}_{it}$ contains variables of input quantities or output and input prices. Based on Baltagi and Griffin (1988)'s general index method, time dummy variables $A(t)$ are incorporated in the production frontier to capture neutral technical change and the interactions between time dummies and inputs $\psi A(t)\boldsymbol{x}_{it}$ present non-neutral technical change. The coefficient ψ is cumulative factor-specific technical change (non-neutral technical change). The error term ε_{it} is specified as $v_{it} \pm u_{it}$, where v_{it} is the statistical "noise" component and is assumed to be independently and identically distributed, and $u_{it} \geqslant 0$ represents technical inefficiency. The sign of u_{it} depends on whether the frontier describes production (-) or cost (+). The stochastic frontier model proposed by Aigner et al. (1977) makes the following distributional assumptions:

$$v_{it} \sim N[0, \sigma_v^2],$$

$$u_{it} \sim N^+[0, \sigma_u^2] \perp v_{it}.$$

Other distributional assumptions, for example, the normal exponential, the normal truncated normal [Stevenson (1980)], or the normal-gamma [Greene (1990)] model are often considered. The SFA model is usually specified in logs, so the degree of technical efficiency of producer i in each period is derived from $TE_{it} = \exp(-u_{it})$.

The following step is how to estimate efficiency change. There is increasing use of time-varying technical efficiency specifications in the estimation of production frontier models based on panel data. When the time periods become longer, it is implausible to assume technical inefficiency remains constant through time. The longer the panel is, the more likely technical efficiency varies over time. In the previous combined model (equation (2.22)), if inefficiency (u_{it}) is constant, it can be absorbed in the firm-specific dummies and cannot affect TFP growth. Otherwise, time-varying inefficiency should be considered. Karagiannis et al. (2002) suggest an approach that uses a general index method to model technical change along the production function, and a quadratic function of the time trend, as in the Cornwell et al. (1990)'s model, to capture the temporal pattern of technical inefficiency. In their setting, it is possible to identify the effect of technical change and the effect of changes in time-varying technical inefficiency without any distributional assumptions.

In order to estimate a time-varying technical efficiency model, two approaches have been pursued: Greene (2005a)'s "true" fixed-effects (TFE) model and Wang and Ho (2010)'s model. The latter proposes a class of stochastic frontier models to solve the incidental parameters problem in the former. Wang and Ho (2010) show that we can separate heteroskedasticity and technical efficiency by performing the first-difference and within transformation on the model. The time-varying inefficiency term u_{it} is specified as

$$\begin{aligned} u_{it} &= h_{it} u_i^*, \\ h_{it} &= f(z_{it}' \delta), \\ u_i^* &\sim N^+[\mu, \sigma_u^2], \qquad i = 1, \cdots, N, \qquad t = 1, \cdots, T. \end{aligned} \tag{2.23}$$

The term h_{it} is a positive function of a vector of variables z_{it}, which explains inefficiency u_{it}. This model is developed from Wang and Schmidt (2002)'s scaling property model, which is adapted to a time-varying specification.

In our theoretical analysis in Section 2.2.1 and 2.2.2, time-varying inefficiency is determined by the changes in labor inputs. In particular, the change in technical efficiency can be explained by the change of efficient workers with different skill levels. According to equation (2.5), we can construct a relation between total efficiency change and efficiency change of labor with different skill levels. As a starting point, total efficiency is supposed to be the weighted sum of the efficiency of different types of labor:

$$TE_t = W_H \eta_{Ht} + W_M \eta_{Mt} + W_L \eta_{Lt}, \tag{2.24}$$

where TE_t is total efficiency at time t, W_{Ht}, W_{Mt}, and W_{Lt} are weights, and η_{Ht}, η_{Mt}, and η_{Lt} are the efficiency index of high-, medium-, and low-skilled workers respectively. As stated in equation (2.5), the weights could be the shares in total labor compensation, because if labor is paid for the value of their marginal product, output elasticities are equal to the income shares of different types of labor. To start with a simple model, we assume that the weights do not change over time. Then, the change of efficiency from period t to period $t+1$ is

$$\begin{aligned} \Delta TE_{t+1} &= TE_{t+1} - TE_t \\ &= W_H \Delta\eta_{Ht+1} + W_M \Delta\eta_{Mt+1} + W_L \Delta\eta_{Lt+1}, \end{aligned} \tag{2.25}$$

which is the weighted sum of efficiency change of different labor inputs. Efficiency change of labor is

$$\Delta\eta_{jt+1} = \lambda_{jt+1}\eta_{jt} - \eta_{jt}, \qquad j = H, M, L, \tag{2.26}$$

where j denotes skill types H, M, or L, which present high-, medium-, and low-skilled labor separately. The variable λ_{jt+1} is the percentage change of the efficiency index, which is determined by the change in the composition of different workers and the inefficiency of newly hired workers. In order to derive λ_{jt+1}, we need to dive into how the adjustment of labor inputs would affect efficiency.

For illustrative purposes, we show the derivation of λ_{Ht+1} for high-skilled labor, and it is the same for medium- and low-skilled labor. High-skilled labor input (H_t) can be decomposed into three components: (1) workers who remain in the labor force, (2) workers who leave the labor force, and (3) new workers who just enter the labor force. In our model, we assume that ω_t^H percent high-skilled labor is retained at time $t+1$, correspondingly $1-\omega_t^H$ percent high-skilled workers leave the labor force, and the growth rate of the new labor force is g_{t+1}^H. An additional assumption is that newly hired workers can only be τ_H percent as efficient as experienced workers due to the learning on the job. Moreover, there is a supplementary assumption that the remaining labor force will increase efficiency at a rate of φ_H. Therefore, the total percentage change in efficiency is

$$\lambda_{Ht+1} = \frac{g_{t+1}^H \tau_H \eta_{Ht} + \omega_t^H \varphi_H \eta_{Ht}}{g_{t+1}^H \eta_{Ht} + \omega_t^H \eta_{Ht}}, \tag{2.27}$$

where $\tau_H \leqslant 1$, and $\varphi_H \geqslant 1$. At this stage, we suppose that τ_H and φ_H stay constant over time. As a result, the higher growth rate of newly hired labor will reduce efficiency, and on the other hand, the higher remaining rate of the labor force will raise efficiency.

In general, total efficiency can be expressed as

$$TE_t = W_H \eta_H \lambda_{Ht} + W_M \eta_M \lambda_{Mt} + W_L \eta_L \lambda_{Lt}, \tag{2.28}$$

where

$$\lambda_{jt} = \frac{\tau_j g_t^j}{g_t^j + \omega_{t-1}^j} + \frac{\varphi_j \omega_t^j}{g_t^j + \omega_{t-1}^j}, \qquad j = H, M, L. \tag{2.29}$$

It is reasonable that λ_{jt} varies among different types of labor and changes over time. Accordingly, the determinants of efficiency are the relative growth rate of new workers and the relative remaining rate of labor, which in turn determine inefficiency as well. Because inefficiency u_{it} can be roughly approximated by $1-TE_t$, the determinants can be the explanatory variables z_{it} in a function h_{it}. However, considering the limitation of the data, we can not observe the growth rate g_t^j and the remaining rate ω_t^j separately and directly. Instead, we can only observe labor inputs and calculate the changes. The general changes of labor inputs (r_t^j) are equal to

$$r_t^j = g_t^j + \omega_t^j, \qquad j = H, M, L, \tag{2.30}$$

where r_t^j can be calculated as the ratio of the labor input at time t to the labor input at time $t-1$. Because efficiency change depends on the changes in labor inputs (r_t^j), we are able to estimate the average compound effects of labor adjustments on efficiency change without separating the distinct effects. Following Wang and Ho (2010)'s model in equation (2.23), we can specify h_{it} by a function of explanatory variables as

$$h_{it} = \delta_1 r_{it}^H + \delta_2 r_{it}^M + \delta_3 r_{it}^L, \tag{2.31}$$

where r_{it} is the growth rate of high-, medium-, and low-skilled labor at time t. The rank of the estimated parameters $delta_1$, δ_2, and δ_3 is the same as the reverse rank of η_H, η_M and η_L, illustrating that the higher the rank of the parameter is, the less efficient the relative type of labor is.

Summing up, we have adopted an SFA method and developed an empirical model that allows us to distinguish technical change and efficiency change. In the next section, we display our data and estimation model.

2.4 Empirical Results

2.4.1 Data Description and Estimation Procedure

We begin this section with a description of the data. To analyze SBTC, we use the industry data of the Socio-economic accounts of the World Input-Output Database (WIOD), which categorize labor into high-, medium- and low-skilled levels. It consists of 18600 observations covering 27 EU countries and 13 other major countries in the world and 31 industries for the period from 1995 to 2009. Timmer et al. (2015) fully describe the usage of the data, and it can be obtained from the WIOD website. The details of the industries and the countries that are included can be found in Table 2.5 and Table 2.4 in Appendix 2.7.2. Table 2.5 displays the name of the countries, the acronym, and the number i of the countries we generate in our analysis. Table 2.4 presents the name of the industries, the specific code, and the number j of the industries we generate for illustrative purposes.

The variables used in the model include one output and four inputs. Table 2.6 in Appendix 2.7.2 shows the variables we adopt from the World Input-Output Database (WIOD) and how we construct output and input variables. We convert all the national currency into US dollars by the provided exchange rates from the WIOD website. All the values are adjusted to 1995 price levels. Output Y_{ijt} is the real value added, calculated as the gross value added (VA) divided by its price indice (VA_P).

We use real fixed capital stock (K_GFCF) as capital input K_{ijt}. High-, medium-, and low-skilled labor inputs are the hours worked by the respective skill type of labor, which are calculated as total hours worked by persons engaged (H_EMP) multiplied by corresponding shares in total hours. The key variables employed in the estimation are as follows:

Y_{ijt} =real value added (in millions);
K_{ijt} =real fixed capital stock (in millions);
HS_{ijt} =hours worked by high-skilled labor (in millions);
MS_{ijt} =hours worked by medium-skilled labor (in millions);
LS_{ijt} =hours worked by low-skilled labor (in millions);
D_{ij} =country-industry pair specific dummy variable, $i = 2, \cdots, 40$, $j = 2, \cdots, 31$;
D_t =time dummy variable, $i = 2, \cdots, 15$.
HS_{ijt}, MS_{ijt}, and LS_{ijt} are the high-, medium-, and low-skilled labor inputs. Labor skill types are classified based on educational attainment levels as defined in the International Standard Classification of Education (ISCED): low-skilled (ISCED categories 1 and 2), medium-skilled (ISCED 3 and 4), and high-skilled (ISCED 5 and 6). All the values are expressed in millions. Table 2.7 in Appendix 2.7.2 demonstrates the descriptive statistics for these variables in natural logarithms. The standard deviations of all the variables are fairly large, which means there is heterogeneity across countries and industries. We control for country-industry pair fixed effects, because the same industry may have different characteristics in different countries.

Based on the sufficient data, we firstly estimate a production function without inefficiency term u, using the fixed-effects regression. Secondly, we applied Wang and Ho (2010)'s model to estimate an SFA model with time-varying efficiency. We choose a translog specification of the production function to identify different types of labor-augmenting technical change, because of its flexibility. Our interest at this point focuses on the estimates of high-, medium-, and low-skilled labor-augmenting technical change. The production frontier model will be

$$\begin{aligned}\ln Y = &\alpha_0 + \sum \alpha_{ij} D_{ij} + \sum \alpha_t D_t + \alpha_k \ln K + \alpha_h \ln HS + \alpha_m \ln MS \\ &+ \alpha_l \ln LS + \frac{1}{2}\alpha_{kk}(\ln K)^2 + \frac{1}{2}\alpha_{hh}(\ln HS)^2 + \frac{1}{2}\alpha_{mm}(\ln MS)^2 \\ &+ \frac{1}{2}\alpha_{ll}(\ln LS)^2 + \alpha_{kh}\ln K \ln HS + \alpha_{km}\ln K \ln MS + \alpha_{kl}\ln K \ln LS \\ &+ \alpha_{hm}\ln HS \ln MS + \alpha_{hl}\ln HS \ln LS + \alpha_{ml}\ln MS \ln LS + \sum \alpha_{kt} D_t \ln K \\ &+ \sum \alpha_{ht} D_t \ln HS + \sum \alpha_{mt} D_t \ln MS + \sum \alpha_{lt} D_t \ln LS + v - u,\end{aligned} \tag{2.32}$$

In the above equation, we omit subscripts of variables for simplicity, and we omit three dummy variables to avoid multicollinearity. As in equation (2.31), u is specified as

$$u = f(\delta_1 \ln HS + \delta_2 \ln MS + \delta_3 \ln LS) N^+[0, \sigma_u^2]. \tag{2.33}$$

We use natural logarithms of labor inputs instead of the ratios between the labor inputs at period t and at period $t-1$, because the effects of labor changes will give the same results. In addition, we impose that inefficiency follows a half-normal distribution, and we let the determinants only affect the variance of inefficiency.

SBTC is the difference between high-skilled labor-augmenting technical change and relatively lower-skilled labor-augmenting technical change, involving unequal responses between specific types of labor. In order to compare high-, medium-, and low-skilled labor-specific technical change, we took the differences between the high- and the medium-skilled ($SBTC_{hm}$), the high- and the low-skilled labor ($SBTC_{hl}$), and the medium- and the low-skilled labor ($SBTC_{ml}$). The rates of SBTC are calculated as

$$\begin{aligned} SBTC_{hm} &= \alpha_{ht} - \alpha_{mt}, \\ SBTC_{hl} &= \alpha_{ht} - \alpha_{lt}, \\ SBTC_{ml} &= \alpha_{mt} - \alpha_{lt}, \end{aligned} \tag{2.34}$$

where t corresponds to each time period. We use the general index approach to measure technical change and non-neutral technical change, because it provides a more flexible time path, which is not constrained to fit a particular functional (linear, quadratic, other) pattern (Baltagi & Rich, 2005). Subsequently, we show our results in the next section.

2.4.2 Skill-Biased Technical Change

In this section, we present the estimation results with several objectives in mind. Our goal is to illustrate how the change in labor composition would affect efficiency change and therefore affect technical change, especially SBTC. The effect of accounting for efficiency change is statistically and economically significant.

Table 2.1 summarizes the parameter estimates for both the fixed-effects production function and the stochastic production frontier. Because coefficients in a translog model are not directly interpretable, estimation results are converted into output elasticities ($\partial \ln Y / \partial \ln X$). Reported elasticities are evaluated at the sample means of the variables, and they are all different from zero at the 1% significance level. The elasticity for medium-skilled labor is -0.059 in the fixed-effects model, which indicates that medium-skilled labor is not efficient. On the contrary, it is 0.992 in the stochastic frontier model. Indeed, the output elasticities for all the inputs have increased after accounting for efficiency change. However, the elasticity for capital does not differ much between the two models.

Moreover, estimated neutral technical change and input-specific technical change are the average annual index changes across the period from 1996 to 2009. Estimates of SBTC are given as simple means across the annual values as well. Neutral technical change is consistently negative and statistically significant in both models. This coincides with the recent productivity slowdown, which is common to all industrialized countries and common to most industries as well (Hornstein et al., 2005). Meanwhile, capital-specific technical change is positive and significant on average. Medium-skilled labor-specific technical change shows a positive and higher average rate than the other input factors, while both high- and low-skilled labor experience average annual decreases related to technical change across the alternative specifications. As a consequence, skill-neutral technical change between high- and medium-skilled labor ($SBTC_{hm}$) and that between medium- and low-skilled labor ($SBTC_{ml}$) are rejected at the 1% significance level. SBTC between high- and low-skilled labor ($SBTC_{hl}$) is positive at 0.3% to 0.34% per year in both specifications, implying that technical change favors high-skilled relatively to low-skilled workers. Although the average estimates of $SBTC_{hl}$ are slightly dissimilar, the fixed-effects specification can not reject skill neutrality. On the other hand, the stochastic frontier yields a significant result.

Furthermore, in the lower part of Table 2.1, the determinants of inefficiency and variance are examined, since the stochastic frontier includes an inefficiency function as equation (2.33). The estimates of inefficiency parameters are reported as the means of the marginal effects. A positive estimate shows that the variable has a negative effect on efficiency. The average marginal effects of all three types of labor are positive and statistically significant at the 1% level, which means that the growth of all three categories of labor will reduce efficiency. Specifically, the marginal effect of the growing medium-skilled labor is the highest, and high-skilled labor has the second highest impact. It is consistent with our model because the weight of medium-skilled labor is the highest. As in equation (2.28), the parameters represent the product of weights and inefficiency change of one percent change of labor. Consequently, a one percent change in medium-skilled labor will increase an 8.36% of the inefficiency index, making production more inefficient. This can also explain the negative output elasticity of medium-skilled labor in the production function model. We perform a likelihood ratio test, which indicates that we can reject the null hypothesis of no technical inefficiency. A full set of parameter estimates is in Table 2.8 and Table 2.9 in Appendix 2.7.2.

Table 2.1: Parameter Estimates in Different Models

Parameter	Production function Estimate	Production function Std. Err.	Stochastic frontier Estimate	Stochastic frontier Std. Err.
Output elasticities				
Capital	0.7003***	(0.0139)	0.7288***	(0.0081)
High-skilled labor	0.1784***	(0.0170)	0.4298***	(0.0249)
Medium-skilled labor	−0.0586***	(0.0210)	0.9917***	(0.0451)
Low-skilled labor	0.1359***	(0.0151)	0.3123***	(0.0229)
Technical change				
Neutral	−0.0504***	(0.0056)	−0.0447***	(0.0028)
Capital specific	0.0048***	(0.0008)	0.0054***	(0.0004)
High-skilled labor specific	−0.0042***	(0.0016)	−0.0039***	(0.0009)
Medium-skilled labor specific	0.0085***	(0.0018)	0.0065***	(0.0010)
Low-skilled labor specific	−0.0072***	(0.0011)	−0.0073***	(0.0006)
Skill-biased technical change				
High-skilled vs. Medium-skilled	−0.0128***	(0.0032)	−0.0104***	(0.0018)
High-skilled vs. Low-skilled	0.0030	(0.0019)	0.0034***	(0.0011)
Medium-skilled vs. Low-skilled	0.0158***	(0.0026)	0.0138***	(0.0013)
Inefficiency determinants				
High-skilled labor			0.0256***	(0.0125)
Medium-skilled labor			0.0836***	(0.0408)
Low-skilled labor			0.0177***	(0.0087)
Observations		17595		17595
R^2 from OLS		0.9925		
Log-likelihood		2090.0606		3758.7927

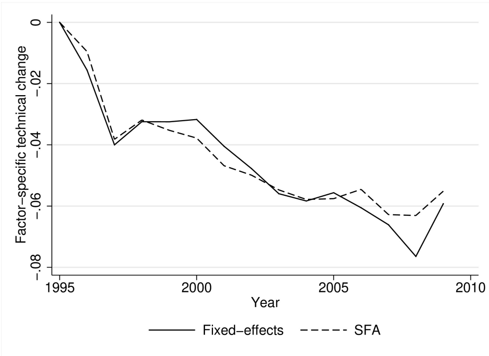
Notes: This table compares the estimates of parameters between a production function model and a stochastic frontier model. Output elasticities are evaluated at the sample means of the variables. Values for technical change represent average annual index changes based on full sample estimates. Skill-biased technical change is calculated as equation (2.34) and presented as average annual index changes. The determinants of inefficiency and variance are examined based on equation (2.33). The estimates of inefficiency parameters are reported as the means of the marginal effects. A positive estimate shows that the variable has a negative effect on efficiency. The standard errors are in parentheses and are computed using the Delta method. Estimates of the parameters for country-industry pair fixed-effects are not reported in the table to save space. */**/*** signifies statistical significance at the 10/5/1% level.

In order to distinguish the distinction between the alternative models and discover the effect of accounting for efficiency change, an effective comparison of the cumulative effects of technical change is displayed in Figure 2.1. Each graph shows the cumulative labor-augmenting technical change for the labor of different skill levels, and each series represents the time path from 1995 to 2009. The trends of each type of labor-augmenting technical change are similar across different models, however, there are some divergences. As analyzed before, technology favors medium-skilled labor, of which the cumulative technical change increased to almost 14% in 2009 without considering efficiency. Meanwhile, both rates of high-skilled and low-skilled labor-augmenting technical change have decreased over time. Technical change harmed low-skilled workers more than the other two skill levels, which dropped about 10% in 2009 in both models. This is a departure from previous studies, which document a phenomenon of the polarization of the labor market. Some studies find the growth of wages and employment occurs in both high-education, high-wage occupations and low-education, low-wage occupations(Autor et al. (2003), Autor et al. (2006), Autor and Dorn (2013), Goos et al. (2014), Bárány and Siegel (2018)). The explanation for the polarization is that information and computer technologies substitute for medium-skilled workers. It is not completely in contrast to our results because medium-skilled workers can work more productively with fewer hours but become less efficient. If technologies have replaced medium-skilled workers, they may need to find lower-skilled jobs and become less efficient. The production frontier model showed higher rates of labor-augmenting technical change in both high-skilled and low-skilled labor cases but presented lower rates in the medium-skilled labor case on the contrary. From the previous analysis in Section 2.2, it is possible that without considering inefficiency change, the estimated rates of high-skilled and low-skilled labor-specific technical change are underestimated, and medium-skilled labor-augmenting technical change is overestimated. In general, all three types of labor-specific technical change have a smaller magnitude after disentangling technical change and efficiency change.

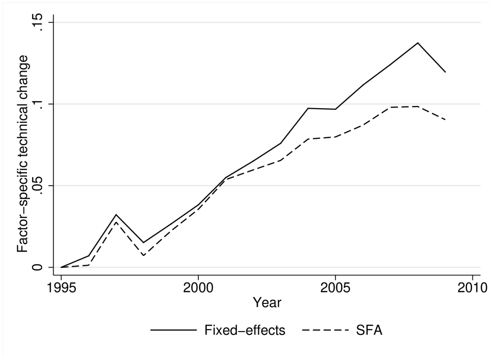
On the basis of Figure 2.1, we focus more on the differences between skill levels. Figure 2.2 examines the cumulative effects of SBTC across two models. Especially, we mainly focus on how much technical change favors high-skilled labor, so we omit the estimation of $SBTC_{ml}$ and present the estimated $SBTC_{hm}$ and $SBTC_{hl}$. Not surprisingly, $SBTC_{hm}$ has been declining, and $SBTC_{hl}$ has been inclining. $SBTC_{hl}$ appears to become positive after 2000. This accords with the results of other literature, which only found positive SBTC before 1983 (e.g.Baltagi and Rich (2005)). Most importantly, $SBTC_{hm}$ is underestimated, and $SBTC_{hl}$ is overestimated over time when efficiency change is not considered. This supports the previous results and our model that high-skilled labor has a smaller effect on efficiency change than medium-skilled labor does and a larger impact on efficiency change than low-skilled labor does. Overall, high-skilled labor does not benefit from technology development.

Figure 2.1: Paths of cumulative labor-augmenting technical change

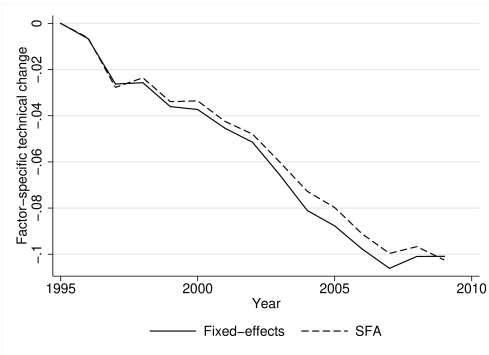
(a) High-skilled labor



(b) Medium-skilled labor



(c) Low-skilled labor



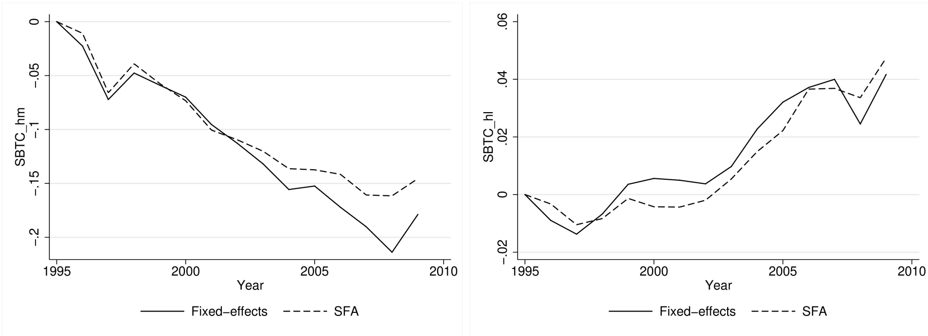
Notes: This figure depicts paths of cumulative labor-augmenting technical change for the labor of three skill levels respectively. The black lines represent the estimated cumulative labor-augmenting technical change from the fixed-effects production function model. The dotted lines show the estimated cumulative labor-augmenting technical change from the production frontier model.

Considering the general index approach supports point-to-point tests for SBTC effects (Baltagi & Rich, 2005). In Table 2.2, we provide the results of SBTC for sub-periods. As Baltagi and Rich (2005), we form the expressions $(\alpha_{ht} - \alpha_{mt}) - (\alpha_{h,t-q} - \alpha_{m,t-q})$ and $(\alpha_{ht} - \alpha_{lt}) - (\alpha_{h,t-q} - \alpha_{l,t-q})$, where $t-q$ represents the earlier comparison year. Generally, the estimates of $SBTC_{hm}$ across alternative models are negative in all sub-periods and significant during most of the time except 2007-

2009. However, the degrees of fluctuations vary over time. Both models display skill-neutral technical change between high- and low-skilled labor, except during the period from 2003 to 2006, $SBTC_{hl}$ is significant at the 1% level and positive at around 3% to 4%. During the financial crisis from 2007 to 2009, there is no evidence of SBTC. The evident deviation between the two models appears during the full sample period from 1995 to 2009. This is because when the time periods become longer, efficiency is more likely to change over time.

Figure 2.2: Paths of cumulative skill-biased technical change

(a) High- versus medium-skilled labor **(b)** High- versus low-skill labor



Notes: This figure depicts paths of cumulative skill-biased technical change. In both panels, the black lines represent the estimated cumulative skill-biased technical change from the fixed-effects production function model. The dotted lines show the estimated cumulative skill-biased technical change from the production frontier model.

Table 2.2: Skill-Biased Technical Change in Different Models

	Production function				Stochastic frontier			
Period	$SBTC_{hm}$	Std. Err.	$SBTC_{hl}$	Std. Err.	$SBTC_{hm}$	Std. Err.	$SBTC_{hl}$	Std. Err.
1995-1998	−0.0476*	(0.0281)	−0.0067	(0.0176)	−0.0391**	(0.0173)	−0.0083	(0.0104)
1999-2002	−0.0652***	(0.0178)	0.0105	(0.0106)	−0.0705***	(0.0179)	0.0064	(0.0108)
2003-2006	−0.0593***	(0.0196)	0.0334***	(0.0112)	−0.0320*	(0.0186)	0.0386***	(0.0113)
2007-2009	−0.0068	(0.0386)	0.0045	(0.0202)	−0.0040	(0.0217)	0.0108	(0.0127)
1995-2009	−0.1789***	(0.0451)	0.0416	(0.0264)	−0.1456***	(0.0248)	0.0474***	(0.0150)

Notes: This table compares the estimates of SBTC in sub-periods between a production function model and a stochastic frontier model. SBTC is presented as point-to-point estimates. $SBTC_{hm}$ is the difference between high- and medium-skilled specific technical change. $SBTC_{hl}$ is the difference between high- and low-skilled specific technical change. The standard errors are in parentheses and computed using the Delta method. */**/*** signifies statistical significance at the 10/5/1% level.

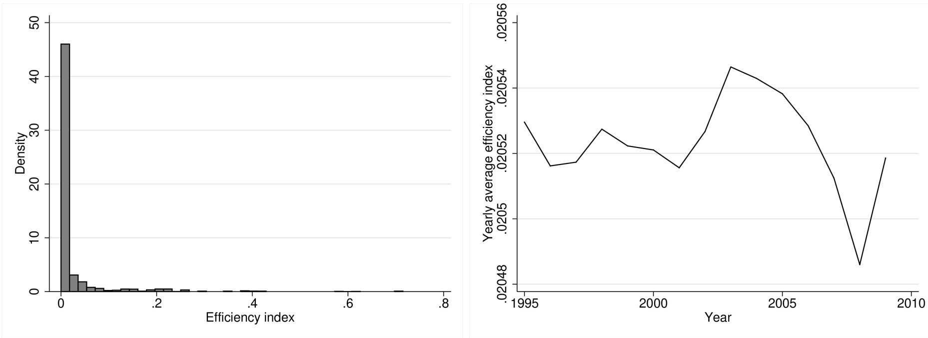
2.4.3 Efficiency Change

Based on the stochastic production frontier estimation, efficiency change is separated from technical change. As is shown in Figure 2.3a, the distribution of the estimated efficiency index shows very low-efficiency estimates, most of which are lower than 0.2. This may be because fixed effects may capture time-invariant inefficiency and we use inputs as determinants. Figure 2.3b displays the estimated annual average efficiency index, which also shows very low average efficiency estimates. The estimated yearly average efficiency went up and down, peaking at around 2.055% and dropping to almost 2.048% in 2008. It coincides with the financial crisis in 2008.

Furthermore, in our assumption, the change in labor can influence efficiency change. To find the relations, we calculate the first differences between labor inputs and efficiency and make a correlation matrix among the growth rates of labor inputs and efficiency change. We can observe from Table 2.3 that the growth rates of high-, medium-, and low-skilled labor are positively and significantly correlated with each other. Moreover, the growth rates of high-skilled (-0.0415), medium-skilled (-0.1042), and low-skilled (-0.1001) labor are all negatively correlated with efficiency change. It can provide some evidence for the previous theory that the growing number of newly hired high- and medium-skilled workers may reduce efficiency and the declining number of low-skilled workers may raise efficiency. As is illustrated in our model, the positive correlation between changes in labor inputs and efficiency change can result in the overestimation of labor-augmenting technical change. On the contrary, the negative correlation can bring about the underestimation of labor-augmenting technical change. As a consequence, it can indicate that without considering efficiency change, the production function model may underestimate the rates of labor-specific technical change, as is shown in Figure 2.1. This finding is also consistent with our assumption that the changes in labor inputs due to the growing number of newly hired workers can reduce efficiency rates. An alternative explanation for the negative relation is that the least efficient workers are replaced by technology and they reduce efficiency further when they switch sectors. Remarkably, the results also suggest that the increases in medium-skilled labor have a larger negative effect on efficiency change, compared with that of high- and low-skilled labor. This confirms the earlier analysis that the different effects of the changes in different labor types can bias the estimation of SBTC. In the next section, we use the estimated results of both models to discover the influence of SBTC on wage gaps.

Figure 2.3: Efficiency distribution and annual change

(a) Efficiency distribution **(b)** Estimated yearly average efficiency



Notes: This figure uses the efficiency rates estimated in the production frontier model.

Table 2.3: Correlation of Labor Changes and Efficiency Change

Variable	$Diff_{HS}$	$Diff_{MS}$	$Diff_{LS}$	$Diff_{efficiency}$
$Diff_{HS}$	1.0000			
$Diff_{MS}$	0.3378	1.0000		
	(0.0000)			
$Diff_{LS}$	0.2969	0.8292	1.0000	
	(0.0000)	(0.0000)		
$Diff_{efficiency}$	-0.0415	-0.1042	-0.1001	1.0000
	(0.0000)	(0.0000)	(0.0000)	

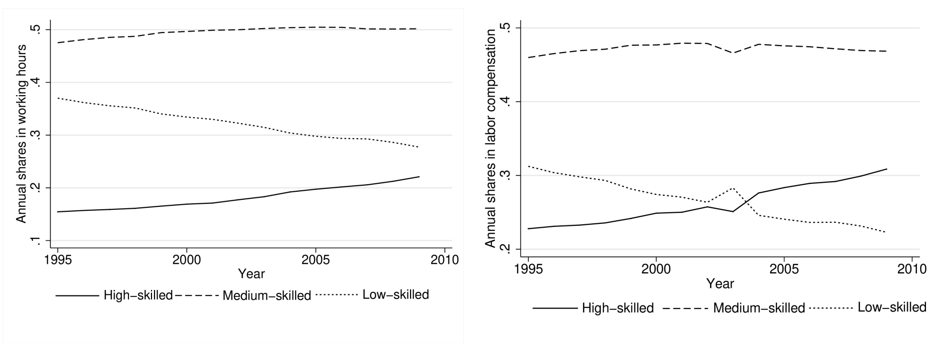
Notes: This table shows the correlation matrix of growth rates of labor and efficiency change. $Diff_x$ stands for the change rate of the variable x. The standard errors are in parentheses. All the correlations are significant at the 1% level.

2.5 Wage Inequality

How does SBTC influence wage differential? After adjusting the measurement of SBTC, in this section, we try to answer this question. During the period from 1995 to 2009, the shares of high-skilled labor in both total working hours and total labor compensation have experienced an increasing trend, and on the contrary, the shares of low-skilled labor have declined (Figure 2.4). Medium-skilled labor had stable and higher shares than the other two categories. It can be seen in Figure 2.4b that high-skilled workers had larger shares in compensation than low-skilled workers had after 2004. However, in Figure 2.4a, high-skilled workers had the smallest shares in working hours. The wage ratios of different skill groups have been rising across countries and industries, and one of the drivers could be SBTC. On the one hand, SBTC can lead to the increasing demand for high-skilled labor and therefore boost wage inequality. On the other hand, the relative wage ratio can be used as an additional source of evidence of SBTC (Hornstein et al., 2005). We now turn to an analysis of the relationship between SBTC and wage inequality.

Figure 2.4: Skill composition in working hours and labor compensation

(a) Yearly average shares in working hours **(b)** Yearly average shares in labor compensation



Notes: This figure shows shares of labor of different skill levels on the y-axis. The yearly average is the average across countries and industries.

2.5.1 SBTC and Wage Inequality

Due to that SBTC can have an impact on the ratio of marginal products of different types of labor (MRTS), an MRTS can be used as evidence of SBTC. We calculated MRTSs based on the translog production model. The MRTS of high-skilled to medium-skilled labor ($MRTS_{hm}$) is

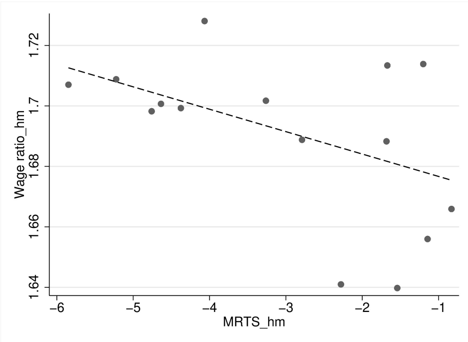
$$MRTS_{hm} = \frac{MP_h}{MP_m} = \frac{\frac{\partial Y}{\partial HS}}{\frac{\partial Y}{\partial MS}} = \left(\frac{\frac{\partial \ln Y}{\partial \ln HS}}{\frac{\partial \ln Y}{\partial \ln MS}} \right) \frac{MS}{HS}. \tag{2.35}$$

In the same way, we can also obtain the MRTS of high-skilled to low-skilled labor ($MRTS_{hl}$) and the MRTS of medium-skilled to low-skilled labor ($MRTS_{ml}$). We omit the analysis of $MRTS_{ml}$ and the wage ratio between medium- and low-skilled workers because we target the wage gap between higher- and relatively lower-skilled workers.

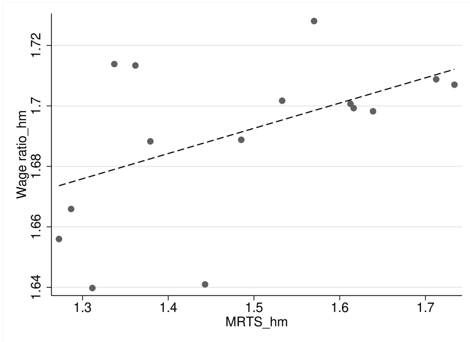
If a labor market is perfectly competitive, an MRTS will equal the wage ratio. Figure 2.5 presents MRTSs and the respective wage ratios, where Figure 2.5a and 2.5b show the differences between high- and medium-skilled labor in alternative models, and Figure 2.5c and 2.5d display the differences between high- and low-skilled labor. As is shown, there is a negative relation between $MRTS_hm$ and the corresponding wage ratio in the fixed-effects model, whereas a positive relation is more obvious and stronger in the frontier model. The negative correlation may be caused by the negative output elasticity for medium-skilled labor. The MRTS between high- and low-skilled labor positively correlates with the wage ratio in both models, but it presents a flatter fitted line in the frontier model (Figure 2.5d). This result implies that if an MRTS increases, the relative wage ratio is likely to rise too. Because Figure 2.5 only presented annual averages, there could be substantial variations among countries and industries. Goldin and Katz (1998) find that capital-intensive industries increased the demand for skills and increased the wage bill of the nonproduction workers considerably. Haskel and Slaughter (2002) contend that the effects of SBTC on relative wage ratios mainly come from the sector bias of SBTC, not factor bias. They find that when skill premia were increasing (decreasing), SBTC was concentrated in skill-intensive (unskill-intensive) sectors. Burstein and Vogel (2017) find that the skill premium has been rising in skill-intensive sectors in all countries. On that account, skill intensity may influence the effects of SBTC on wage differential. SBTC may concentrate on specific industries, especially high-skilled intensive industries, so we expect higher wage inequality in high-skilled intensive industries. In order to investigate the association between skill intensity and wage ratios, we plotted the relevant wage ratio against the relative industry skill intensity in Figure 2.6. The relative industry skill intensity is measured as the ratio of the share in total working hours of one skill group to that of the other skill group. The lines of best fit validate a slightly positive relation between skill intensity and the corresponding wage ratio. In high-skilled labor-intensive industries, the average wage of high-skilled labor is relatively higher than

Figure 2.5: MRTS and relative wage ratios in alternative models

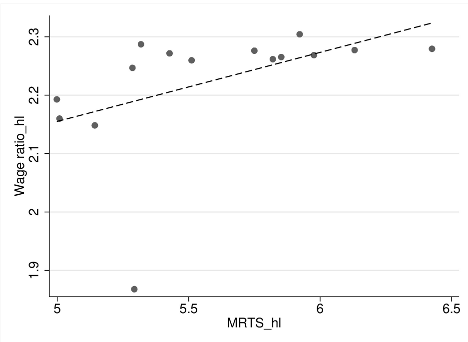
(a) High- vs. medium-skilled in fixed-effects model



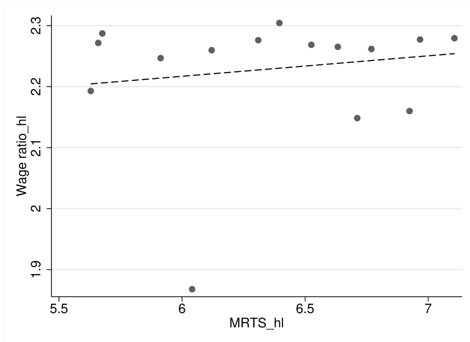
(b) High- vs. medium-skilled in frontier model



(c) High- vs. low-skilled in fixed-effects model



(d) High- vs. low-skilled in frontier model

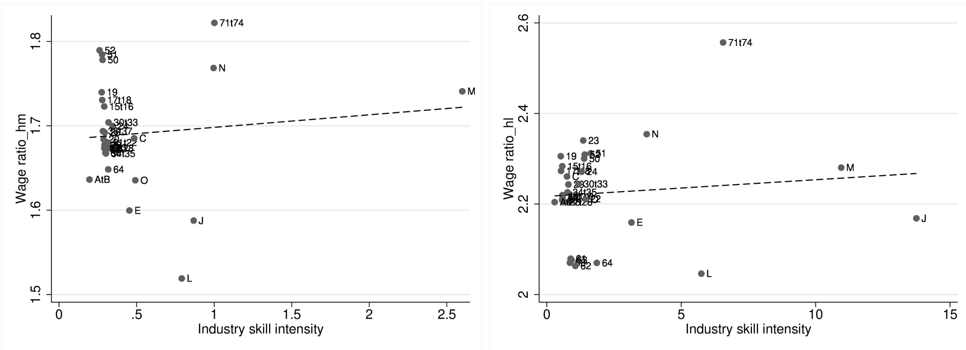


Notes: This figure demonstrates the relation between a marginal rate of technical substitution(MRTS) and the relative wage ratio. On the x-axis, MRTSs are estimated from the fixed-effects model and the frontier model. On the y-axis, wage ratios are calculated based on the data from WIDO. The upper panels show the ratios between high- and medium-skilled labor. The lower panels represent the ratios between high- and low-skilled labor.

that of the other two types of labor. Especially in industries of renting of m&eq and other business activities, health and social work, and education, the relative wage of high-skilled workers is higher than the relative wage in most industries.

Figure 2.6: Industry skill intensity and relative wage ratios

(a) High- versus medium-skilled labor **(b)** High- versus low-skilled labor

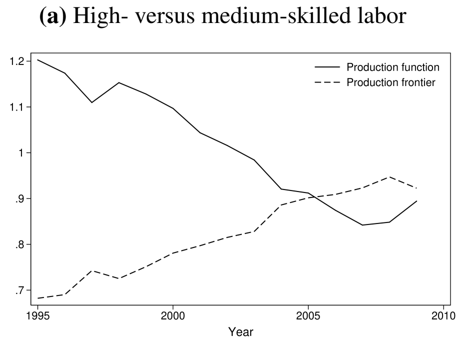


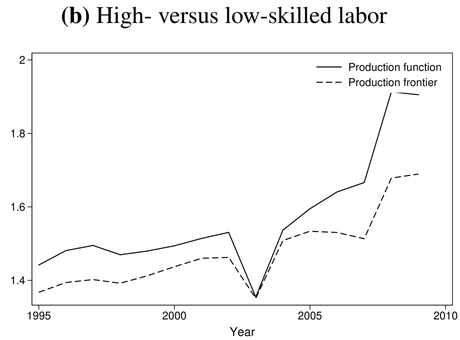
Notes: This figure demonstrates the relation between industry skill intensity and relative wage ratios. Industry skill intensity is on the x-axis, and wage ratios are on the y-axis. The left panel shows the ratios between high- and medium-skilled labor, and the right panel presents the ratios between high- and low-skilled labor.

2.5.2 The Gap between MRTS and Wage Inequality

So far, we find little evidence that SBTC can affect wage differentials in either model. However, the relations between the estimated MRTSs and the wage ratios do vary across models. Therefore, we assume that efficiency change may play a role in affecting MRTSs, especially when the changes in different categories of labor influence efficiency change variously. In consequence, accounting for efficiency change may give a better estimation for MRTSs and close the gap between the relative wage ratio and the corresponding MRTS. To find out whether this is the case, we compare the gaps between wage ratios and MRTSs between alternative models in Figure 2.7. It is worth noting that we take the absolute values of the differences between wage ratios and MRTSs to calculate the yearly average. Otherwise, the differences may be canceled out. As we expect, in both Figure 2.7a and 2.7b, the gaps are much smaller in the frontier model when efficiency is taken into account. In Figure 2.7a, when we compare high- and medium-skilled labor, the gap is more stable and smaller (close to zero) in the frontier model than that in the fixed-effects model. Comparing high- and low-skilled wage gaps in Figure 2.7b, we find a smaller gap in the frontier model as well, but it declines over time and rises after 2008.

Figure 2.7: Gap between wage ratio and MRTS in alternative models





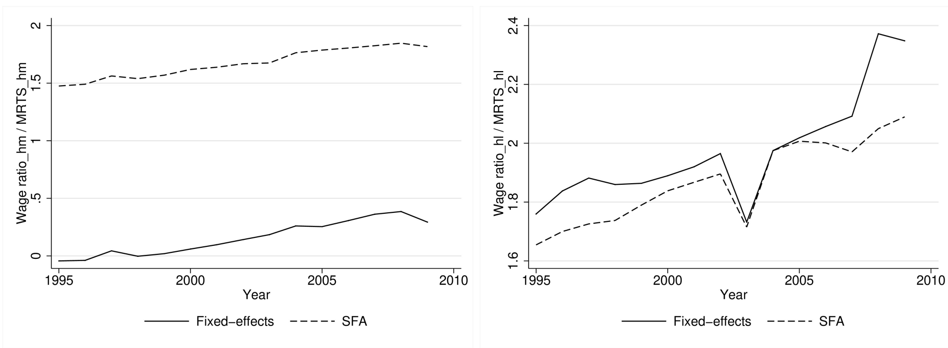
Notes: This figure shows the differences between wage ratios and MRTSs over time. The differences are calculated as wage ratios minus the relative MRTSs. The black lines illustrate the estimation from the fixed-effects model. The dotted lines display the estimation from the production frontier model. The left panel shows the ratios between high- and medium-skilled labor, and the right panel presents the ratios between high- and low-skilled labor.

Furthermore, the ratio of the relative wage ratio to the MRTS may reflect the overcompensation or undercompensation of different labor inputs. In order to compare alternative models, we plot the ratio of the relative wage ratio to the MRTS over time. We can observe from Figure 2.8, different models present distinct results. In Figure 2.8a, in comparison to medium-skilled labor, high-skilled labor is under-compensated in the fixed-effects model, whereas it is over-compensated in the frontier model. It is more reasonable and realistic that high-skilled labor is over-compensated than under-compensated. In Figure 2.8b, both models illustrate similar results: compared with low-skilled workers, high-skilled workers are overcompensated, and the ratio increases over time. However, high-skilled wages are less overcompensated in the SFA model. In sum, it provides some evidence that the gap between wage ratios and MRTSs can be smaller after considering efficiency change. It implies that efficiency change can have an impact on the wage gap.

In a perfectly competitive labor market, the wage ratio among different skill groups of labor directly reflects the relative marginal productivity, MRTS. However, in reality, there are frictions in the labor market, for example, labor markets institutions, which include unemployment benefits, a minimum wage, taxes on labor, and a trade union. Those institutions interfere with the exchange of labor power for the wages paid and hence introduce a wedge between the wage of workers and the value of the marginal product of labor (Boeri & van Ours, 2013). We will not discuss how those frictions influence wage inequality and therefore influence the effects of technical change on wages, which is beyond the scope of this paper. Since the labor market is not perfectly competitive and labor market institutions have played a crucial role, an MRTS may not equal the corresponding wage ratio. Even though technical change can influence wages of different skill levels of labor and thus inequality, we may not observe the direct effects. Based on observations, wage inequality differs across industries and countries. Therefore, the ratio of the relative wage ratio to the MRTS may be divergent among different industries and countries.

Figure 2.8: Ratio of wage ratio to MRTS over the years

(a) High- versus medium-skilled labor **(b)** High- versus low-skilled labor



Notes: This figure shows the ratios between wage ratios and MRTSs over time. The ratios are calculated as wage ratios divided by the relative MRTSs. The black lines illustrate the estimation from the fixed-effects model. The dotted lines display the estimation from the production frontier model. The left panel shows the ratios between high- and medium-skilled labor, and the right panel presents the ratios between high- and low-skilled labor.

Figure 2.9 and 2.10 indicate the variations of the ratio of the relative wage ratio to the MRTS across industries, and across countries respectively. On the basis of preceding discussions, we only present the analysis of the result of the frontier model estimation, which takes efficiency change into account and provides a more reasonable and less biased result. In Figure 2.9a and 2.9b, we find that high-skilled workers are more likely to be overcompensated in high-skilled intensive industries, such as education, health, social work, financial intermediation, renting of m&eq and other business activities, and public admin and defense and compulsory social security industries. There is a positive relationship between industry skill intensity and the overcompensation of high-skilled labor. Particularly, there is no overcompensation in the agriculture, hunting, forestry, and fishing industry, because this industry is mainly focused on low-skilled work and needs more low-skilled workers.

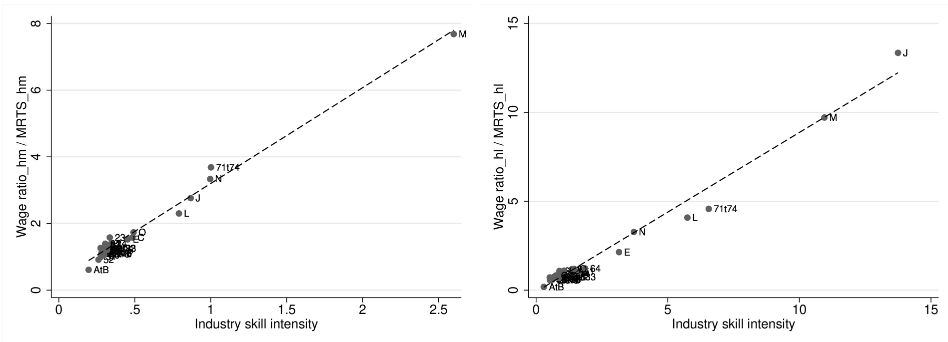
Because of different institutional systems and different degrees of flexibility of the labor markets, economies have a great impact either on employment or on wage differentials between skilled and unskilled (Vivarelli, 2014). In empirical studies, an increase in wage differentials between skilled and unskilled has been found in the United States (Autor et al., 1998; Dinardo & Card, 2002; Goldin & Katz, 2007), and in the United Kingdom (Haskel & Slaughter, 2002). Dustmann et al. (2009) have found that wage inequality in West Germany has increased from 1975 to 2004, and the wage differential between medium-skilled and low-skilled workers started rising in the late 1980s. They also provide some evidence that technological change asymmetrically affects the bottom and the top of the wage distribution. Despite that, the increase in wage differentials has been modest in continental European countries, for example, France (Card et al., 1999; Goux & Maurin, 2000), Belgium (Hertveldt & Michel, 2013), Sweden (Lindquist, 2005), and Italy (Casavola et al., 1996). Distinct labor market institutions, chiefly the wage-setting mechanisms provide a persuasive explanation for the differences in wage gaps between the USA and continental European countries (Blau & Kahn, 1996; Guvenen et al., 2014; Okazawa, 2013). Countries that feature generous non-employment benefits, strict employment protection legislation, and a strong influence of unions have lower wage inequality. To differentiate wage inequality across countries, We plotted the relative wage ratio against the capital intensity of each country. Figure 2.10 indicates a negative relation between the capital intensity (capital-labor ratio) and wage ratios. Countries with relatively high capital intensity are more developed and they have relatively lower wage inequality among different skill workers, especially Japan, Nordic countries, Ireland, and Australia. We also find that the USA and Germany have higher wage differentials. In less developed countries, Brazil, Hungry, Russia, Turkey, Indonesia, and India have a relatively higher wage differential between high- and medium-skilled labor and high- and low-skilled labor, while the wage differentials are lower in China, Cyprus, Estonia, and Lithuania. In countries with higher wage differentials, where the labor market is more flexible, high-skilled labor is more likely to overcompensate. As we expected, Figure 2.10a demonstrates that high-skilled and medium-skilled workers gain relatively higher wages in most developing countries where the wage gap is wider. Spain, Korea, Brazil, Cyprus, and some less developed countries compensate high-skilled workers more than medium-skilled workers. Compared with low-skilled workers, high-skilled workers are overcompensated in most countries in Figure 2.10b.

Last but not least, as is analyzed at the beginning of this subsection, inefficiency change may exert an impact on the relative overcompensation or undercompensation of one skill group. In Figure 2.11, we plotted the ratio of the relative wage ratio to the MRTS against efficiency. Both figures 2.11a and 2.11b illustrate a non-linear and negative relation. It indicates that lower efficiency may lead to the relatively higher overcompensation of high-skilled workers. One explanation is that the recent relative increases in high-skilled workers have decreased efficiency rates, so high-skilled workers are overcompensated. Another explanation could be that overcompensation or undercompensation of one skill group might induce inefficiency. The first explanation is consistent with our assumption that newly hired high-skilled workers are less efficient than experienced workers. However, the causality between overcompensation and efficiency change remains an issue for further investigation.

Figure 2.9: Industry skill intensity and ratio of wage ratio to MRTS

(a) High- versus medium-skilled labor

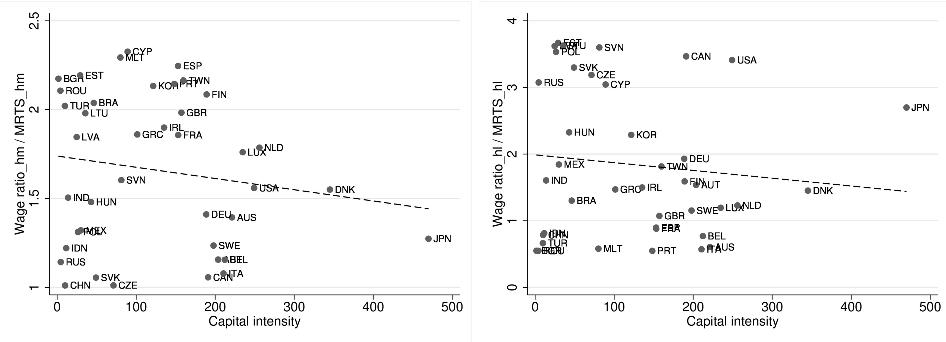
(b) High- versus low-skilled labor



Notes: This figure shows the relation between industry skill intensity and relative ratios of wage ratios to MRTSs. Industry skill intensity is on the x-axis, and the relative ratios are on the y-axis. The left panel depicts the ratios between high- and medium-skilled labor, and the right panel presents the ratios between high- and low-skilled labor.

Figure 2.10: Ratio of wage ratio to MRTS across countries

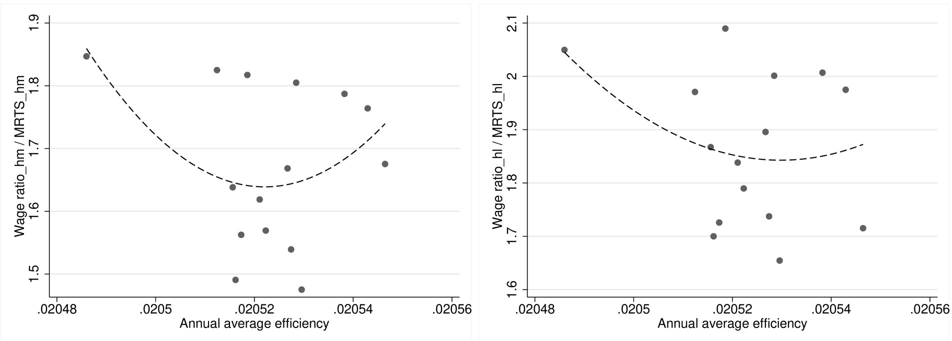
(a) High- versus medium-skilled labor **(b)** High- versus low-skilled labor



Notes: This figure shows the relation between capital intensity and relative ratios of wage ratios to MRTSs. On the x-axis, capital intensity is the average for each country. The relative ratios are the y-axis. The left panel depicts the ratios between high- and medium-skilled labor, and the right panel presents the ratios between high- and low-skilled labor.

Figure 2.11: Efficiency and ratio of wage ratio to MRTS

(a) High- versus medium-skilled labor **(b)** High- versus low-skilled labor



Notes: This figure shows the relationship between efficiency and relative ratios of wage ratios to MRTSs. Annual average efficiency rates are on the x-axis, and the relative ratios are on the y-axis. The left panel depicts the ratios between high- and medium-skilled labor, and the right panel presents the ratios between high- and low-skilled labor.

2.6 Conclusion

Recent literature has emphasized the effects of SBTC on labor markets, which causes the shift in the structure of wages and employment toward high-skilled against low-skilled workers. This paper considers efficiency change in the production process and measures how ignorance of efficiency change can bias the estimation of SBTC.

Theoretically, we show the bias in the measurement of SBTC due to efficiency change and how the increases in newly hired workers may influence efficiency change. In our model, inefficiency changes are driven by the changes in the skill composition of workers. The underlying reasoning is that newly hired workers are less efficient than experienced workers due to learning on the job, and the jobs for high-skilled labor need more time to learn. Hence, the recent rising supply of high-skilled labor can decrease efficiency rates. Our subsequent empirical analysis shows negative relationships between the change in labor inputs and the change in efficiency, which is consistent with the theoretical model. We find that the average annual SBTC between high- and low-skilled labor has increased 13,3% after accounting for efficiency change. It implies that production loses more efficiency to change high-skilled than low-skilled workers. We further show a positive relationship between SBTC and the relative wage ratio. In addition, the empirical results also provide evidence that the skill intensity and institutional effects can also influence wage differentials and thus contribute to the overcompensation or undercompensation of high-skilled labor. Our results suggest that in high-skilled labor-intensive industries, high-skilled workers are more likely to be overcompensated.

There are several limitations to this paper. First, we use education levels as a proxy for different skill levels, which are not identical. Skill levels may depend on the tasks of the job or be occupation-specific. Future research can consider the influence of technical change and efficiency change on specific occupations. Second, since the data is highly aggregated, we only observe the average effects of SBTC and efficiency change. Some industries focus more on research and development (R&D) and thus experience more technical change. However, workers lose their work experience and efficiency if they move to other industries, so industry-specific analyses might be interesting. Lastly, we cannot observe newly hired workers and their skill levels in the current dataset, a more detailed dataset is needed for future research.

2.7 Appendix

2.7.1 Appendix A: TFP Growth, Technical Change, and Efficiency Change revisited

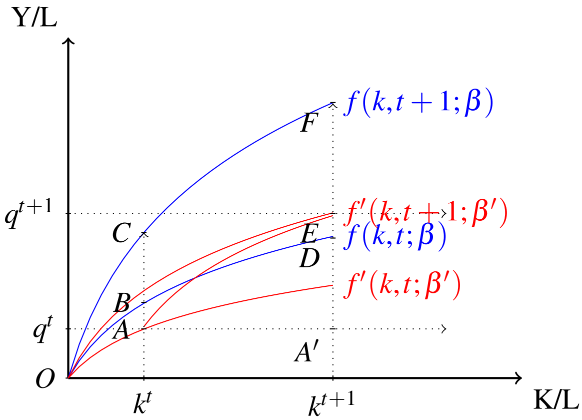
Both technical change and efficiency change are important components of TFP. Nevertheless, they affect production differently. Technical progress can shift the production function to a higher level and raise the maximum feasible output level, while the improvement of efficiency can increase output towards the maximum feasible output based on the current technology. Without separation, technical change embodies time-varying efficiency change. If all the firms are efficient, efficiency does not matter and it cannot affect TFP growth. If inefficiency is time-invariant, then it can be captured in the individual characteristics. However, if inefficiency exists and it changes over time, it can provide an independent contribution to TFP. If efficiency change is not separated from technical change, it will lead to erroneous measurement of the latter. To be more specific, if inefficiency is correlated with input factors, which is a reasonable assumption, omitted-variable bias will occur. In other words, the estimation of non-neutral technical change (e.g., SBTC) will be biased by the omission of the efficiency term.

As is shown in Figure 2.12, a producer utilizes capital (K) and labor (L) to produce a single output (Y). Technical change is labor augmenting if technical progress increases labor productivity and results in more output with the same amount of labor. In Figure 2.12, the output per unit of labor q is on the vertical axis, and the capital-labor ratio k is on the horizontal axis. In the figure, $f(k,t;\beta)$ is the production frontier before technical change (i.e., at time t) and $f(k,t+1;\beta)$ is the production frontier after technical change (at time $t+1$). With a capital-labor ratio k^t, the frontier shifting technical change in Figure 2.12 means labor productivity increases from B to C, and technical change is labor-augmenting.

However, in practice, labor may be used in an inefficient manner, for example, because of on-the-job learning. In that case, the actual relationship between the labor productivity q and the capital-labor ratio k is represented by the red lines in Figure 2.12. Now we are presented with two frontier changes: one ignoring changes in efficiency (depicted in blue) and one accounting for the changes in efficiency (depicted in red). To see why that matters, consider an increase in the capital-labor ratio from k^t to k^{t+1} that results in an increase in labor productivity from A to E.

With this shift from t to $t+1$, the gap between the maximum possible labor productivity and the actual labor productivity widens from $B-A$ to $F-E$. If we ignore this decrease in efficiency and consider point A and point E as efficient labor productivity, technical change would be the shift from $f'(k,t;\beta')$ to $f'(k,t+1;\beta')$ instead of the shift from $f(k,t;\beta)$ to $f(k,t+1;\beta)$. As a result, the real labor-augmenting technical change is underestimated because of the decrease in efficiency.[2]

Figure 2.12: Bias in Labor-augmenting technical change



Notes: This figure depicts paths of output per unit of labor with different capital-labor ratios, representing production frontiers. The output per unit of labor q is on the vertical axis, and the capital-labor ratio k is on the horizontal axis. β is the coefficient of the production frontier. The shift between two blue lines $f(k,t;\beta)$ and $f(k,t+1;\beta)$ shows the change in production frontier with labor-augmenting technical change. The shift between two red lines $f'(k,t;\beta')$ and $f'(k,t+1;\beta')$ presents the change in production frontier with labor-augmenting technical change and efficiency change. Due to decreases in efficiency, labor-augmenting technical change is lower for red production frontiers.

2.7.2 Appendix B: Tables and Graphs

[2] It is worth noting that it follows that the direction of the bias of labor-augmenting technical change is dependent on the change of efficiency.

Table 2.4: Industry Description

Industry	Code	Number
Agriculture, hunting, forestry and fishing	AtB	24
Mining and quarrying	C	25
Food, beverages and tobacco	15t16	1
Textiles and textile	17t18	2
Leather and footwear	19	3
Wood and of wood and cork	20	4
Pulp, paper, printing and publishing	21t22	5
Coke, refined petroleum and nuclear fuel	23	6
Chemicals and chemical	24	7
Rubber and plastics	25	8
Other non-metallic mineral	26	9
Basic metals and fabricated metal	27t28	10
Machinery, Nec	29	11
Electrical and optical equipment	30t33	12
Transport equipment	34t35	13
Manufacturing nec and recycling	36t37	14
Electricity, gas and water supply	E	26
Sales, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	50	15
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51	16
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52	17
Hotels and restaurants	H	29
Other inland transport	60	18
Other water transport	61	19
Other air transport	62	20
Other supporting and auxiliary transport activities; activities of travel agencies	63	21
Post and telecommunications	64	22
Financial intermediation	J	27
Renting of m&eq and other business activities	71t74	23
Public admin and defence; compulsory social security	L	28
Education	M	29
Health and social work	N	30
Other community, social and personal services	O	31

Notes: This table shows the industries and their codes in the data set. The data is retrieved from the World Input-Output Database (WIOD). We also presented the id number generated for each industry.

Table 2.5: Country Description

Country	Acronym	Number
Australia	AUS	1
Austria	AUT	2
Belgium	BEL	3
Brazil	BRA	4
Bulgaria	BGR	5
Canada	CAN	6
China	CHN	7
Cyprus	CYP	8
Czech Republic	CZE	9
Denmark	DNK	10
Estonia	EST	11
Finland	FIN	12
France	FRA	13
Germany	DEU	14
Greece	GRC	15
Hungary	HUN	16
India	IND	17
Indonesia	IDN	18
Ireland	IRL	19
Italy	ITA	20
Japan	JPN	21
Korea	KOR	22
Latvia	LVA	23
Lithuania	LTU	24
Luxembourg	LUX	25
Malta	MLT	26
Mexico	MEX	27
Netherlands	NLD	28
Poland	POL	29
Portugal	PRT	30
Romania	ROU	31
Russia	RUS	32
Slovak Republic	SVK	33
Slovenia	SVN	34
Spain	ESP	35
Sweden	SWE	36
Taiwan	TWN	37
Turkey	TUR	38
United Kingdom	GBR	39
United States	USA	40

Notes: This table shows the countries and their codes in the data set. The data is retrieved from the World Input-Output Database (WIOD). We also presented the id number generated for each country.

Table 2.6: Data Description

VA	Gross value added at current basic prices (in millions of national currency)
VA_P	Price levels of gross value added, 1995=100
K_GFCF	Real fixed capital stock, 1995 prices
H_EMP	Total hours worked by persons engaged (millions)
H_HS	Hours worked by high-skilled persons engaged (share in total hours)
H_MS	Hours worked by medium-skilled persons engaged (share in total hours)
H_LS	Hours worked by low-skilled persons engaged (share in total hours)
LAB	labor compensation (in millions of national currency)
LABHS	High-skilled labor compensation (share in total labor compensation)
LABMS	Medium-skilled labor compensation (share in total labor compensation)
LABLS	Low-skilled labor compensation (share in total labor compensation)

Notes: This table shows the variables we adopt from the World Input-Output Database (WIOD). We convert all the national currency into US dollars. Output is calculated as the gross value added (VA) divided by its price indices (VA_P). We use real fixed capital stock (K_GFCF) as capital input. Multiplying total hours worked by persons engaged (H_EMP) by respective shares in total hours, we obtain high-, medium-, and low-skilled labor inputs. By the same measure, we can obtain the respective labor compensation.

Table 2.7: Descriptive Statistics of Variables

Label	Variable	Obs	Mean	Std. Dev.	Min	Max
$\ln Y_{ijt}$	Output	18,529	7.683	2.457	-2.383	14.123
$\ln K_{ijt}$	Capital Stock	17,608	8.417	2.488	-1.747	16.464
$\ln HS_{ijt}$	High-Skilled Labor	18,526	3.387	2.375	-8.374	10.386
$\ln MS_{ijt}$	Medium-Skilled Labor	18,531	4.590	2.343	-7.411	11.853
$\ln LS_{ijt}$	Low-Skilled Labor	18,530	3.925	2.430	-5.578	13.159

Notes: This table shows summary statistics for the main variables used in the analysis. All the variables are shown in natural logarithms. The data is the industry data of WIOD. It consists of 18600 observations covering 40 countries and 31 industries for the period from 1995 to 2009. The observations are specific to ith country and jth industry at time t. The standard deviations of all the variables are fairly large, which means there is heterogeneity across countries and industries.

Table 2.8: Parameter Estimates in Different Models

	Fixed-Effects		True Fixed-Effects		Wang& Ho	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
α_k	0.9833	(0.0777)	1.0388	(0.0154)	0.9053	(0.0154)
α_h	0.1232	(0.0191)	0.0138	(0.0178)	0.3277	(0.0242)
α_m	0.1395	(0.0322)	0.1160	(0.0266)	0.9856	(0.0444)
α_l	0.1958	(0.0305)	0.0597	(0.0180)	0.3595	(0.0245)
α_{kk}	-0.0349	(0.0098)	-0.0431	(0.0019)	-0.0222	(0.0021)
α_{hh}	0.0164	(0.0043)	0.0470	(0.0044)	0.0266	(0.00334)
α_{mm}	-0.0480	(0.0066)	-0.0458	(0.0051)	-0.0008	(0.0076)
α_{ll}	-0.0147	(0.0066)	0.0120	(0.0036)	-0.0124	(0.0044)
α_{kh}	-0.0004	(0.0001)	-0.0002	(0.0001)	-0.0005	(0.0001)
α_{km}	0.0003	(0.0001)	0.0001	(0.0001)	0.0004	(0.0001)
α_{kl}	0.0005	(0.0001)	0.0006	(4e-05)	0.0006	(0.0001)
α_{hm}	0.0023	(0.0003)	0.0022	(0.0002)	0.0021	(0.0003)
α_{hl}	-0.0006	(0.0002)	-0.0008	(0.0001)	-0.0003	(0.0002)
α_{ml}	0.0003	(0.0003)	0.0003	(0.0002)	-0.0007	(0.0002)

Notes: This table shows estimated coefficients in different models. From column 2 to 3, the estimates are based on the fixed-effects model, from column 4 to 5, the estimates are based on the true fixed-effects, and from column 6 to 7, the estimates are based on the production frontier model.

Table 2.9: Technical Change in Different Models

	Production Function				Stochastic Frontier			
Period	Neutral	High	Medium	Low	Neutral	High	Medium	Low
1996	-0.1400	-0.0156	0.0070	-0.0066	-0.1358	-0.0096	0.0013	-0.0063
	(0.0644)	(0.0165)	(0.0175)	(0.0103)	(0.0327)	(0.0084)	(0.0094)	(0.0055)
1997	-0.1212	-0.0244	0.0252	-0.0196	-0.1458	-0.0286	0.0264	-0.0214
	(0.0590)	(0.0139)	(0.0146)	(0.0088)	(0.0319)	(0.0085)	(0.0095)	(0.0055)
1998	-0.0499	0.0076	-0.0170	0.0006	-0.0509	0.0063	-0.0205	0.0042
	(0.0482)	(0.0116)	(0.0120)	(0.0072)	(0.0301)	(0.0085)	(0.0096)	(0.0054)
1999	-0.0385	-0.0000	0.0113	-0.0103	-0.0458	-0.0034	0.0151	-0.0103
	(0.0428)	(0.0100)	(0.0110)	(0.0066)	(0.0300)	(0.0086)	(0.0097)	(0.0054)
2000	-0.0171	0.0008	0.0118	-0.0013	-0.0193	-0.0025	0.0133	0.0004
	(0.0369)	(0.0086)	(0.0100)	(0.0059)	(0.0294)	(0.0086)	(0.0096)	(0.0054)
2001	-0.0312	-0.0088	0.0167	-0.0081	-0.0307	-0.0090	0.0182	-0.0089
	(0.0301)	(0.0075)	(0.0092)	(0.0053)	(0.0292)	(0.0087)	(0.0097)	(0.0054)
2002	-0.0204	-0.0073	0.0101	-0.0060	-0.0010	-0.0031	0.0059	-0.0055
	(0.0285)	(0.0071)	(0.0090)	(0.0052)	(0.0293)	(0.0087)	(0.0097)	(0.0054)
2003	0.0036	-0.0082	0.0109	-0.0142	0.0360	-0.0048	0.0058	-0.0122
	(0.0313)	(0.0067)	(0.0081)	(0.0048)	(0.0294)	(0.0087)	(0.0097)	(0.0054)
2004	-0.0006	-0.0024	0.0214	-0.0153	0.0193	-0.0031	0.0131	-0.0126
	(0.0572)	(0.0083)	(0.0132)	(0.0073)	(0.0295)	(0.0088)	(0.0098)	(0.0054)
2005	-0.0361	0.0027	-0.0006	-0.0067	-0.0292	0.0003	0.0013	-0.0070
	(0.0469)	(0.0095)	(0.0135)	(0.0070)	(0.0300)	(0.0090)	(0.0100)	(0.0054)
2006	-0.0222	-0.0049	0.0148	-0.0100	-0.0105	0.0030	0.0072	-0.0114
	(0.0391)	(0.0106)	(0.0116)	(0.0060)	(0.0303)	(0.0091)	(0.0101)	(0.0055)
2007	-0.0098	-0.0056	0.0126	-0.0084	-0.0249	-0.0082	0.0109	-0.0085
	(0.0518)	(0.0136)	(0.0154)	(0.0085)	(0.0308)	(0.0090)	(0.0101)	(0.0055)
2008	-0.0611	-0.0104	0.0132	0.0051	-0.0472	-0.0003	0.0005	0.0029
	(0.0620)	(0.0181)	(0.0209)	(0.0104)	(0.0334)	(0.0103)	(0.0117)	(0.0059)
2009	-0.1607	0.0172	-0.0177	0.0001	-0.1400	0.0079	0.0080	-0.0058
	(0.0700)	(0.0219)	(0.0261)	(0.0114)	(0.0351)	(0.0141)	(0.0131)	(0.0063)
average	-0.0504	-0.0042	0.0085	-0.0072	-0.0447	-0.0039	0.0065	-0.0073
	(0.0056)	(0.0016)	(0.0018)	(0.0011)	(0.0028)	(0.0009)	(0.0010)	(0.0006)

Notes: This table shows estimated neutral, high-skilled labor augmenting, medium-skilled labor augmenting, and low-skilled labor augmenting technical change for each year. From column 2 to 5, the estimates are based on the fixed-effects model, and from column 6 to 9, the estimates are based on the production frontier model.

3

The Dynamics of Labor Market Adjustments to Industry-Specific Technology Shocks

This chapter is a single-authored manuscript.

3.1 Introduction

The developments in frontier technologies, including artificial intelligence, robotics, and biotechnology, have brought tremendous potential for our future lives. Meanwhile, it has raised concerns for workers. Technology shocks can have a persistent and significant impact on the labor market, leading to a reallocation of labor forces and skill upgrading. Some industries can experience technology shocks when they substantially invest in R&D. Sometimes these industries transition from less advanced technology to advanced technology (Bos et al., 2010). When technology shocks occur in a particular industry, they bring about inter-industry reallocation and contraction of other industries. More importantly, technology shocks increase technical change (TC), the main driver of economic growth. More often than not, TC is skill-biased, which illustrates a shift in production technology that favors high-skilled over low-skilled labor by increasing high-skilled labor's relative productivity and thus relative demand. In the presence of skill-biased technical change (SBTC), technology shocks increase the relative demand for high-skilled labor and the need to upgrade skills.

This paper theoretically explores how the labor market adjusts to industry-specific technology shocks in the short run, especially when adjustment costs exist. I analyze to what extent SBTC and human capital specificity can affect the labor market's response to technology shocks. In particular, I ask several related questions: Does human capital specificity constrain the inter-industry reallocation of high- and low-skilled labor from a contracting to an expanding industry? How does the specificity of human capital influence skill upgrading? Who should pay for skill upgrading? And what are the implications for policy-making?

The contribution of this paper is fourfold. First, I provide a bridge between the literature on skill-biased technical change and the literature on skill specificity. Second, I provide a model to show how the interaction between education and building skills on the job will affect switching jobs and human capital dynamics. Third, I fill the gap in understanding how adjustment costs would influence the partial and general equilibrium in the labor market. Fourth, I put forward implications for the labor market and education policies.

Haskel and Slaughter (2002) propose that it is sector-biased TC rather than factor-biased TC that influences the labor market. The underlying reasoning is that TC can concentrate on particular sectors and result in more extensive skill upgrading in those sectors. They find that in both the United States and the United Kingdom, SBTC was concentrated in unskill-intensive sectors during the 1970s and in skill-intensive sectors during the 1980s. For example, if TC concentrates on low-skill intensive industries, more high-skilled labor is needed and therefore flows to those industries. Many researchers find evidence that SBTC is greater in industries that use skilled labor intensively (Baldwin & Cain, 2000; Gera et al., 2001; Mincer, 1989; Simon, 2004; Xu, 2001). Goos et al. (2014) also find that job polarization between industries can not be ignored quantitatively.

Reallocation between industries may encounter obstacles. Inter-industry labor mobility has adjustment costs since individuals face the costs of switching jobs. Arias et al. (2018) find large inter-industry labor mobility costs for workers in Brazil and Mexico. Based on human capital theory, labor mobility has a cost in the form of the destruction of specific human capital. The human capital accumulated for the task is valuable only to firms or industries requiring the same specific skills. Some skills or work experience are not substitutable between firms or industries. For example, the telephone engineer whose job was eliminated may not have the computer skills required to work at an e-commerce company. Direct mobility costs and specific human capital have been considered as obstacles to frictionless responses to labor demand shocks (Lee & Wolpin, 2006). Because of the specificity of human capital, labor mobility is not perfectly transferable. Lamo et al., 2011 suggest that impediments to labor mobility due to skill specificity may be key determinants of the speed of labor market adjustments. Job creation in one industry may not attract workers from another industry. It is relatively easier to switch jobs within one industry rather than across different ones. Neal (1995) and Parent (2000) suggest that industry specificity of human capital is much more important than firm specificity. On an aggregate level, if a large proportion of a country's human capital is industry-specific, then part of the gain from the reallocation of different types of workers across industries would be offset by the destruction of industry-specific human capital. Substantial industry-specific investments could tend to lock in labor to specific industries, consequently making adjustment difficult.

Nevertheless, measuring the specificity of human capital can be challenging. The empirical study of specific human capital remains challenging. There are two main challenges. First, it is not easy to quantify how specific on-the-job learning or work experience is. Especially, it is challenging to measure specific human capital for different skill levels. Some research uses educational attainment as the indicator for the specificity of human capital. Most research assumes vocational education provides specific skills, and tertiary education offers general and transferable skills (Hanushek et al., 2017; Krueger & Kumar, 2004; Lamo et al., 2011; Lindner, 1998). This assumption is implausible when work experience is more specific than education and plays a more crucial role in productivity growth. Elliott and Lindley (2006) empirically find that unskilled labor is generally more likely to move sectors. Other literature widely uses occupation-specific human capital (Gathmann & Schönberg, 2010; Poletaev & Robinson, 2008), firm-specific human capital (Lazear, 2009), or industry-specific human capital (Neal, 1995). Second, we can not directly observe and measure how much specific human capital contributes to productivity and wage differentials, particularly at an aggregate level. Most empirical work studies the effects of tenure and work experience on wages (e.g., Hashimoto, 1979; Marshall & Zarkin, 1987; Mincer, 1997; Sullivan, 2010; Topel, 1991). However, those effects may not reflect the effects of specific human capital. Third, productivity growth attributed to specific human capital does not necessarily transfer to wage growth. As opposed to previous research, I consider the interaction between education attainment and on-the-job learning as a measure of the level of human capital specificity. Due to the above challenges, I use a theoretical model to analyze specific human capital, which can already give implications for policy-making. Moreover, many theoretical studies focus on who pays for training or mismatch (Jovanovic & Moffitt, 1990; Lazear, 2009; Wasmer, 2006). Few studies pay attention to what happens in the passage from one equilibrium to another.

In this paper, I build a two-industry model, incorporated with skill-biased technical change, and compare the outcomes with perfect and imperfect inter-industry labor mobility. In particular, I investigate how the interaction between skill levels and human capital specificity affects inter-industry labor mobility, skill premiums, and skill upgrading. I consider those effects under different circumstances, for example, the partial equilibrium or the general equilibrium, and with wage compression or without it. Through analyses, I show that policymakers should consider four factors while making policies: the competitiveness of product markets, the specificity of human capital, the bargaining power of firms, and education costs.

I first illustrate the results in a competitive labor market. In the partial equilibrium, both high- and low-skilled labor will move to the expanding industry after a technology shock, and more high-skilled labor will switch industries. In the general equilibrium, the elasticity of substitution between two goods plays an important role in labor mobility. When the elasticity of substitution is large, there will be more labor mobility and vice versa.

Second, I outline the analysis in an imperfect labor market. In the partial equilibrium, when high-skilled human capital is more specific than low-skilled, the skill premium will be higher in the expanding industry than the contracting one after a technology shock. There will be relatively fewer high-skilled workers switching industries but more skill upgrading in the expanding industry. In addition, firms that have bargaining power can compress the wages of high-skilled workers and invest in skill upgrading. Wage compression assists skill upgrading, especially when high-skilled labor has higher specific human capital than low-skilled labor. Furthermore, in the general equilibrium, the price effect and the effect of specificity mitigate the reaction of the labor market to technology shocks and make inter-industry labor mobility and skill upgrading difficult.

The rest of the paper is organized as follows. In the next section, I demonstrate the basic framework for a two-factor two-industry model. In this section, I present the production structure and the steady state of the labor market. In Section 3.3, I introduce technology shocks in a perfect labor market and analyze the adjustments in the partial and general equilibrium. Section 3.4 illustrates the adjustments of an imperfect labor market to technology shocks. In this section, I model the specificity of human capital and show how specificity influences adjustments in different cases. Section 3.5 demonstrates the policy implications of this paper and Section 3.6 concludes the main results and discusses future research.

3.2 Skill-Biased Technical Change and Skill Premium

To model how labor markets adjust to industry-specific technology shocks, I start with the basic framework for analyzing the steady state of the labor market. In this section, I present the general features of the model and the equilibrium of the labor market. I assume that both the labor market and product markets are competitive, the labor market is closed, and product markets are open. Since my contribution does not involve international trade flows, I do not use a Heckscher-Ohlin (HO) model as other papers have (e.g., Haskel & Slaughter, 2002). I consider a two-factor, two-industry economy. Each industry produces one good. Specifically, I follow Acemoglu (2002a) and use a general constant elasticity of substitution (CES) production function. Another key feature of the model is that one industry employs high-skilled labor relatively more intensively than the other. I define this industry as a high-tech industry and the other as low-tech. In the next section, I will introduce a technology shock in the relatively low-tech industry. Firms in this industry will adopt new technologies and become high-tech. Then I will explore how the labor market responds to this industry-specific shock and reach a partial and general equilibrium.

3.2.1 Production Structure

I begin with the production side of the model. Competitive firms produce good I in industry I and produce good J in industry J. I adopt a production function with SBTC in each industry at the aggregate, rather than firm, level. This is because the main goal is to model the equilibrium of the labor market, namely, the demand and supply of labor of different skill levels. For simplicity, I only incorporate skill-biased, rather than Hicks-neutral, TC in the production technology. The aggregate production function has constant returns to scale in two inputs: high-skilled (H)

and low-skilled labor (L).[1] Skill units of labor of individual skill levels employed in each industry are additive. The output of each industry is produced by the following production functions: [2]

$$Y_I = F(A_I^H H_I, A_I^L L_I), \tag{3.1a}$$
$$Y_J = G(A_J^H H_J, A_J^L L_J), \tag{3.1b}$$

where Y_k is the quantity of output of industry k (for $k = I, J$), H_k denotes efficient high-skilled labor input, and L_k denotes efficient low-skilled labor input in industry k. A_k^H and A_k^L define high-skilled and low-skilled labor augmenting TC. High-skilled labor augmenting TC indicates how much TC could increase the marginal productivity of high-skilled labor. It is defined similarly for low-skilled labor. Consequently, if A_k^H/A_k^L increases, TC is skill-biased, meaning that TC increases the marginal productivity of high-skilled labor more than that of low-skilled labor.[3]

In the model, TC is industry-specific if $A_I^H/A_I^L \neq A_J^H/A_J^L$. Otherwise, there is industry-pervasive TC if $A_I^H/A_I^L = A_J^H/A_J^L$. To boil down the model to its essence, I normalize A_k^L to one and assume that it is fixed over time, which means that technological progress has little or no impact on low-skilled workers' productivity change. Accordingly, SBTC indicates that $A_k^H > 1$. In the meantime, I suppose that industry I has a relatively technological advantage over industry J, and thus $A_I^H > A_J^H$.

Because both inputs are measured in efficient units, I define efficient units as

$$H_k = N_k^H h_k \quad \text{and} \quad L_k = N_k^L l_k,$$

where N_k^H and N_k^L are the quantities of high- and low-skilled labor in industry k, and h_k and l_k are accordingly average efficient human capital of one unit of labor. The total quantity of high-skilled labor, N^H, and the total quantity of low-skilled labor, N^L, are

$$N^H = N_I^H + N_J^H \quad \text{and} \quad N^L = N_I^L + N_J^L.$$

As industry I is more high-tech, it needs relatively more high-skilled labor, and thus $N_I^H/N_I^L > N_J^H/N_J^L$ for all possible factor prices. Therefore, industry I is relatively

[1]To clarify the model, I only assume two inputs in the production, but it is easy to generalize the model by including capital stocks. It is not crucial for my discussion to include capital.

[2]It is worth noting that all the variables are at time t. For simplicity, I eliminate time t in the subscript for the steady state.

[3]I only consider non-neutral (skill-biased) TC and do not include neutral TC, which increases the marginal product of high- and low-skilled labor at the same rate. This is because neutral TC does not play an imperative role in influencing the shift in the labor market.

intensive in high-skilled labor, and industry J is relatively intensive in low-skilled labor.

Now, let us be more specific about production. Firms produce two goods according to a general CES production function with the elasticity of substitution σ between two factors (Arrow et al., 1961).[4] Output in industry k, Y_k, is

$$Y_k = \left[\gamma_k (A_k^H H_k)^{\frac{\sigma-1}{\sigma}} + (1-\gamma_k) L_k^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \quad \text{for} \quad k = I, J, \tag{3.2}$$

where $\gamma_k \in (0,1)$ is a share parameter that determines how important those two factors are. According to the previous assumption that high-skilled labor is more important in industry I, thus $\gamma_I > \gamma_J$. Take the first derivatives with respect to the inputs, and the relative marginal product of high- to low-skilled labor is

$$\frac{MP_k^H}{MP_k^L} = \left(\frac{\gamma_k}{1-\gamma_k}\right) (A_k^H)^{\frac{\sigma-1}{\sigma}} \left(\frac{N_k^H}{N_k^L}\right)^{-\frac{1}{\sigma}} \left(\frac{h_k}{l_k}\right)^{\frac{\sigma-1}{\sigma}}, \tag{3.3}$$

where MP_k^H and MP_k^L are the marginal products of high- and low-skilled labor, respectively. The relative marginal product is also called the marginal rate of technical substitution (MRTS). It measures how many low-skilled workers firms can replace by hiring one extra high-skilled worker to produce the same output. Under the empirically reasonable assumption that $\sigma > 1$, high- and low-skilled workers are imperfect substitutes. Because $(\sigma - 1)/\sigma > 0$, MRTS is monotonically increasing in variable A_k^H. Therefore, if A_k^H increases, TC raises MRTS and becomes more skill-biased.

3.2.2 Relative Demand and Relative Wages

Next, let us examine how SBTC affects relative demand and relative wages. Since both labor markets and product markets are competitive, factor prices and product prices are exogenous. Firms in each industry maximize their profits as follows

$$V(N_k^H, N_k^L) \equiv \max P_k Y_k - W_k^H N_k^H - W_k^L N_k^L, \tag{3.4}$$

where P_k is the price of good k, and W_k^H and W_k^L are the wages of high- and low-skilled labor in industry k individually. The first-order conditions for these optimization problems imply that the relative demand for high-skilled to low-skilled

[4] σ is constant and $\sigma \in (0,\infty)$. When σ approaches 1, the production function is Cobb-Douglas.

labor in each industry is

$$D_k \equiv \frac{N_k^H}{N_k^L} = \left(\frac{\gamma_k}{1-\gamma_k}\right)^{\sigma} \left(\frac{A_k^H h_k}{l_k}\right)^{\sigma-1} \left(\frac{W_k^H}{W_k^L}\right)^{-\sigma}. \tag{3.5}$$

The partial derivative of D_k with respect to A_k^H is larger than zero, that is,

$$\frac{\partial D_k}{\partial A_k^H} > 0.$$

Everything else being constant, as A_k^H increases, D_k increases. Therefore, SBTC can induce a rise in the relative demand for high-skilled workers.

In equilibrium, a factor's price equals its marginal product. Thus the wage of high-skilled labor is

$$W_k^H = P_k \gamma_k (A_k^H h_k)^{\frac{\sigma-1}{\sigma}} (N_k^H)^{-\frac{1}{\sigma}} \left[\gamma_k (A_k^H N_k^H h_k)^{\frac{\sigma-1}{\sigma}} + (1-\gamma_k)(N_k^L l_k)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}, \tag{3.6}$$

which can be also written as

$$W_k^H = P_k \gamma_k (A_k^H h_k)^{\frac{\sigma-1}{\sigma}} (N_k^H)^{-\frac{1}{\sigma}} Y_k^{\frac{1}{\sigma}}. \tag{3.7}$$

In a similar manner, the wage of low-skilled labor is

$$W_k^L = P_k (1-\gamma_k) l_k^{\frac{\sigma-1}{\sigma}} (N_k^L)^{-\frac{1}{\sigma}} Y_k^{\frac{1}{\sigma}}. \tag{3.8}$$

As a result, the skill premium, namely, the wage of high-skilled labor divided by the wage of low-skilled labor, in industry k, ω_k, is

$$\omega_k \equiv \frac{W_k^H}{W_k^L} = \left(\frac{\gamma_k}{1-\gamma_k}\right) (A_k^H)^{\frac{\sigma-1}{\sigma}} \left(\frac{N_k^H}{N_k^L}\right)^{-\frac{1}{\sigma}} \left(\frac{h_k}{l_k}\right)^{\frac{\sigma-1}{\sigma}}. \tag{3.9}$$

Equation (3.9) can be rewritten in natural logarithms,

$$\ln \omega_k = \ln\left(\frac{\gamma_k}{1-\gamma_k}\right) + \frac{\sigma-1}{\sigma} \ln A_k^H - \frac{1}{\sigma} \ln\left(\frac{N_k^H}{N_k^L}\right) + \frac{\sigma-1}{\sigma} \ln\left(\frac{h_k}{l_k}\right). \tag{3.10}$$

The skill premium is equal to MRTS. Same as MRTS, the skill premium is monotonically increasing in variable A_k^H. When everything else remains unchanged and A_k^H rises, the skill premium $\left(W_k^H / W_k^L\right)$ rises. Technological progress increases the marginal product of high-skilled workers faster than that of low-skilled workers and thus increases the skill premium. On the other hand, $-1/\sigma < 0$, so W_k^H/W_k^L is monotonically decreasing in N_k^H/N_k^L. If the relative quantity of high-skilled workers $\left(N_k^H/N_k^L\right)$ increases, ceteris paribus, the skill premium $\left(W_k^H/W_k^L\right)$ will decrease.

In these competitive product markets, I suppose that households have homothetic preferences over two goods. They are represented by a CES utility function

$$U = \left[\lambda Y_I^{\frac{\rho-1}{\rho}} + (1-\lambda) Y_J^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{3.11}$$

where again λ is a share parameter, ρ is the elasticity of substitution, and $\rho \in (0, \infty)$. The budget constraint of the household is

$$P_I Y_I + P_J Y_J = M, \tag{3.12}$$

where M is the aggregate income, and

$$M = W_I^H N_I^H + W_I^L N_I^L + W_J^H N_J^H + W_J^L N_J^L.$$

Market clearing implies that

$$P \equiv \frac{P_I}{P_J} = \left(\frac{\lambda}{1-\lambda}\right)\left(\frac{Y_I}{Y_J}\right)^{-\frac{1}{\rho}}. \tag{3.13}$$

Because $-1/\rho < 0$, P is monotonically decreasing in Y_I/Y_J. This illustrates that the higher the relative supply (Y_I/Y_J), the lower the relative price (P_I/P_J).

In a steady state, A_k^H is constant. In a competitive labor market, inter-industry labor mobility is perfect, and hence there is one equilibrium wage for each skill level. Then the skill premiums are the same across industries, $W_I^H/W_I^L = W_J^H/W_J^L$. In consequence, the relative allocation of high- and low-skilled workers of industry I to J would be

$$\hat{D} \equiv \frac{\frac{N_I^H}{N_I^L}}{\frac{N_J^H}{N_J^L}} = \left(\frac{\frac{\gamma_I}{1-\gamma_I}}{\frac{\gamma_J}{1-\gamma_J}}\right)^{\sigma}\left(\frac{A_I^H}{A_J^H}\right)^{\sigma-1}\left(\frac{\frac{h_I}{l_I}}{\frac{h_J}{l_J}}\right)^{\sigma-1}. \tag{3.14}$$

If there is industry-specific TC, A_I^H/A_J^H will change and thus change the relative allocation $\hat{D}$. For example, if TC only occurs in industry J, A_J^H will increase, and A_I^H/A_J^H will decrease. Because $\sigma - 1 > 0$, $\hat{D}$ is monotonically increasing in A_I^H/A_J^H. As A_I^H/A_J^H decreases, the relative allocation of high-skilled labor of industry I to J will decline. The reasoning is that industry-specific TC will raise the relative demand for high-skilled labor in industry J, and thereby, high-skilled labor will move from industry I to J.

3.3 Technology Shocks in a Perfect Labor Market

The previous section demonstrates the steady state of the labor market. In this section, the important question to answer is how the labor market would react to a technology shock in the short and long run. I assume that technology shocks are exogenous and independent of the labor composition. My goal is to model the adjustments of a perfect labor market across industries. First, I assume fixed product prices in Subsection 3.3.1 and analyze the adjustments in the partial equilibrium. Second, I examine the general equilibrium in Subsection 3.3.2, which provides a more dynamic analysis of the adjustments. The general equilibrium considers that a technology shock can affect product prices and presents how changing product prices can affect wages and inter-industry labor mobility.

To distinguish between short-run and long-run effects, the analysis includes three time periods and ignores time discounting for simplicity. The first period is the steady state when there is no new TC. In the second period, technological breakthroughs take place in the low-skilled labor-intensive industry. And they have a direct effect on the demand for skills and the skill premium. The supplies of high- and low-skilled labor do not change. The main adjustment of the labor market is inter-industry labor mobility. Meanwhile, during this period, low-skilled workers can invest in education accordingly after observing the new equilibrium wages. In the last period, because of the change in education investments in the previous period, the supply of labor adjusts to the demand, and the proportion of high-skilled labor increases.

3.3.1 Partial Equilibrium

I start with a partial equilibrium analysis, which assumes that product prices are constant. To focus on labor mobility and skill upgrading, I suppose that the supply of labor is inelastic. On this account, the whole working population does not change over time. Furthermore, in the short run, the composition of the labor force does not change. The allocation of high- and low-skilled workers in two industries through initial education is fixed and exogenous. The underlying reasoning is that the government controls the distribution of education resources and the change of investment in education takes time. That is why education investments can not increase the proportion of high-skilled labor in a specific industry immediately. As a consequence, the adjustments in labor supply come from inter-industry mobility and skill upgrading.

In the first period, at time $t = 0$, the rates of TC are constant, and there is a long-run steady state. So far, skill premiums are stable, and so is the labor composition. I denote the equilibrium wages of high- and low-skilled labor by $W_{k,0}^H$ and $W_{k,0}^L$ individually, and the skill premium is $\omega_{k,0}$. Moreover, I denote the education cost by C and assume that it is invariable. Another key feature of this period is no skill upgrading, so low-skilled workers do not invest in education to upgrade their skill level. This means that the higher wage after skill upgrading can not cover the education cost, and therefore $W_{k,0}^H - C \leqslant W_{k,0}^L$.

Subsequently, to model the labor market dynamics, I introduce an exogenous technology shock in industry J at time $t = 1$. Those technology shocks may come from industry policies, which induce more investment in technological innovations to assist the low-tech industry. Technology shocks occur with a probability of q, following a Poisson process. I consider that the technology shock is industry-specific and skill-biased, common to all firms in that industry. The effect of the shock is enduring. Correspondingly, it increases the rate of SBTC and the relative marginal productivity of high-skilled to low-skilled workers in industry J.

After a technology shock, I presume that high-skilled labor augmenting TC, A_J^H, increases at a rate of δ, where $\delta > 1$. Consequently, output in industry J becomes

$$Y_J{}' = \left[\gamma_J(\delta A_J^H N_J^H h_J)^{\frac{\sigma-1}{\sigma}} + (1-\gamma_J)(N_J^L l_J)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{3.15}$$

where $Y_J{}'$ denotes output immediately after the technology shock.[5] Then output rises at a rate less than δ because of SBTC. To simplify the basic model, I also assume that unit efficient human capital of each skill level is the same between industries, that is,

$$h_I = h_J \quad \text{and} \quad l_I = l_J.$$

Additionally, unit-efficient human capital does not change over time in this model.

At the beginning of the adjustments, all other things being equal, SBTC increases the relative marginal product of high-skilled to low-skilled workers in industry J and makes the industry profitable at initial wages and fixed product prices. Thus firms will expand their production and employ more high-skilled labor. The relative

[5] After a technology shock, variables with a prime symbol denote the values before inter-industry labor mobility.

demand for high-skilled to low-skilled labor will change to

$$D_J{}' = \left(\frac{\gamma_J}{1-\gamma_J}\right)^{\sigma}\left(\frac{\delta A_J^H h_J}{l_J}\right)^{\sigma-1}\left(\frac{W_J^H}{W_J^L}\right)^{-\sigma}. \tag{3.16}$$

In this equation, $\delta^{\sigma-1} > 1$ and it increases $D_J{}'$. Hence, SBTC raises the relative demand for high-skilled workers. If the technology shock is large enough to change the relative skill intensity, there will be a shift in the demand for skills across industries. They will compete for the limited resource, high-skilled labor.

For a given composition of the labor force, technological breakthroughs, despite favoring high-skilled over low-skilled labor, raise the productivity of labor in all skill levels. Consequently, the marginal products of high-skilled and low-skilled workers in industry J increase, and so do their wages. Since TC is skill-biased, the wage of high-skilled labor increases more than that of low-skilled labor, and thus the skill premium in J rises. Without inter-industry labor mobility, the skill premium in J will become

$$\omega_J{}' = \left(\frac{\gamma_J}{1-\gamma_J}\right)(\delta A_J^H)^{\frac{\sigma-1}{\sigma}}\left(\frac{N_J^H}{N_J^L}\right)^{-\frac{1}{\sigma}}\left(\frac{h_J}{l_J}\right)^{\frac{\sigma-1}{\sigma}}. \tag{3.17}$$

According to equation (3.17), the skill premium in J will become $\delta^{(\sigma-1)/\sigma}$ higher than that in I.

Since wages are more appealing in industry J, high-skilled and low-skilled workers in industry I will leave and move to J. Thus, N_J^H and N_J^L rise, while N_I^H and N_I^L drop. The mobility, therefore, pushes down the wages in industry J and pushes up the wages in I, until the wages of the same skill level are equal across industries. In the partial equilibrium, the equilibrium wages will eventually become higher than those in the previous period. I specify this as the *mobility effect*. The mobility effect will lead to the following propositions. The first proposition demonstrates the effect of an industry-specific technology shock on labor mobility.

Proposition 1 *Suppose that the labor market is competitive and a technology shock occurs in a low-tech industry. In the partial equilibrium, both high- and low-skilled labor moves to the expanding industry, and more high-skilled rather than low-skilled labor switches industries. The percentage of high-skilled labor that switches industries is positively correlated with the growth rate of SBTC.*

Proof: At $t = 0$, there is one equilibrium wage for high- and low-skilled labor, respectively, so $\ln W^H_{I,0} = \ln W^H_{J,0}$ and $\ln W^L_{I,0} = \ln W^L_{J,0}$. After a technology shock in industry J, workers migrate until wages are equalized across industries again. In the partial equilibrium, $\ln W^H_{I,1} = \ln W^H_{J,1}$ and $\ln W^L_{I,1} = \ln W^L_{J,1}$, where $W^H_{k,1}$ and $W^L_{k,1}$ are the equilibrium wages for high- and low-skilled labor separately at $t = 1$. All the other variables have the same subscript at time t in the equilibrium.

Aiming to calculate inter-industry labor mobility, I define μ^H_t as the relative high-skilled labor of industry I to industry J, and hence $\mu^H_t = N^H_{I,t}/N^H_{J,t}$. Based on equation (3.7) and the equality of wages, I derive that the change of the relative high-skilled labor of I to J is

$$\Delta \ln \mu^H_1 = \sigma \left[\ln\left(\frac{\gamma_{I,1}}{\gamma_{J,1}}\right) - \ln\left(\frac{\gamma_{I,0}}{\gamma_{J,0}}\right) \right] - (\sigma - 1)\ln\delta + \left[\ln\left(\frac{Y_{I,1}}{Y_{J,1}}\right) - \ln\left(\frac{Y_{I,0}}{Y_{J,0}}\right) \right], \tag{3.18}$$

where $\Delta \ln \mu^H_1 = \ln\left(N^H_{I,1}/N^H_{J,1}\right) - \ln\left(N^H_{I,0}/N^H_{J,0}\right)$.[6] The first term on the right side of the equation is negative because the share of high-skilled labor declines in I and inclines in J. As $\sigma - 1 > 0$ and $\ln\delta > 0$, the second term is negative as well. The last term is negative too, since the relative output of I to J drops. This equation shows that $\Delta \ln \mu^H_1 < 0$, indicating that the relative high-skill workers decrease in industry I and increase in J. We can also see that as δ rises, $\Delta \ln \mu^H_1$ decreases, which means that more high-skilled labor moves to industry J.

For low-skilled workers, the growth rate (δ) of SBTC does not influence their mobility directly. Based on equation (3.8), the change of the relative low-skilled labor of I to J is

$$\Delta \ln \mu^L_1 = \sigma \left[\ln\left(\frac{1-\gamma_{I,1}}{1-\gamma_{J,1}}\right) - \ln\left(\frac{1-\gamma_{I,0}}{1-\gamma_{J,0}}\right) \right] + \left[\ln\left(\frac{Y_{I,1}}{Y_{J,1}}\right) - \ln\left(\frac{Y_{I,0}}{Y_{J,0}}\right) \right], \tag{3.19}$$

where $\mu^L_t = N^L_{I,t}/N^L_{J,t}$ and $\Delta \ln \mu^L_1 = \ln\left(N^L_{I,1}/N^L_{J,1}\right) - \ln\left(N^L_{I,0}/N^L_{J,0}\right)$. Although low-skilled workers move to industry J, their share in industry I rises because relatively more high-skilled workers switch industries. Consequently, the first term of the right side of the equation is positive. The second term is negative as before. Thus the change of the relative low-skilled labor is subject to two parts with opposite directions.

Subtracting equation (3.18) from equation (3.19) and then rearranging terms gives:

$$\Delta \ln \mu^L_1 - \Delta \ln \mu^H_1 = \sigma(\Delta\gamma_{J,1} - \Delta\gamma_{I,1}) + (\sigma - 1)\ln\delta, \tag{3.20}$$

[6] Δ denotes the first difference.

where

$$\Delta\gamma_{J,1} = \ln\left(\frac{\gamma_{J,1}}{1-\gamma_{J,1}}\right) - \ln\left(\frac{\gamma_{J,0}}{1-\gamma_{J,0}}\right), \tag{3.21}$$

and

$$\Delta\gamma_{I,1} = \ln\left(\frac{\gamma_{I,1}}{1-\gamma_{I,1}}\right) - \ln\left(\frac{\gamma_{I,0}}{1-\gamma_{I,0}}\right). \tag{3.22}$$

Because the relative share of high-skilled to low-skilled labor increases in J and decreases in I, $\Delta\gamma_{J,1} > 0$, $\Delta\gamma_{I,1} < 0$, and thus $\Delta\gamma_{J,1} - \Delta\gamma_{I,1} > 0$. As a consequence, I arrive that $\Delta\ln\mu_1^L - \Delta\ln\mu_1^H > 0$, which illustrates that industry I loses more high-skilled than low-skilled workers. □

Next, I analyze the effect of labor mobility on skill premiums.

Proposition 2 *An industry-specific technology shock increases the skill premium in that industry, and perfect labor mobility between industries decreases the difference in the skill premiums. In the partial equilibrium, the equilibrium wages of all skill levels increase.*

Proof: This proposition is straightforward. As discussed before, SBTC increases the marginal productivity of both skill levels in industry J and thus their wages. The skill premium in J will increase at the rate of $\delta^{(\sigma-1)/\sigma}$, which is larger than one since $\delta > 1$ and $\sigma > 1$. Attracted to the higher wages, both types of labor in I will move to J. The mobility effect will eliminate the differences in wages until they reach a new equilibrium. The equilibrium wages are somewhere between the original steady state and the increased wages in J before the mobility. I denote the changes in the skill premiums in both industry I and J accordingly by $\Delta\ln\omega_{I,1}$ and $\Delta\ln\omega_{J,1}$. According to equation (3.10), I can express the change in the skill premium in I as

$$\Delta\ln\omega_{I,1} = \Delta\gamma_{I,1} - \frac{1}{\sigma}\left[\ln\left(\frac{N_{I,1}^H}{N_{I,1}^L}\right) - \ln\left(\frac{N_{I,0}^H}{N_{I,0}^L}\right)\right], \tag{3.23}$$

whereas in J, it is

$$\Delta\ln\omega_{J,1} = \Delta\gamma_{J,1} - \frac{1}{\sigma}\left[\ln\left(\frac{N_{J,1}^H}{N_{J,1}^L}\right) - \ln\left(\frac{N_{J,0}^H}{N_{J,0}^L}\right)\right] + \left(\frac{\sigma-1}{\sigma}\right)\ln\delta. \tag{3.24}$$

The mobility term $1/\sigma\left[\ln\left(N_{I,1}^H/N_{I,1}^L\right) - \ln\left(N_{I,0}^H/N_{I,0}^L\right)\right]$ in equation (3.23) is negative, whereas $1/\sigma\left[\ln\left(N_{J,1}^H/N_{J,1}^L\right) - \ln\left(N_{J,0}^H/N_{J,0}^L\right)\right]$ is positive in equation

(3.24). Accordingly, the mobility effect increases the skill premium in the contracting industry and decreases it in the expanding industry. □

Despite the mobility effect, when the impact of a technology shock is remarkable, skill premiums can rise significantly in the new partial equilibrium. This may motivate skill upgrading, which in turn lowers the skill premium further.

Proposition 3 *Suppose that the labor market is competitive, a technology shock occurs in a low-tech industry, and there are no financial constraints for labor. In the partial equilibrium, if $W_{k,1}^{H} - C \geqslant W_{k,1}^{L}$, low-skilled workers pay to upgrade their skills after observing the new equilibrium wages.*

Proof: During the same period, low-skilled labor will make decisions about education investments. I assume that inter-industry labor mobility precedes education investments. Because education takes longer than switching jobs between industries, low-skilled labor would perceive inter-industry labor mobility. Thus, they will make education investments after observing the new equilibrium wages of high-skilled and low-skilled labor. If $W_{k,1}^{H} - C \geqslant W_{k,1}^{L}$, they have incentives to pay to obtain higher education and upgrade their skills. If there are no financial constraints, low-skilled workers can receive loans from banks to pay for education costs. The higher wage they will receive in the next period after becoming high-skilled can compensate for education costs. It is, therefore, beneficial for low-skilled workers to obtain higher education and a higher wage in both industries. It is worth noting that firms will not pay education costs because, according to equation (3.4), they do not gain profits from skill upgrading. This is in line with the standard human capital theory developed by Becker (1962). The theory of human capital advocates that general human capital is useful in all firms, and firms do not receive returns from general training and thus do not invest.

On the other hand, if there are financial constraints, there will be skill upgrading only when the wage of low-skilled labor is larger or equal to education costs. Skill upgrading will happen only when the wage of high-skilled labor is more than twice as high as that of low-skilled labor. Otherwise, there is no education investment despite that it is socially optimal to upgrade skills. □

After low-skilled workers decide to upgrade their skills, at time $t = 2$, the skill premiums will decline until $W_{k,2}^{H} - C = W_{k,2}^{L}$. In the long run, education investments can change the proportion of high-skilled labor.

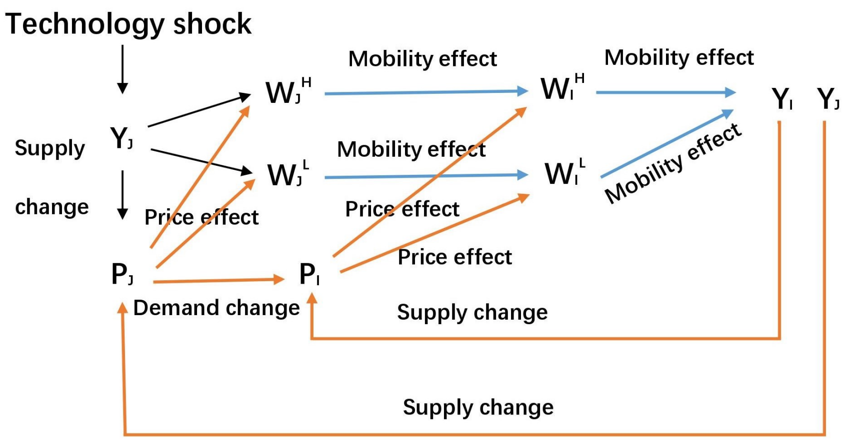
3.3.2 General Equilibrium

I now consider that TC can affect both labor and product markets. TC will influence the product market by adjusting the quantities supplied at a given price. In consequence, TC shifts supply curves and induces changes in product prices. Furthermore, the adjustments in product markets can reversely influence the labor market. According to equation (3.7)and (3.8), prices and outputs can in turn affect wages. In this subsection, I will analyze the dynamics of labor market adjustments when product prices can change.

As is in the partial equilibrium, the first period is the steady state. In the second period, $t = 1$, a technology shock increases the production of good J and thus shifts the supply curve of J to the right. I consider that the relative demand curve stays the same. Consequently, the price of J will decrease. Nevertheless, this can still raise the wage of high-skilled labor in industry J and bring about inter-industry labor mobility. The mobility of high-skilled labor will reduce the supply of good I and contrarily increase the supply of good J. Correspondingly, technological innovation shifts the supply curve of I to the left and the supply curve of J to the right. The smaller supply of I increases the equilibrium level of P_I, and the larger supply of J lowers the equilibrium level of P_J.

In addition, the adjustments in the product markets can reversely influence the labor market. According to equations (3.7) and (3.8), the increase in the product price P_I will increase the wages (W_I^H and W_I^L) in industry I. On the other hand, industry J will face lower wages (W_J^H and W_J^L) caused by the decline in P_J. Evidently, the price changes counteract the wage gaps, attributed to TC, between industries. I call this the *price effect*. Since the price effect can affect wages, it can influence inter-industry labor mobility as well. Together the mobility effect and the price effect adjust the labor market. Figure 3.1 summarizes the dynamics of the two effects. We can see that an industry-specific technology shock increases the supply of product J and changes P_J and P_I. The price effect, depicted by orange lines, affects wages of high- and low-skilled labor in industry J and I, and thus mitigates the mobility effect. The mobility effect, depicted by blue lines, further decreases output Y_I and increases output Y_J. It subsequently induces more price changes. Hence, the mobility effect contrarily influences the price effect. In the partial equilibrium, the wages for both skill levels in J would initially increase after the technology shock. In comparison, in the general equilibrium, the initial increase in wages in J would be lessened. High-skilled workers will still move from industry I to J, because TC favors them and industry J needs more of them.

Figure 3.1: Dynamics of the mobility effect and the price effect



Notes: This figure illustrates the dynamics of the mobility effect and the price effect. The orange lines present the price effect, and the blue lines display the mobility effect. Any technology shock in industry J increases its supply (Y_J) and decreases its price(P_J). The decrease in P_J can decrease wages W_J^H and W_J^L and affect P_I. Wages in J are higher than wages in I, and thus labor moves to J. The mobility effect increases the supply of J and decreases the supply of I. Supply changes will again lead to price changes. The mobility effect reversely influences the price effect.

Simultaneously, low-skilled labor faces different situations through the price effect. Low-skilled workers will migrate to industry J, if the wage, adjusted to the price effect, is still higher in industry J ($W_J^{L'} > W_I^{L'}$). If the wages are equal across industries ($W_J^{L'} = W_I^{L'}$), they do not switch industries. In contrast, they will migrate to industry I, if the wage is lower in industry J ($W_J^{L'} < W_I^{L'}$) in the case of a significant fall in the product price. Together the mobility effect and the price effect will bridge the gaps between the wages across industries until both industries face the same wage for the same skill level. I summarize these results in the following.

Proposition 4 *Suppose that the labor market is competitive and a technology shock occurs in a low-tech industry. In the general equilibrium, the price effect will influence the relative price and wages and decrease inter-industry labor mobility. High-skilled labor will switch to industry J, but low-skilled labor mobility depends on the wage difference between the two industries.*

Proof: In the general equilibrium, the change of the relative high-skilled labor in industry I compared with industry J is

$$\begin{aligned}\Delta\ln\mu_1^H =&\sigma\left[\ln\left(\frac{\gamma_{I,1}}{\gamma_{J,1}}\right)-\ln\left(\frac{\gamma_{I,0}}{\gamma_{J,0}}\right)\right]+\sigma\left[\ln\left(\frac{P_{I,1}}{P_{J,1}}\right)-\ln\left(\frac{P_{I,0}}{P_{J,0}}\right)\right]\\ &-(\sigma-1)\ln\delta+\left[\ln\left(\frac{Y_{I,1}}{Y_{J,1}}\right)-\ln\left(\frac{Y_{I,0}}{Y_{J,0}}\right)\right],\end{aligned} \tag{3.25}$$

whereas the change of the relative low-skilled labor in industry I compared with industry J is

$$\begin{aligned}\Delta\ln\mu_1^L =&\sigma\left[\ln\left(\frac{1-\gamma_{I,1}}{1-\gamma_{J,1}}\right)-\ln\left(\frac{1-\gamma_{I,0}}{1-\gamma_{J,0}}\right)\right]\\ &+\sigma\left[\ln\left(\frac{P_{I,1}}{P_{J,1}}\right)-\ln\left(\frac{P_{I,0}}{P_{J,0}}\right)\right]+\left[\ln\left(\frac{Y_{I,1}}{Y_{J,1}}\right)-\ln\left(\frac{Y_{I,0}}{Y_{J,0}}\right)\right].\end{aligned} \tag{3.26}$$

Because the price effect increases P_I and decreases P_J, the relative price $(P_{I,1}/P_{J,1})$ increases, and thus $\ln(P_{I,1}/P_{J,1})-\ln(P_{I,0}/P_{J,0})>0$. The term, $\sigma[\ln(P_{I,1}/P_{J,1})-\ln(P_{I,0}/P_{J,0})]$, can increase $\Delta\ln\mu_1^H$ and $\Delta\ln\mu_1^L$. If this term is large, it can make $\Delta\ln\mu_1^L$ positive, meaning that low-skilled labor flows to industry I. As a result, the increase in the relative price can reduce labor mobility from industry I to J. □

The change in the relative price of two goods depends on the relative supply and therefore the elasticity of substitution. I substitute equation (3.13) into equation (3.25) and (3.26), and then obtain the following results.

Proposition 5 *In the general equilibrium, the elasticity of substitution between two goods, ρ, plays a critical role in inter-industry labor mobility after a technology shock. The larger the ρ is, the more labor moves from industry I to J, and vice versa.*

Proof: Based on equation (3.13), I can write equation (3.25) as

$$\begin{aligned}\Delta\ln\mu_1^H =&\sigma\left[\ln\left(\frac{\gamma_{I,1}}{\gamma_{J,1}}\right)-\ln\left(\frac{\gamma_{I,0}}{\gamma_{J,0}}\right)\right]-(\sigma-1)\ln\delta\\ &+\left(1-\frac{\sigma}{\rho}\right)\left[\ln\left(\frac{Y_{I,1}}{Y_{J,1}}\right)-\ln\left(\frac{Y_{I,0}}{Y_{J,0}}\right)\right],\end{aligned} \tag{3.27}$$

assuming λ stays constant. Similarly, equation (3.26) becomes

$$\Delta \ln \mu_1^L = \sigma \left[\ln\left(\frac{1-\gamma_{I,1}}{1-\gamma_{J,1}}\right) - \ln\left(\frac{1-\gamma_{I,0}}{1-\gamma_{J,0}}\right) \right] + \left(1-\frac{\sigma}{\rho}\right) \left[\ln\left(\frac{Y_{I,1}}{Y_{J,1}}\right) - \ln\left(\frac{Y_{I,0}}{Y_{J,0}}\right) \right]. \tag{3.28}$$

Because ρ is the elasticity of substitution, a large ρ means that it is easy to substitute one good for the other, and vice versa. When ρ is larger than σ, $1-\sigma/\rho$ is positive. The larger ρ is, the larger $1-\sigma/\rho$ is. Since output increases in industry J and decreases in I, the relative supply, Y_I/Y_J, drops, meaning that $\ln(Y_{I,1}/Y_{J,1}) - \ln(Y_{I,0}/Y_{J,0}) < 0$. Thus, when ρ is larger, $\Delta \ln \mu_1^H$ and $\Delta \ln \mu_1^L$ are smaller. In other words, when everything else stays constant, as it is easier to substitute good J for I, there will be more labor mobility from I to J.

In contrast, if it is harder to substitute J for I, there will be less labor moving from I to J. If ρ is smaller than σ, $1-\sigma/\rho$ is negative, for example, both goods are perfect complements. When ρ is small enough and the absolute value of $\ln(Y_{I,1}/Y_{J,1}) - \ln(Y_{I,0}/Y_{J,0})$ is large enough, low-skilled labor would start moving from industry J to I. □

To illustrate how the elasticity of substitution affects the price effect, I compare substitute goods and complementary goods in Figure 3.2. It displays the relative supply (RS) and the relative demand (RD) for substitute goods in the left panel and complementary goods in the right panel. In the left panel, the slopes of both the RS and RD curves are flat, whereas, in the right panel, the slopes are steep. Any technology shock in industry J shifts the RS curve leftwards to RS', and the RD curve does not move. This leads to an increase in the relative price and a decrease in the relative quantity for both cases. Because of the steeper slopes, complementary goods face a larger increase in the relative price than substitute goods. On the contrary, the relative quantity decreases at a lower rate in the right panel than in the left panel. Based on equation (3.25) and (3.26), a higher relative price and a lower relative quantity can reduce labor mobility from I to J. Therefore, the price effect is more significant on complementary goods than on substitute goods.

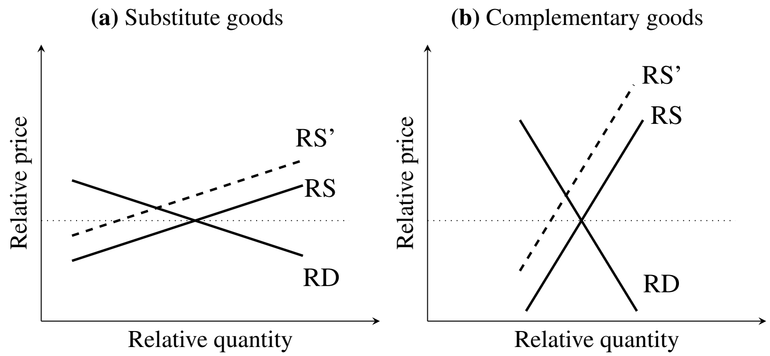
The price effect compensates for the mobility effect to equalize wages of the same skill level across industries. If the price effect is insignificant, then the mobility effect is profound, and vice versa. Specifically, when two goods are highly substitutable, the price effect is small, and more labor switches industries. Conversely, as two goods are more complementary, the price effect is more significant, less high-skilled labor switches industries, and low-skilled labor would reversely switch to the contracting industry. In general, the price effect mitigates the effects of technology shocks on the labor market.

Moreover, the difference between the change in the relative low-skilled labor and the change in the relative high-skilled labor is the same as equation (3.20). On the right side of the equation, it is monotonically increasing in variable δ. It means that the higher rate of SBTC, the relatively more high-skilled labor switches industries. This is consistent with the result of the partial equilibrium.

Furthermore, the price effect does not affect skill premiums directly. As in equation (3.23) and (3.24), only the mobility effect will affect the changes in the skill premiums. The price effect only influences the skill premiums indirectly through its impact on the mobility effect.

Finally, I pay attention to the price effect on education investments. As is discussed in the previous section, the equilibrium skill premium determines education investments. The price effect exerts an impact on skill premiums indirectly. However, its impact on skill premiums and education investments is ambiguous. If the skill premium is smaller in the general equilibrium than in the partial equilibrium, there will be less skill upgrading and vise versa. Another occasion is that the skill premium may be the same in both cases, so the price effect has no impact on education investments.

Figure 3.2: Relative supply and relative demand



Notes: This figure shows the relative supply (RS) and the relative demand (RD) for substitute goods in the left panel and complementary goods in the right panel. Any technology shock in industry *J* shifts the RS curve leftwards to RS', and the RD curve does not move. Before the shock, the relative price in the left panel is the same as it in the right panel. After the shock, the relative price is higher in the right panel than in the left panel. The relative quantity decreases less in the right panel than in the left panel.

3.4 Technology Shocks in an Imperfect Labor Market

The previous section outlines how an industry-specific technology shock affects the adjustments of the perfectly competitive labor market. The next step is to consider adjustment costs in the labor market, which may depend on the mobility costs of switching industries and specific human capital. Those costs hinder labor mobility. The crucial question to answer is how adjustment costs would affect wages and labor mobility and further affect skill premiums and skill upgrading. First, in the following subsection, I will show how direct mobility costs can bring about wage differentials across industries. After that, I will demonstrate how to model specific human capital and its impact on the adjustments in the labor market.

3.4.1 Mobility Cost

This subsection explains how a constant mobility cost will affect inter-industry labor mobility in different situations. The next subsection provides a more detailed analysis of the effect of specific human capital. In fact, the loss of specific human capital can be considered as one type of mobility costs. I assume that the direct mobility cost is fixed and denote it by ϕ. The most crucial difference between the constant mobility cost and the loss of specific human capital is that the former is not correlated with skill levels, while the latter is. Because of mobility costs, firms afford to pay less to their employees. The underlying reasoning is that employees can not switch to another job freely. For that reason, if firms have some bargaining power, they do not pay the marginal product to their employees. In that case, there will be wage compression.

After industry-specific SBTC takes place in industry J, initially, the marginal product of high-skilled labor will become

$$MP_J^{H'} = P_J \gamma_J (\delta A_J^H h_J)^{\frac{\sigma-1}{\sigma}} (N_J^H)^{-\frac{1}{\sigma}} (Y_J')^{\frac{1}{\sigma}}, \tag{3.29}$$

and that of low-skilled labor will be

$$MP_J^{L'} = P_J (1-\gamma_J) l_J^{\frac{\sigma-1}{\sigma}} (N_J^L)^{-\frac{1}{\sigma}} (Y_J')^{\frac{1}{\sigma}}. \tag{3.30}$$

Because of the growth of output (Y_J'), the marginal products of both skill levels have been improved. It is similar to the perfect mobility case. Wages of both skill levels would rise, and labor in industry I seeks a higher wage and moves to J. Nevertheless, workers switching industries need to pay for the mobility cost, so they can not receive the marginal product as the case in the perfect labor market.

Consequently, if high- and low-skilled labor migrates to industry J, they will have the mobility cost deducted from the marginal product, shown as $MP_J^{H'} - \phi$. This brings about four distinct situations. First, if $MP_J^{H'} - \phi > W_{I,0}^H$ and $MP_J^{L'} - \phi > W_{I,0}^L$, both high- and low-skilled labor will switch to industry J. Second and third, only one type of labor will move to the higher wage industry if the mobility cost of another type of labor is too costly, either if $MP_J^{H'} - \phi > W_{I,0}^H$ and $MP_J^{L'} - \phi \leqslant W_{I,0}^L$, or if $MP_J^{H'} - \phi \leqslant W_{I,0}^H$ and $MP_J^{L'} - \phi > W_{I,0}^L$. Fourth, if $MP_J^{H'} - \phi \leqslant W_{I,0}^H$ and $MP_J^{L'} - \phi \leqslant W_{I,0}^L$, there will be no industry switching.

If labor does move between industries, their mobility will push down the wages in J and push up the wages in I. The difference between equilibrium wages in two industries equals the mobility cost. This is the case when there is no wage compression. In equilibrium, it shows that $W_{J,1}^H - \phi = W_{I,1}^H$, and $W_{J,1}^L - \phi = W_{I,1}^L$. In the end, the wages in industry J are higher than that in I. Alternately, firms in J can compress their original workers' wages. They pay their own workers what the job switchers from I to J can receive. Thereby, wages in J are the same as in I, but they are lower than the marginal products in J. This can be demonstrated as $MP_{J,1}^H - \phi = W_{J,1}^H = W_{I,1}^H$ for high-skilled, and the same for low-skilled labor. In this case, because TC only improves productivity in industry J, and there is wage compression, firms find it profitable to invest in skill upgrading (Acemoglu & Pischke, 1999). Generally, wage compression stimulates skill upgrading. This also applies to specific human capital. In the next section, I will illustrate how specific human capital has an impact on skill premiums, labor mobility, and skill upgrading in detail.

3.4.2 Specific Human Capital

Most labor economists believe that there are two distinct types of human capital: general and specific human capital. The former contributes to a worker's productivity equally at all firms, and the latter only affects the productivity at the current firm. Becker's theory, the main idea of the human capital theory, is that employers have no incentives to pay for general skill training but pay for specific skill training.

Specific human capital can come not only from on-the-job learning but also from the network and connections within the firm and the knowledge of the firm and the industry (Lazear, 2009). Employees have more information about their current employers and acquire extensive specific skills attributed to the firm- or industry-specific experience. It is a crucial part of human capital.

However, specific human capital cannot be fully transferable when labor switches jobs. The acquired skills through working are not easily transferable between industries. Even though some skills are similar, employers may not recognize the similarities. Thereby, labor mobility is imperfect. When human capital is industry-specific, workers can not switch to another industry without losing some productivity. Employers are unwilling to pay the same wage to workers from another industry. Workers will face a lower wage if they leave their current job. Consequentially, specificity creates an industry wage gap between workers with the same skill level.

In a competitive labor market, switching to another industry does not change workers' average efficient human capital, so h_k and l_k stay constant. However, part of unit efficient human capital could be specific to the current industry because of learning on the job. Workers that move to another industry will lose their specific human capital. Suppose that efficient human capital per unit has a specificity rate s_k^H for high-skilled workers and s_k^L for low-skilled ones in industry k. They can be represented as

$$h_k = h_0(1 + s_k^H), \tag{3.31a}$$

$$l_k = l_0(1 + s_k^L), \tag{3.31b}$$

where h_0 and l_0 are the initial efficient human capital, which does not differ between industries. This assumption arises from the fact that newly hired workers have the same initial efficient human capital and will improve efficiency from learning on the job (Bos & Li, 2022). Efficiency gain from work experience in a certain industry is considered industry-specific human capital. In consequence, $h_0 s_k^H$ and $l_0 s_k^L$ are specific human capital in industry k by construction. To simplify the model and comply with the previous assumption in Section 3.3 [7], I suppose that high-skilled labor can gain similar efficiency from work experience in dissimilar industries, and hence the specificity rates have the same percentage. The same applies to low-skilled labor. Therefore,

$$s_I^H = s_J^H \quad \text{and} \quad s_I^L = s_J^L.$$

Since the subscripts I and J for s are inconsequential, the specificity rate is presented as s hereafter.

However, even if workers in industry I share the same specificity rate with those in J, specific human capital can not be transferred to a fairly different industry. Thus, when a worker switches to another industry, the accumulated work experience in the origin industry produces less efficiency gain in the destination industry. This indicates that there is a loss of specific human capital.

[7] $h_I = h_J$ and $l_I = l_J$.

The marginal product of a high-skilled worker switching from I to J can be expressed as

$$MP_{IJ}^{H} = MP_{J}^{H}\theta, \tag{3.32}$$

where θ is the transferable rate from switching industries for high-skilled workers. The transferability of specific human capital can be determined by the distance between occupations in terms of how similar skill sets (or tasks) required are (Poletaev & Robinson, 2008; Robinson, 2018). Gathmann and Schönberg (2010) also find that skills are partially transferable across occupations with similar tasks performed. In this case, a transferable rate is a function of the specificity rate, and thereby θ is constructed as

$$\theta = \left(\frac{1}{1+s^{H}}\right)^{\frac{\sigma-1}{\sigma}}. \tag{3.33}$$

When $s^H = 0$, accordingly, $\theta = 1$, which means that specific human capital can be perfectly transferred. Otherwise, if $0 < s^H \leqslant 1$, the transferable rate θ is smaller than one. In other words, only part of human capital can be transferred. The loss of the marginal product is $MP_J^H(1-\theta)$, which also can be considered mobility cost. Equally, since I suppose that $s_I^H = s_J^H$ and $h_I = h_J$, the marginal product of a high-skilled worker switching from J to I is $MP_I^H\theta$. [8]

In the same vein, low-skilled workers can transfer at the rate η, and hence their marginal product of switching from I to J is

$$MP_{IJ}^{L} = MP_{J}^{L}\eta, \tag{3.34}$$

where

$$\eta = \left(\frac{1}{1+s^{L}}\right)^{\frac{\sigma-1}{\sigma}}. \tag{3.35}$$

Conversely, the marginal product of a low-skilled worker switching from J to I is the same as $MP_I^L\eta$.

Transferable rates can differ between high- and low-skilled levels. Workers of different skill levels acquire distinct levels of specific human capital. On-the-job learning and education can be highly complementary (Acemoglu & Pischke, 1999). Accordingly, high-skilled workers benefit more from on-the-job training and gain

[8] If $s_I^H \neq s_J^H$, the transferable rate for a high-skilled worker switching from J to I is not θ, and thus the marginal product is not $MP_I^H\theta$. This analysis mainly concerns labor mobility from I to J after industry-specific TC. I do not dive into the reverse labor mobility from J to I, so I assume $s_I^H = s_J^H$ and $s_I^L = s_J^L$ for simplicity.

a higher increase in productivity. As technology is more industry-specific, experienced high-skilled workers will lose more productivity in changing jobs than their low-skilled counterparts. They get a larger wage deduction when they switch to another industry.

In this analysis, I compare how transferable rates can affect adjustments in the labor market. I will mainly investigate how the specificity of human capital affects wages, skill premiums, labor mobility, and skill upgrading. As explained before, specific human capital causes imperfect labor mobility and thus wage gaps between industries. Firms will pay lower wages to industry switchers or even to all workers if they have bargaining power. In the former circumstance (no wage compression), whether high-skilled or low-skilled labor has more specific human capital can induce divergence in wages. In the latter circumstance (wage compression), the effects of specificity on inter-industry mobility do not differ from what we considered earlier. It does, however, influence education investments notably, since it determines how much firms will contribute to education costs. I begin with the partial equilibrium with no wage compression and then analyze the effect of wage compression and the price effect.

How Does Specificity Affect Adjustments?

When prices stay the same, the initial change following a technology shock is consistent with the perfect labor market. As is illustrated in Section 3.4.2, the marginal products of both skill levels will rise in industry J, followed by increases in demand and wages. The loss of specific human capital allows the original high-skilled workers in J and those from I to have non-identical marginal products and wages. Comparable with the fixed mobility cost, this loss consequently generates four cases as well. What is divergent is that high-skilled and low-skilled labor do not share the same amount of loss thanks to their distinct skill specificity. The more specific the human capital is, the larger loss the inter-industry mobility causes.

Table 3.1 summarizes the four cases in the partial equilibrium with no wage compression. It shows the variations in transferable rates between high- and low-skilled labor. The second column presents a lower transferable rate for the high-skilled, where $\theta < \eta$, and the third column demonstrates the opposite, $\theta \geqslant \eta$. The first column displays the conditions for those cases. In the first case, the loss of human capital is not huge enough to impede inter-industry mobility. This means that both high- and low-skilled labor will move to industry J, when $MP_J^{H'}\theta > W_{I,0}^H$ and $MP_J^{L'}\eta > W_{I,0}^L$. Employers in J will still pay both types of workers from I higher wages than that in I. Workers in I will move to a higher-paying job in J until there is no benefit to switching industries. Therefore, in the partial equilibrium, the original workers in J receive the full marginal products as wages, namely $W_{J,1}^{H}$ and $W_{J,1}^{L}$. In contrast, workers from I to J contribute less productivity and only obtain the transferred marginal products as wages. In the equilibrium, it is arbitrary for workers to stay in I or to move to J, so the following condition is met: $W_{J,1}^{H}\theta = W_{I,1}^{H}$ and $W_{J,1}^{L}\eta = W_{I,1}^{L}$.

Compared with the perfect labor market, inter-industry labor mobility has declined. The change of the relative high-skilled labor in I compared with J becomes $\Delta\ln\mu_1^H - \sigma\ln\theta$, and that of the relative low-skilled labor alters to $\Delta\ln\mu_1^L - \sigma\ln\eta$. Because $\ln\theta \geqslant 0$, $\ln\eta \geqslant 0$, and $\sigma > 1$, the absolute values of the changes above will decrease, representing a drop in mobility. This drop lessens the mobility effect.

When high-skilled workers have more specific human capital and a lower transferable rate, meaning $\theta < \eta$, the relative high-skilled to low-skilled labor that moves to J drops. Meanwhile, the skill premium is higher in industry J than I. If skill premiums are high enough, namely $W_{k,1}^{H} - W_{k,1}^{L} > C$, low-skilled labor could pay for skill upgrading. There will be more skill upgrading in J, because high-skilled workers can not easily switch industries, and low-skilled workers have more incentives to upgrade their skills. Conversely, on the condition that low-skilled labor has more specific human capital, implying $\theta \geqslant \eta$, more high-skilled relative to low-skilled labor will switch to J. Industry I thus has a higher skill premium and more skill upgrading.

The second case illustrates what happens if it is too costly for low-skilled labor to move to J. Evidently, if the transferred marginal products are lower than the wages in I for low-skilled labor, only high-skilled labor would switch to J. It can be expressed as $MP_J^{H'}\theta > W_{I,0}^{H}$ and $MP_J^{L'}\eta < W_{I,0}^{L}$ in Table 3.1. In the partial equilibrium, I obtain the following: $W_{J,1}^{H}\theta = W_{I,1}^{H}$ and $W_{J,1}^{L}\eta < W_{I,1}^{L}$. Even if the transferable rate is lower for high-skilled labor, the productivity growth because of a technology shock can still compensate for human capital loss. On this occasion, the skill premium is higher in J. On the contrary, if low-skilled labor has a lower transferable rate, the difference in skill premiums between industries hinges on the transferable rates for both skill levels. However, on both occasions, the skill premiums are higher than that at $t = 0$.

Then, I consider the loss is too expensive for high-skilled workers, so only low-skilled workers move to J in the third case. This is the opposite of the previous case, but if high-skilled labor still has a higher transferable rate, it will be too costly for low-skilled counterparts to switch to J as well.

Lastly, if $MP_J^{H'}\theta < W_{I,0}^H$ and $MP_J^{L'}\eta < W_{I,0}^L$, there will be no inter-industry switching. The transferable rates of both types of labor are too low for them to lose their specific human capital. The skill premium in I remains the same, and it in J stays higher in the equilibrium despite which skill level has a higher transferable rate. Skill upgrading can only happen in J, if $W_{J,1}^H - W_{J,1}^L \geqslant C$.

In general, when high-skilled human capital is more specific, meaning that θ is small, there will be relatively less high-skilled labor switching industries but more skill upgrading in the expanding industry. When low-skilled labor is more specific, it is comparatively easier for high-skilled labor to move. Therefore, the contracting industry will lose relatively more high-skilled labor and need to upgrade skills. If the cost of inter-industry mobility is too high for both skill levels, the technologically changing industry can only expand by investing in education. Some empirical studies find that the increase in the relative demand for skilled labor does not come from labor reallocation across sectors but from skill upgrading within firms (Bustos, 2011). This could be due to the high mobility costs. Hence, the high specificity of human capital can help change labor composition within the industry as long as the education cost is not too high for low-skilled labor. Then the transformation of this industry is not easy to achieve otherwise. Meanwhile, high specific human capital can also prevent the contracting industry from losing human capital and shrinking.

How Does Wage Compression Affect Education Investments?

When wages are not compressed, the loss of specific human capital associated with switching industries creates industry gaps in skill premiums. It hinders inter-industry labor mobility and promotes intra-industry skill upgrading. However, firms can compress wages if they have some bargaining power. Compared with the former circumstance of no wage compression, the latter will also come across four cases of inter-industry labor mobility and similarly affect mobility. Importantly, it will have a considerable impact on education investments. The detailed comparison between no wage compression and wage compression in four cases is illustrated in Table 3.3 and 3.4 of Appendix 3.7. Table 3.3 displays the partial equilibrium when high-skilled labor has more specific human capital, whereas Table 3.4 presents the case where low-skilled labor has higher specific human capital.

Since the loss of specific human capital hinders workers from changing jobs across industries, workers do not get paid for their marginal product. Firms can pay the same to their original workers as to the workers coming from another industry. It is

Table 3.1: Partial Equilibrium with No Wage Compression

<table>
<tr><td></td><td>$\theta < \eta$
High-skilled labor is more specific</td><td>$\theta \geqslant \eta$
Low-skilled labor is more specific</td></tr>
<tr><td>High- and low-skilled labor switches to industry J
$MP_J^{H'}\theta > W_{I,0}^H$
$MP_J^{L'}\eta > W_{I,0}^L$</td><td>$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta = W_{I,1}^L$
$\omega_{J,1} > \omega_{I,1}$
Less relative high-skilled to low-skilled labor switches industries.
If $W_{I,1}^H - W_{I,1}^L \geqslant C$,
upgrade skills in both industries.
If $W_{I,1}^H - W_{I,1}^L < C$,
upgrade skills only in industry J.
If $W_{J,1}^H - W_{J,1}^L < C$,
no skill upgrading.</td><td>$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta = W_{I,1}^L$
$\omega_{J,1} \leqslant \omega_{I,1}$
More relative high-skilled to low-skilled labor switches industries.
If $W_{J,1}^H - W_{J,1}^L \geqslant C$,
upgrade skills in both industries.
If $W_{J,1}^H - W_{J,1}^L < C$,
upgrade skills only in industry I.
If $W_{I,1}^H - W_{I,1}^L < C$,
no skill upgrading.</td></tr>
<tr><td>Only high-skilled labor switches to industry J
$MP_J^{H'}\theta > W_{I,0}^H$
$MP_J^{L'}\eta < W_{I,0}^L$</td><td>$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta < W_{I,1}^L$
$\omega_{J,1} > \omega_{I,1}$
Skill upgrading more likely happens in industry J.
Both skill premiums increase.</td><td>$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta < W_{I,1}^L$
If $W_{J,1}^L\theta \leqslant W_{I,1}^L$, $\omega_{J,1} \geqslant \omega_{I,1}$, and skill upgrading more likely happens in industry J.
If $W_{J,1}^L\theta > W_{I,1}^L$, $\omega_{J,1} < \omega_{I,1}$, and skill upgrading more likely happens in industry I.
Skill premium in industry I increases.</td></tr>
<tr><td>Only low-skilled labor switches to industry J
$MP_J^{H'}\theta < W_{I,0}^H$
$MP_J^{L'}\eta > W_{I,0}^L$</td><td>$W_{J,1}^H\theta < W_{I,1}^H$, $W_{J,1}^L\eta = W_{I,1}^L$
If $W_{J,1}^H\eta \geqslant W_{I,1}^H$, $\omega_{J,1} \geqslant \omega_{I,1}$, and skill upgrading can only happen in industry J.
If $W_{J,1}^H\eta < W_{I,1}^H$, $\omega_{J,1} < \omega_{I,1}$, and no skill upgrading.</td><td>Not applicable</td></tr>
<tr><td>No switch
$MP_J^{H'}\theta < W_{I,0}^H$
$MP_J^{L'}\eta < W_{I,0}^L$</td><td>$W_{J,1}^H > W_{I,1}^H = W_{I,0}^H$
$W_{J,1}^L > W_{I,1}^L = W_{I,0}^L$
$\omega_{J,1} > \omega_{I,1}$
Skill upgrading can only happen in industry J, if $W_{J,1}^H - W_{J,1}^L \geqslant C$.
No skill upgrading in industry I.</td><td>$W_{J,1}^H > W_{I,1}^H = W_{I,0}^H$
$W_{J,1}^L > W_{I,1}^L = W_{I,0}^L$
$\omega_{J,1} > \omega_{I,1}$
Skill upgrading can only happen in industry J, if $W_{J,1}^H - W_{J,1}^L \geqslant C$.
No skill upgrading in industry I.</td></tr>
</table>

Notes: This table summarizes four cases of inter-industry labor mobility after a technology shock in industry J. It shows the partial equilibrium for those cases under the assumption of no wage compression. Because of the specificity of human capital, workers switching industries earn wages lower than their marginal products. The table compares cases when high-skilled labor has more specific human capital and when low-skilled labor has more specific human capital. High-skilled labor has a transferable rate θ, and low-skilled labor has a transferable rate η. When $\theta < \eta$, high-skilled labor is more specific, and when $\theta > \eta$, low-skilled labor is more specific.

worth noting that this is different from the wage compression in Acemoglu and Pischke (1999). In this analysis, at the start of the adjustment, employers in J can not lower wages further to employees' outside option, which employees would receive from another industry. The underlying reason is that the expanding industry can not attract workers from another industry if wages are the same across industries. As workers move from I to J, the mobility effect decreases wages in J and increases those in I until they are equal. As a result, in the partial equilibrium, I arrive at the following conditions: $MP^H_{J,1}\theta = W^H_{J,1} = W^H_{I,1}$, and $MP^L_{J,1}\eta = W^L_{J,1} = W^L_{I,1}$. There is one universal skill premium. Therefore, firms can reap some of the benefits of the productivity growth caused by SBTC and invest in skill upgrading.

Table 3.2 juxtaposes skill upgrading under two circumstances: no wage compression and wage compression. Skill upgrading may also face four scenarios, corresponding to how sizeable wage differentials are and how expensive education costs are. The first scenario considers that wage differentials are large enough to cover education costs in both industries. When wages are not compressed, skill premiums are discrepant. The industry that has a higher skill premium has more skill upgrading. Moreover, low-skilled workers pay education costs themselves to upgrade their skills no matter where they are.

On the contrary, wage compression drives skill premiums equally. However, this universal skill premium still needs to be higher than education costs. This is because low-skilled workers in I still need to pay for skill upgrading if they want a high-skilled job. The more profound difference is that their counterparts at the same skill level in J have fewer burdens and more chances to upgrade skills. The reason is that firms in J have the incentives and benefits to invest in skill upgrading. They make profits, a part of marginal products, from compressing wages. They gain $MP^H_{J,1} - W^H_{J,1}$ from high-skilled and $MP^L_{J,1} - W^L_{J,1}$ from low-skilled labor. If firms make more profit from high-skilled labor, they will invest in skill upgrading. The profit of upgrading a low-skilled worker is the difference between the profits from a high-skilled and a low-skilled worker, expressed as $(MP^H_{J,1} - W^H_{J,1}) - (MP^L_{J,1} - W^L_{J,1})$. Rearranging it, we can express the profit of skill upgrading by subtracting the cost $(W^H_{J,1} - W^L_{J,1})$ from the benefit $(MP^H_{J,1} - MP^L_{J,1})$. This profit determines how much firms invest in education. If $(MP^H_{J,1} - MP^L_{J,1}) - (W^H_{J,1} - W^L_{J,1}) \geqslant C$, firms will pay for all the education costs. If not, they will pay a maximum of $(MP^H_{J,1} - MP^L_{J,1}) - (W^H_{J,1} - W^L_{J,1})$, and low-skilled workers pay the rest.

What makes high-skilled labor more profitable? Firms reap more high-skilled labor's marginal products if high-skilled labor faces worse outside opportunities. The high loss of human capital as in mobility costs plays a vital role in preventing inter-industry labor mobility and thereby determines how firms compress wages. The more specific human capital the high-skilled labor has, the more the firms compress the wage structure. And this leads to more profits. Thus, if high-skilled labor has a higher specificity rate than low-skilled labor, firms pay more to upgrade low-skilled ones.

In the second scenario, low-skilled workers in I can not afford to upgrade their skills, no matter whether wages are compressed or not. If there is wage compression, the conclusion is similar to the above scenario, except the equalized wage differential can not compensate for education costs. However, when there is no wage compression, the skill premium in J must be higher than that in I. This includes situations when it is harder for high-skilled labor to switch industries, when only high-skilled or low-skilled labor switches to J, and when the costs are too high for both skill levels to move to another industry. Even though wages are not compressed, how skills would be upgraded pivots on specificity rates.

The opposite scenario is that there is skill upgrading only in industry I. This can never happen when wages are compressed in J. Wage compression especially favors skill upgrading in J. In contrast, industry I can have a higher skill premium than that in J, when there is no wage compression, and it is easier for high-skilled rather than low-skilled labor to transfer human capital. In this case, low-skilled labor has more specific human capital and would lose it when they switch industries. As industry I will lose more high-skilled labor, the increasing wage of high-skilled attracts more low-skilled labor to invest in skills.

Last but not least, skill upgrading could not occur in any industry. In both circumstances, wage differentials are not large enough to compensate for education costs. When education costs are too expensive, low-skilled labor can not afford the total education costs. Furthermore, they can not afford part of the education costs, even when firms share part of the costs. This demonstrates that skill upgrading is too costly, and the productivity gain can not compensate. In the circumstance of wage compression, $MP^H_{J,1} - MP^L_{J,1} \leqslant C$, meaning the increase in the marginal product from skill upgrading, is lower than education costs.

Overall, wage compression assists skill upgrading, especially when high-skilled labor has higher specific human capital than low-skilled labor. It is hard to attract high-skilled labor from another industry. Accordingly, firms in industry J can invest more in skill upgrading as long as education costs are not too expensive. In this case, industry-specific SBTC would not give rise to high skill premiums. Some empirical research provides evidence of wage expression. For example, Barron et al. (1999) and Hidalgo et al. (2014) find that low-skilled labor does not have a significant increase in their wages after participating in training. On the contrary, TC, even favoring high skills, benefits both high- and low-skilled labor. The contradiction between economic growth and equality has never been fully resolved, although we always attempt to reconcile this contradiction. The important point to grasp is equality can be ensured by curtailing the benefits of those who are better off.

How Does the Price Effect Play a Role?

The previous analysis focuses on a partial equilibrium and shows that the specificity of human capital can mitigate the mobility effect and protect the shrinking industry. Now suppose product prices can change. As is analyzed in Section 3.3.2, the elasticity of substitute affects how prices change and bring about the price effect. The price effect reduces the mobility effect, decreasing labor mobility from the shrinking industry to the innovating one. In turn, the mobility effect influences the price effect. When a labor market is imperfect, the specificity and the price effect will mitigate the mobility effect together and reduce inter-industry mobility further. The latter effect will not alter the preceding conclusions about how specificity affects adjustments in the partial equilibrium, but it adds more possible cases. More importantly, the price effect decreases wages. The more substitutable the goods are, the lower the product prices will be. Low prices lower wages and diminish skill upgrading. Therefore, for the innovating industry, it is difficult not only to attract high-skilled labor but also to upgrade skills.

In the general equilibrium, if goods are complementary, the expanding supply of J will give rise to increases in the price of I. While rising, the relative price between I and J manifests the price effect and brings about the reverse mobility of low-skilled labor from J to I. Consequently, this leads to two more cases when there is specific human capital. Table 3.5 of Appendix 3.7 shows the total six cases in the general equilibrium with more specific high-skilled labor and compares the cases with and without wage compression. As is shown in the table, the first four cases have similar results as those in the partial equilibrium. In addition, when high-skilled labor switches to J and low-skilled labor switches to I reversely, industry J has a higher skill premium. When high-skilled labor has too much specific human capital and goods are highly complementary, only low-skilled labor will move to I, industry I could benefit from TC in J.

As a consequence, the price effect, together with the influence of specificity, can protect the shrinking industry to a great extent. On the other hand, it also hampers the development of the expanding industry. The price effect and the effect of specificity decrease the degree of reaction of the labor market to technology shocks considerably and make inter-industry labor mobility and skill upgrading difficult. Wage compression and education policy would be more crucial to skill upgrading in the general equilibrium.

Table 3.2: Skill Upgrading with or without Wage Compression

	No Wage Compression	Wage Compression
Skill upgrading in both industries	Skill premiums are different across industries. $W^H_{I,1} - W^L_{I,1} > C$, $W^H_{J,1} - W^L_{J,1} > C$ When both types of labor switches to industry J. When $\theta < \eta$ and only high-skilled labor switches to industry J. Low-skilled labor pays for education in both industries. The industry that has a higher skill premium has more skill upgrading.	Skill premiums are equal. When both types of labor switches to industry J. When only high-skilled labor switches to industry J. In industry I, $W^H_{I,1} - W^L_{I,1} > C$, and low-skilled labor pays for education. In industry J, if $(MP^H_{J,1} - MP^L_{J,1}) - (W^H_{J,1} - W^L_{J,1}) \geqslant C$, employers pay for skill upgrading; if $(MP^H_{J,1} - MP^L_{J,1}) - (W^H_{J,1} - W^L_{J,1}) < C$, employers pay a maximum of $(MP^H_{J,1} - MP^L_{J,1}) - (W^H_{J,1} - W^L_{J,1})$, and low-skilled labor pays $C - (MP^H_{J,1} - MP^L_{J,1}) + (W^H_{J,1} - W^L_{J,1})$. More skill upgrading in industry J.
Skill upgrading only in industry J	$W^H_{I,1} - W^L_{I,1} \leqslant C$, $W^H_{J,1} - W^L_{J,1} > C$ $\omega_{J,1} > \omega_{I,1}$ When $\theta < \eta$ and only low-skilled labor switches to industry J. When there is no switching. Low-skilled labor pays for education in industry J.	$W^H_{I,1} - W^L_{I,1} = W^H_{J,1} - W^L_{J,1} \leqslant C$ When $\theta < \eta$ and only low-skilled labor switches to industry J. When there is no switching. In industry J, if $(MP^H_{J,1} - MP^L_{J,1}) - (W^H_{J,1} - W^L_{J,1}) \geqslant C$, employers pay for skill upgrading; if $(MP^H_{J,1} - MP^L_{J,1}) - (W^H_{J,1} - W^L_{J,1}) < C$, employers pay a maximum of $(MP^H_{J,1} - MP^L_{J,1}) - (W^H_{J,1} - W^L_{J,1})$, and low-skilled labor pays $C - (MP^H_{J,1} - MP^L_{J,1}) + (W^H_{J,1} - W^L_{J,1})$.
Skill upgrading only in industry I	$W^H_{I,1} - W^L_{I,1} > C$, $W^H_{J,1} - W^L_{J,1} \leqslant C$ $\omega_{J,1} < \omega_{I,1}$ When $\theta \geqslant \eta$ and only high-skilled labor switches to industry J. Low-skilled labor pays for education in I.	Not applicable
No skill upgrading	$W^H_{I,1} - W^L_{I,1} \leqslant C$, $W^H_{J,1} - W^L_{J,1} \leqslant C$	$W^H_{I,1} - W^L_{I,1} = W^H_{J,1} - W^L_{J,1} \leqslant C$ $MP^H_{J,1} - MP^L_{J,1} \leqslant C$

Notes: This table shows skill upgrading in the partial equilibrium after a technology shock in industry J. It demonstrates in which cases skill upgrading will happen. It compares those cases under two circumstances: no wage compression and wage compression.

3.5 Policy Implications

As discussed in previous sections, in the responses to technology shocks, the specificity of human capital can depress inter-industry labor mobility but encourage skill upgrading. Furthermore, firms with more bargaining power can compress the wages of high-skilled labor and invest in upgrading the skills of low-skilled labor. Last but not least, if products are highly substitutable and high-skilled labor has more specific human capital, the expanding industry will hardly attract high-skilled labor and upgrade skills to a small extent. Policy-making should focus on facilitating the adjustments to technology shocks. Policymakers should consider different factors and different economic contexts to coordinate distinct policies. In this section, I will illustrate the policy implications of this paper and the potential options for developing existing programs and policies.

Before policymakers try to help make better policy options, they should understand the overall economy, industry developments, and the skill composition of labor forces. They also should consider various factors while making labor market policies and education investments. Those factors include the specificity of human capital, the bargaining power of firms in the target industry, product markets, and education costs. In particular, we need to pay close attention to the main focus of this paper, specificity. There is no consensus about how to measure specificity. Christenko et al. (2020) propose two main dimensions to measure the specificity of human capital, including skill specificity (transferability of skills) and economic factors. The former depends on the types of skills acquired in education and gained as part of learning by doing. The latter refers to the ease of switching jobs, depending on labor market frictions, institutions, etc. Hence, labor market policies and human capital enhancing programs aiming at acquiring skills are vital for human capital specificity and thus for the adjustments to technological progress. There are specific questions, described next, that policymakers should consider in identifying and evaluating their policy options. What is the objective of policy-making? How specialized is the economy? Do firms in target industries have bargaining power? How expensive are education investments? If the economy is not specialized, high skills are more specific, and firms do not have bargaining power, there will be a big obstacle to expanding industries. Hence, labor market policies and education investment policies need to adapt accordingly.

3.5.1 Labor Market Policies

There are various labor market policies, programs, and institutions. They have distinct objectives. They never exist in isolation because they complement each other to avoid the undesirable effects of one single institution (Boeri & van Ours, 2013). They influence how flexible and efficient a labor market is.

Iversen and Soskice (2001) propose that specific skills, which are valuable only within a single firm or industry, are risky investments, so employees with specific skills demand more job security regulations. On the contrary, Emmenegger (2009) supports Goldthorpe (2000)'s reasoning that employees with highly specific skills are difficult to replace, so they are less concerned about losing their jobs. The analysis of this paper agrees with the latter reasoning. In a growing industry, when high-skilled labor has specific skills and is in high demand, they do not need to worry about job security. It is the same in a declining industry, and specificity can protect the loss of human capital. Therefore, policymakers can apply less strict job security regulations, such as moderate employment protection legislation (EPL). It suggests whether to adopt a strict job security regulation or not depends on the goal of policy-making. If the goal is to assist the expanding industry to grow and that industry is distinct, a less strict EPL can reduce mobility costs. If the goal is to protect the declining industry, a strict EPL and subsidies for skill upgrading could benefit both industries. In addition, another question to consider is how specialized the economy is. If the economy is highly specialized, products are highly substitutable. My analysis also suggests that when products are highly substitutable (competitive product markets), the wages in the expanding industry will still be appealing to labor to switch jobs, compared with complementary products. If the economy is not specialized, products are more complementary. In this case, the price effect will hinder labor mobility. It will be difficult for the low-tech industry to expand. In this case, a less strict job security regulation is preferred, such as unemployment benefits (Boeri & van Ours, 2013).

The trade union is another key labor market institution. They bargain with employers on a collective basis, and they tend to pursue egalitarian wage policies by compressing wage structure (Boeri & van Ours, 2013). Research about the effect of unions shows that unions raise the wages of low-wage workers (or low-skilled workers) but reduce their employment (e.g., Card et al., 2020; Frandsen, 2012; Schmitt, 2008; Vogel, 2007). The negative effect is that the specificity of human capital confers bargaining power on workers. Unions can help to enhance the acquisition of specific knowledge and skills by workers (Williamson, 1975). Workers with experience and training are hard to replace, and thus they can renegotiate their wages. It is consistent with the previous reasoning that workers with specific skills are difficult to substitute (Goldthorpe, 2000). As a result, this causes problems for innovative sectors requiring considerable investment in human capital (Boeri & van Ours, 2013). Bradley et al. (2017) find that innovation activities decrease considerably after firms elect to unionize. According to the analysis of this paper, firms with bargaining power can invest more in skill upgrading. Unions can influence the bargaining power of firms and thus skill upgrading. To develop the low-tech industry, policymakers should consider collective bargaining at the industry level. The unions in the innovating industry can help compress high-skilled workers' wages and increase low-skilled workers' wages, making skill upgrading more profitable for firms. In the presence of the specificity of human capital, the equilibrium wages can not be equal across industries because of productivity differentials. If centralized agreements make wages equal, centralized wages are higher than the equilibrium wages in the declining industry, increasing unemployment in that industry. Thereby, unions should assist in upgrading skills instead of raising wages for low-skilled labor in the declining industry. It is consistent with Boeri and van Ours (2013)'s observation. They present that countries with an intermediate degree of bargaining centralization (industry-level) would achieve better economic performance.

While EPL and unions tend to increase the degree of specificity and reduce labor mobility across jobs, firms, and industries, active labor market policies (ALMPs) are designed to stimulate mobility and facilitate responses to structural changes. ALMPs aim at improving the labor market outcomes of unemployed workers. Those ALMP programs include job search assistance, training, and subsidized employment (Crépon & van den Berg, 2016). There is substantial variation in training programs, from acquiring a general education and skills to the type of apprenticeship (Crépon & van den Berg, 2016). Caliendo et al. (2017) evaluate German active labor market policy that offers a subsidy covering moving costs to incentivize unemployed job seekers to search/accept jobs in distant regions. It shows that subsidies for skill upgrading increase the supply of high-skilled labor. Many studies find little evidence that ALMPs are effective at reducing unemployment and enhancing skills of the labor force (e.g., Card et al., 2011; Forslund & Krueger, 1997). On the aggregate level, the total effect of ALMPs may be ambiguous because of the general equilibrium effects (Boeri & van Ours, 2013; Caliendo et al., 2017). As is shown in this paper, the price effect and the effect of specificity can mitigate the responses of the labor market to technology shocks. The price effect plays a vital role in affecting the impact of ALMPs. Card et al. (2018) conduct a meta-analysis of over 200 recent studies of active labor market programs. They conclude that programs that emphasize human capital accumulation have larger average gains. Accordingly, my analysis suggests that instead of designing programs to cultivate demand, policymakers should propose programs that shift supply in specific industries and regions. Moreover, training and retraining programs should target expanding industries or jobs.

3.5.2 Education Investments

Labor market policies can assist in reducing mobility costs, reallocation of labor of different skill levels, and enhancing human capital. Despite those policies, governments can make a profound impact on education and training by cutting costs for individuals to invest in human capital. Governments invest in education and training is vital for human capital accumulation and economic growth.

As discussed before, the first question to think about is how specialized the economy is. If products are substitutes, the economy is specialized in specific products. The price effect will be slight. Nevertheless, it will still mitigate the effects of technology shocks. It will make investments in skill upgrading less profitable. Heckman et al. (1998) find that the general-equilibrium impacts of tuition fees on college enrollment are smaller than the micro-econometric treatment effects. To enhance total human capital and reduce wage inequality, governments need to invest in relatively higher education.

The second question to examine is how specific human capital is. If the specificity rate of high-skilled labor is much higher than the specificity rate of low-skilled labor, it will be more beneficial to upgrade skills than reallocate high-skilled labor. Workers can increase their specific human capital through on-the-job training. Ferreira et al. (2017) find that employees who participated in training or informal learning exhibited greater improvement in their skills than those who did not. If the objective of a policy is to protect the declining industry, governments should encourage firms to invest in on-the-job training. Subsequently, another question is who pays for education or training. The answer depends on the bargaining power of firms. If firms have bargaining power, they can curtail the benefits of high-skilled workers and invest in low-skilled ones. There will be skill upgrading without government investments. Barron et al. (1999) and Van de Wiele (2010) illustrate that firms pay most of the cost for on-the-job training. Even if so, governments still need to enhance human capital when education costs are considerably expensive or provide retraining services to help reallocate workers to new industries.

On the whole, if the economy is highly specialized, high-skilled labor has high specific human capital, and firms do not have bargaining power, industries with technology shocks will face a huge hurdle to attracting high-skilled labor. If education costs are expensive, skill upgrading is difficult for individuals. Workers do not invest in higher education often because of financial constraints. Consequently, firms can not hire enough high-skilled workers to develop. In the end, technology shocks can not be transformed into economic growth. To adjust the labor market to technology shocks, governments should emphasize upgrading skills. Kugler et al. (2020) examine a large-scale vocational training program for disadvantaged youth in Colombia. They find that training helped relax credit constraints, so trainees were more likely to enroll in formal tertiary education, and their relatives were more likely to complete secondary schooling. Hence, governments need to invest in education to reduce education costs, especially for individuals with financial constraints.

3.6 Conclusion

Many countries' industrial strategy focuses on technologically emerging industries. Technological progress will change the demand for skills. It will inevitably affect the labor market in the future. In the long run, the change in population and education policies can increase the supply of high-skilled labor and thus change labor composition. In the short run, it is difficult to change the skill composition of the workforce. When the supply can not adjust to meet the demand, high-skilled workers become a scarce resource.

This paper theoretically explores how the labor market adjusts to industry-specific technology shocks in the short run. In particular, I analyze to what extent SBTC and human capital specificity can affect the labor market's response to technology shocks. I compare the outcomes with perfect and imperfect inter-industry labor mobility.

My analysis illustrates that in the partial equilibrium of a competitive labor market, the expanding industry, after a technology shock, attracts both high- and low-skilled labor, and more high-skilled labor would switch industries. It is more likely to have skill upgrading in both industries. In the general equilibrium, the elasticity of substitution between two goods plays a crucial role in labor mobility. When the elasticity of substitution is large, products are more substitutable, and there will be more labor mobility. The price effect mitigates the mobility effect. Together both effects equalize wages of the same skill level across industries.

When skills are not fully transferable, inter-industry labor mobility is not perfect. In the partial equilibrium of an imperfect labor market, when high-skilled labor has more specific human capital than low-skilled labor, the skill premium will be higher in the expanding industry than in the contracting one. This is consistent with the empirical finding from Bos and Li (2022). In that paper, we found that high-skilled workers are more likely to be overcompensated in high-skilled intensive industries. There will be relatively fewer high-skilled workers switching industries but more skill upgrading in the expanding industry. If the cost of inter-industry mobility is too high for both skill levels, the technologically changing industry can only develop by investing in education. Moreover, wage compression assists skill upgrading, especially when high-skilled labor has higher specific human capital than low-skilled labor. In this case, industry-specific TC would not give rise to high skill premiums. Furthermore, the price effect and the effect of specificity mitigate the reaction of the labor market to technology shocks and make inter-industry labor mobility and skill upgrading difficult.

This paper provides implications for labor market policies and education investments. Before making decisions, policymakers should understand the overall economy, industry developments, and the skill composition of the labor force. They also should consider four crucial factors for decision-making. These factors contain the specificity of human capital, the bargaining power of firms, product markets, and education costs.

The specificity of human capital is the main focus of this paper, but there are other labor market frictions, which will increase mobility costs between industries. Future research can include other labor market frictions, for example, job search costs. In addition, we can consider Christenko et al. (2020)' method to empirically measure the specificity of human capital. Another key factor that can influence specificity rates is skill-relatedness between industries. Skill-relatedness measures how industries are connected to one another in terms of their human-capital requirements (Neffke et al., 2017). For future research, if we can measure the specificity of human capital, we can empirically test the following hypotheses. First, high-skilled labor has more specific human capital than low-skilled labor. Second, the higher specificity of human capital, the less inter-industry labor mobility. Third, if the transferable rate of high-skilled labor is much lower than that of low-skilled labor, the difference between skill premiums in different industries is higher. Fourth, if the specificity rate of high-skilled labor is much higher than the specificity rate of low-skilled labor, there will be more skill upgrading.

3.7 Appendix

Table 3.3: Partial Equilibrium with More Specific High-Skilled Labor

$\theta < \eta$	No Wage Compression	Wage Compression
High- and low-skilled labor switches to industry *J* $MP_J^{H'}\theta > W_{I,0}^H$ $MP_J^{L'}\eta > W_{I,0}^L$	$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta = W_{I,1}^L$ $\omega_{J,1} > \omega_{I,1}$ $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L - \sigma\ln\eta$ Low-skilled labor pays for education. If $W_{I,1}^H - W_{I,1}^L \geqslant C$, upgrade skills in both industries. If $W_{J,1}^H - W_{J,1}^L \geqslant C$ and $W_{I,1}^H - W_{I,1}^L < C$, upgrade skills in industry *J*. If $W_{J,1}^H - W_{J,1}^L < C$ and $W_{I,1}^H - W_{I,1}^L < C$, no skill upgrading.	$MP_{J,1}^H\theta = W_{J,1}^H = W_{I,1}^H$ $MP_{J,1}^L\eta = W_{J,1}^L = W_{I,1}^L$ $\omega_{J,1} = \omega_{I,1}$ $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L - \sigma\ln\eta$ In industry *I*, if $W_{I,1}^H - W_{I,1}^L > C$, low-skilled labor pays for education. In industry *J*, if $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L) \geqslant C$, employers pay for skill upgrading; if $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L) < C$, employers pay a maximum of $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L)$, and low-skilled labor pays $C - (MP_{J,1}^H - MP_{J,1}^L) + (W_{J,1}^H - W_{J,1}^L)$.
Only high-skilled labor switches to industry *J* $MP_J^{H'}\theta > W_{I,0}^H$ $MP_J^{L'}\eta < W_{I,0}^L$	$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta < W_{I,1}^L$ $\omega_{J,1} > \omega_{I,1}$ Both skill premiums increase. $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L = 0$ Same skill upgrading as the first case.	$MP_{J,1}^H\theta = W_{J,1}^H = W_{I,1}^H$ $MP_{J,1}^L\eta < W_{J,1}^L = W_{I,1}^L$ Both skill premiums increase. $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L = 0$ Same skill upgrading as the first case.
Only low-skilled labor switches to industry *J* $MP_J^{H'}\theta < W_{I,0}^H$ $MP_J^{L'}\eta > W_{I,0}^L$	$W_{J,1}^H\theta < W_{I,1}^H$, $W_{J,1}^L\eta = W_{I,1}^L$ $\omega_{J,1} \geqslant \omega_{I,1}$ or $\omega_{J,1} < \omega_{I,1}$ Skill premium in industry *I* decreases. $\Delta\ln\mu_1^H = 0$, $\Delta\ln\mu_1^L - \sigma\ln\eta$ Low-skilled labor pays for education. If $\omega_{J,1} \geqslant \omega_{I,1}$, skill upgrading can only happen in industry *J*. If $\omega_{J,1} < \omega_{I,1}$, no skill upgrading.	$MP_{J,1}^H\theta < W_{J,1}^H = W_{I,1}^H$ $MP_{J,1}^L\eta = W_{J,1}^L = W_{I,1}^L$ Both skill premiums decrease. $\Delta\ln\mu_1^H = 0$, $\Delta\ln\mu_1^L - \sigma\ln\eta$ No skill upgrading in industry *I*. In industry *J*, same skill upgrading as the first case.
No switch $MP_J^{H'}\theta < W_{I,0}^H$ $MP_J^{L'}\eta < W_{I,0}^L$	$W_{J,1}^H > W_{I,1}^H = W_{I,0}^H$ $W_{J,1}^L > W_{I,1}^L = W_{I,0}^L$ $\omega_{J,1} > \omega_{I,1}$ Low-skilled labor pays for education. No skill upgrading in industry *I*. If $W_{J,1}^H - W_{J,1}^L \geqslant C$, upgrade skills in industry *J*. If $W_{J,1}^H - W_{J,1}^L < C$, no skill upgrading.	$W_{J,1}^H = W_{I,1}^H = W_{I,0}^H$ $W_{J,1}^L = W_{I,1}^L = W_{I,0}^L$ Skill premiums stay the same. No skill upgrading in industry *I*. In industry *J*, same skill upgrading as the first case.

Notes: This table summarizes four cases of inter-industry labor mobility after a technology shock in industry *J*. It shows the partial equilibrium for those cases when high-skilled labor has more specific human capital. It compares cases under two circumstances: no wage compression and wage compression.

Table 3.4: Partial Equilibrium with More Specific Low-Skilled Labor

$\theta \geqslant \eta$	No Wage Compression	Wage Compression
High- and low-skilled labor switches to industry J $MP_J^{H'}\theta > W_{I,0}^H$ $MP_J^{L'}\eta > W_{I,0}^L$	$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta = W_{I,1}^L$ $\omega_{J,1} \leqslant \omega_{I,1}$ $\Delta \ln \mu_1^H - \sigma \ln \theta$, $\Delta \ln \mu_1^L - \sigma \ln \eta$ Low-skilled labor pays for education. If $W_{J,1}^H - W_{J,1}^L \geqslant C$, upgrade skills in both industries. If $W_{I,1}^H - W_{I,1}^L \geqslant C$ and $W_{J,1}^H - W_{J,1}^L < C$, upgrade skills in industry J. If $W_{I,1}^H - W_{I,1}^L < C$ and $W_{J,1}^H - W_{J,1}^L < C$, no skill upgrading.	$MP_{J,1}^H\theta = W_{J,1}^H = W_{I,1}^H$ $MP_{J,1}^L\eta = W_{J,1}^L = W_{I,1}^L$ $\omega_{J,1} = \omega_{I,1}$ $\Delta \ln \mu_1^H - \sigma \ln \theta$, $\Delta \ln \mu_1^L - \sigma \ln \eta$ In industry I, if $W_{I,1}^H - W_{I,1}^L > C$, low-skilled labor pays for education. In industry J, if $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L) \geqslant C$, employers pay for skill upgrading; if $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L) < C$, employers pay a maximum of $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L)$, and low-skilled labor pays $C - (MP_{J,1}^H - MP_{J,1}^L) + (W_{J,1}^H - W_{J,1}^L)$.
Only high-skilled labor switches to industry J $MP_J^{H'}\theta > W_{I,0}^H$ $MP_J^{L'}\eta < W_{I,0}^L$	$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta < W_{I,1}^L$ $\omega_{J,1} \geqslant \omega_{I,1}$ or $\omega_{J,1} < \omega_{I,1}$ Skill premium in industry I increases. $\Delta \ln \mu_1^H - \sigma \ln \theta$, $\Delta \ln \mu_1^L = 0$ Low-skilled labor pays for education. If $\omega_{J,1} \geqslant \omega_{I,1}$, skill upgrading more likely happens in industry J. If $\omega_{J,1} < \omega_{I,1}$, skill upgrading more likely happens in industry I.	$MP_{J,1}^H\theta = W_{J,1}^H = W_{I,1}^H$ $MP_{J,1}^L\eta < W_{J,1}^L = W_{I,1}^L$ Both skill premiums increase. $\Delta \ln \mu_1^H - \sigma \ln \theta$, $\Delta \ln \mu_1^L = 0$ Same skill upgrading as the first case.
No switch $MP_J^{H'}\theta < W_{I,0}^H$ $MP_J^{L'}\eta < W_{I,0}^L$	$W_{J,1}^H > W_{I,1}^H = W_{I,0}^H$ $W_{J,1}^L > W_{I,1}^L = W_{I,0}^L$ $\omega_{J,1} > \omega_{I,1}$ Low-skilled labor pays for education. No skill upgrading in industry I. If $W_{J,1}^H - W_{J,1}^L \geqslant C$, upgrade skills in industry J. If $W_{J,1}^H - W_{J,1}^L < C$, no skill upgrading.	$W_{J,1}^H = W_{I,1}^H = W_{I,0}^H$ $W_{J,1}^L = W_{I,1}^L = W_{I,0}^L$ Skill premiums stay the same. No skill upgrading in industry I. In industry J, same skill upgrading as the first case.

Notes: This table summarizes three cases of inter-industry labor mobility after a technology shock in industry J. It shows the partial equilibrium for those cases when low-skilled labor has more specific human capital. It compares cases under two circumstances: no wage compression and wage compression.

Table 3.5: General Equilibrium with More Specific High-Skilled Labor

$\theta < \eta$	No Wage Compression	Wage Compression
High- and low-skilled labor switches to industry J $MP_J^{H'}\theta > W_I^{H'}$ $MP_J^{L'}\eta > W_I^{L'}$	$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta = W_{I,1}^L$ $\omega_{J,1} > \omega_{I,1}$ $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L - \sigma\ln\eta$ Low-skilled labor pays for education. If $W_{I,1}^H - W_{I,1}^L \geqslant C$, upgrade skills in both industries. If $W_{J,1}^H - W_{J,1}^L \geqslant C$ and $W_{I,1}^H - W_{I,1}^L < C$, upgrade skills in industry J. If $W_{J,1}^H - W_{J,1}^L < C$ and $W_{I,1}^H - W_{I,1}^L < C$, no skill upgrading.	$MP_{J,1}^H\theta = W_{J,1}^H = W_{I,1}^H$ $MP_{J,1}^L\eta = W_{J,1}^L = W_{I,1}^L$ $\omega_{J,1} = \omega_{I,1}$ $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L - \sigma\ln\eta$ In industry I, if $W_{I,1}^H - W_{I,1}^L > C$, low-skilled labor pays for education. In industry J, if $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L) \geqslant C$, employers pay for skill upgrading; if $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L) < C$, employers pay a maximum of $(MP_{J,1}^H - MP_{J,1}^L) - (W_{J,1}^H - W_{J,1}^L)$, and low-skilled labor pays $C - (MP_{J,1}^H - MP_{J,1}^L) + (W_{J,1}^H - W_{J,1}^L)$.
Only high-skilled labor switches to industry J $MP_J^{H'}\theta > W_I^{H'}$ $MP_J^{L'}\eta < W_I^{L'}$	$W_{J,1}^H\theta = W_{I,1}^H$, $W_{J,1}^L\eta < W_{I,1}^L$ $\omega_{J,1} > \omega_{I,1}$ $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L = 0$ Same skill upgrading as the first case.	$MP_{J,1}^H\theta = W_{J,1}^H = W_{I,1}^H$ $MP_{J,1}^L\eta < W_{J,1}^L = W_{I,1}^L$ $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L = 0$ Same skill upgrading as the first case.
Only low-skilled labor switches to industry J $MP_J^{H'}\theta < W_I^{H'}$ $MP_J^{L'}\eta > W_I^{L'}$	$W_{J,1}^H\theta < W_{I,1}^H$, $W_{J,1}^L\eta = W_{I,1}^L$ $\omega_{J,1} \geqslant \omega_{I,1}$ or $\omega_{J,1} < \omega_{I,1}$ The more substitutable the goods are, the lower wages in industry I. $\Delta\ln\mu_1^H = 0$, $\Delta\ln\mu_1^L - \sigma\ln\eta$ If $\omega_{J,1} \geqslant \omega_{I,1}$, skill upgrading can only happen in industry J. If $\omega_{J,1} < \omega_{I,1}$, no skill upgrading.	$MP_{J,1}^H\theta < W_{J,1}^H = W_{I,1}^H$ $MP_{J,1}^L\eta = W_{J,1}^L = W_{I,1}^L$ The more substitutable the goods are, the lower wages. $\Delta\ln\mu_1^H = 0$, $\Delta\ln\mu_1^L - \sigma\ln\eta$ No skill upgrading in industry I. In industry J, same skill upgrading as the first case.
No switch $MP_J^{H'}\theta < W_I^{H'}$ $MP_J^{L'}\eta < W_I^{L'}$	$W_{J,1}^H\theta < W_{I,1}^H$, $W_{J,1}^L\eta < W_{I,1}^L$ $\omega_{J,1} > \omega_{I,1}$ The more substitutable the goods are, the lower wages in industry I. Skill premium stays the same in industry I. No skill upgrading in industry I. If $W_{J,1}^H - W_{J,1}^L \geqslant C$, upgrade skills in industry J.	$W_{J,1}^H = W_{I,1}^H$, $W_{J,1}^L = W_{I,1}^L$ Skill premiums stay the same. The more substitutable the goods are, the lower wages. No skill upgrading in industry I. In industry J, same skill upgrading as the first case.
High-skilled switches to J Low-skilled switches to I $MP_J^{H'}\theta > W_I^{H'}$ $MP_J^{L'} < W_I^{L'}\eta$	$W_{J,1}^H\theta = W_{I,1}^H$, $W_{I,1}^L\eta = W_{J,1}^L$ $\omega_{J,1} > \omega_{I,1}$ $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L + \sigma\ln\eta$ Same skill upgrading as other cases.	$MP_{J,1}^H\theta = W_{J,1}^H = W_{I,1}^H$ $MP_{I,1}^L\eta = W_{I,1}^L = W_{J,1}^L$ $\Delta\ln\mu_1^H - \sigma\ln\theta$, $\Delta\ln\mu_1^L + \sigma\ln\eta$ Same skill upgrading as other cases.
Only low-skilled labor switches to I $MP_J^{H'}\theta < W_I^{H'}$ $MP_J^{L'} < W_I^{L'}\eta$	$W_{J,1}^H\theta < W_{I,1}^H$, $W_{I,1}^L\eta = W_{J,1}^L$ $\omega_{J,1}^{GE} \geqslant \omega_{I,1}$ or $\omega_{J,1} < \omega_{I,1}$ $\Delta\ln\mu_1^H = 0$, $\Delta\ln\mu_1^L + \sigma\ln\eta$ Same skill upgrading as other cases.	$W_{J,1}^H = W_{I,1}^H$ $MP_{I,1}^L\eta = W_{I,1}^L = W_{J,1}^L$ $\Delta\ln\mu_1^H = 0$, $\Delta\ln\mu_1^L + \sigma\ln\eta$ Same skill upgrading as other cases.

Notes: This table summarizes six cases of inter-industry labor mobility after a technology shock in industry J. It shows the general equilibrium for those cases when high-skilled labor has more specific human capital. It compares cases under two circumstances: no wage compression and wage compression.

4

Mind the Gap: a Global Phillips Curve with Labor Market Frictions

This chapter is co-authored with Jaap Bos (Maastricht University).

4.1 Introduction

Price rises and job losses can change lives and often carry considerable social costs. Managing inflation and curbing unemployment are thereby at the heart of many policymakers' recurring agendas. The relationship between inflation and unemployment is the topic of many debates ever since Phillips (1958) reported a negative correlation between the unemployment rate and nominal wages in the UK. His conclusion that policymakers face a trade-off between managing inflation and lowering unemployment has been the starting point for many policymakers ever since, in particular for many central banks (Mavroeidis et al., 2014).

The notion of the Phillips curve as Phillips (1958) reported it at the time has not withstood the test of time without its critics, however. Empirically, the downward slope of the Phillips curve has certainly flattened in advanced economies, attributable perhaps to changes in firms' and households' expectations (Coibion & Gorodnichenko, 2015; Davig, 2016). Some have gone so far as to suggest that the negative relationship originally reported by Phillips (1958) no longer holds or never has truly existed (Atkeson & Ohanian, 2001; Forder, 2014), while others argue that the Phillips curve is alive and well (Blanchard, 2016; Gordon, 2013; Mankiw & Reis, 2018). Meanwhile, an updated version of the traditional Phillips curve found its way into the analysis of aggregate demand and supply in macroeconomic models (Calvo, 1983; Friedman, 1968; Galí, 2011; Phelps, 1968; Rotemberg, 1982; Taylor, 1980). Throughout, many central banks have continued using the augmented Phillips curve when forecasting prices for policy-making (Mavroeidis et al., 2014).

Regardless of the final outcome of this ongoing debate, the fact of the matter is, that for policymakers, minimizing inflation and unemployment remains very important. And regardless of the shape of the Phillips curve, some countries appear to fair much better than others, achieving the same inflation with much lower levels of unemployment, surviving with the same level of unemployment but much lower levels of inflation, or even 'beating' similar countries on both accounts.

In this paper, we benchmark the extent to which countries are able to minimize inflation and unemployment. In doing so, we build a global best practice frontier, that describes the optimal combinations of low unemployment and inflation that are deemed feasible given the data at hand. We also account for deviations from this frontier and relate those deviations to labor market frictions, in particular to minimum wage, trade union density, and collective bargaining coverage (Babecký et al., 2010; Fallick et al., 2016; Holden & Wulfsberg, 2008). The key consequence of these frictions is that they are often deemed to result in downward nominal wage rigidities (DNWR) (e.g., Daly and Hobijn (2014)). DNWR means that nominal wages do not adjust downwards in response to a decrease in the demand for labor or a decrease in the price level. As a consequence, some countries may - ceteris paribus - drift upwards from the optimal frontier, whereas others are able to maintain a combination of low inflation and unemployment. Drifts can result from downward nominal wage rigidity (Akerlof et al., 1996; Dickens et al., 2007; Fallick et al., 2016), but can be amplified in the presence of shocks (Blanchard & Galí, 2007; Daly & Hobijn, 2014).

Our paper contributes to our understanding of inflation and unemployment policy in four ways. First, we separate the *optimal* trade-off between maintaining low inflation and low unemployment from suboptimal, inefficient drifts from the best practice frontier. Whereas most studies estimate a Phillips curve for an individual country and subsequently compare curves across countries, we build a single frontier but allow for deviations from that frontier. Second, in estimating our best practice frontier, we distinguish between uncertainty and inefficiency and allow both to vary depending on the mix of inflation and unemployment. Third, we investigate whether institutional labor market reforms can help close the gap between the best performing, 'frontier' countries and the rest. Our fourth contribution is that we test whether inefficient countries can move closer to the best-performing countries over time (convergence).

Overall, our results show that there is a significantly negative relationship between inflation and unemployment, though some countries have succeeded in curbing unemployment when keeping low inflation rates. The negative relation is nonlinear, and it becomes more pronounced when inflation rates are lower. In addition, we also find that in a low inflationary environment, it is harder to fight inefficient unemployment and the responses to shocks are more volatile. Sequentially, we find that the gap between efficient performance and inefficient performance can be driven by labor market frictions and different friction indicators can influence the average level of inefficiency distinctly. It illustrates that expanding collective bargaining coverage can reduce the gap, and in contrast, increasing trade union density and minimum wages can enlarge the gap. Finally, our findings show significant convergence across countries, and mostly across low-friction countries. It suggests that high labor market frictions could lower the speed of convergence and hinder the improvement of economic performance.

The remainder of the paper is organized as follows. In Section 4.2, we first briefly review the notion of the Phillips curve. Second, we introduce a model that allows us to estimate the best practice frontier. Next, we show how to close the gaps among countries and how we are able to distinguish between differences in uncertainty and inefficiency along the Philips curve. In Section 4.3, we provide data description and some empirical evidence. We discuss our results in Section 4.4 and conclude in Section 4.5.

4.2 Methodology

Our goal is to study how labor market frictions drive a gap between the best practice combinations of low inflation and unemployment and the rest. To reach that goal, we start in Section 4.2.1 by constructing a global Phillips curve. As a next step, in Section 4.2.2, we then envision that global curve as a best-practice frontier, where inefficient combinations of inflation and unemployment result in countries operating above best-practice levels. Finally, in Section 4.2.3, we introduce labor market frictions in our model and show how they can explain the gap that exists - and may persist - between those countries that apply best practice and those that struggle to reach that global Phillips curve.

We start with an introduction of an inverse Phillips curve in Section 4.2.1. Sequentially, we introduce a frontier with inefficiency and explain how we are able to distinguish between differences in uncertainty and inefficiency along the Phillips curve. In Section 4.2.3, we then illustrate how labor market frictions could influence inefficiency and thus contribute to a flatter Phillips curve.

4.2.1 A global Phillips curve

In its most basic constellation, a Phillips curve describes the inverse relationship between rates of unemployment and wage inflation. The traditional and simple form is

$$\pi_{it} = c - \lambda u_{it} + e_{it}, \tag{4.1}$$

where π_{it} is the observed inflation rate of country i in the period t; c is the constant; u_{it} is the unemployment rate; and e_{it} is the error term.

Although central banks employ the Phillips curve to predict inflation and make monetary policies, Friedman (1968) inspected that unemployment is caused by people's reaction to unexpected inflation. Due to the fact that labor market frictions have strong effects on how people react to inflation changes, frictions may cause more unemployment during recessions. Correspondingly, we invert the Phillips curve and use unemployment as the dependent variable instead of inflation. Since the empirical evidence suggests that there is a nonlinear relation between inflation and unemployment, we consider a nonlinear form of the Phillips curve. Nevertheless, economic theories do not provide much advice on the functional form of nonlinearity. In order to obtain closed-form solutions, we estimate a nonlinear Phillips curve and generalize it for panel data as

$$u_{it} = \alpha_i - \beta\pi_{it} + \theta{\pi_{it}}^2 + \boldsymbol{\gamma}'\boldsymbol{x}_{it} + e_{it}, \tag{4.2}$$

where α_i captures country-specific characteristics; β is the inverse of λ; and $\boldsymbol{x}_{it}$ is a set of proxies for other factors normally included in the empirical estimation of Phillips curves (e.g., oil prices, import prices, and unit labor costs). The linear model is nested within the nonlinear model. If $\theta = 0$, the nonlinear model is reduced to the linear model. It is worth mentioning that we do not incorporate a New Keynesian framework, which commonly includes the natural rate of unemployment or NAIRU (non-accelerating inflation rate of unemployment). NAIRU is the natural unemployment rate in the absence of wage rigidities (e.g., Galí, 2011). However, NAIRU is not observable and it is difficult to obtain reliable estimation (e.g., Staiger et al., 1997; Ball and Mankiw, 2002). Additionally, if NAIRU is constant, it can be absorbed by the fixed effects. For now, we continue with the model depicted in equation (4.2).

4.2.2 A global Phillips curve frontier

The inverse nonlinear Phillips curve described by equation (4.2) is depicted by the convex curve in Figure 4.1. The Figure also illustrates our notion of inefficient combinations of inflation and unemployment. Consider points A and B in Figure 4.1. Here, the Phillips curve frontier is depicted as a downward sloping line through point A, which is one among a set of the best attainable combinations of inflation and unemployment, along with all other combinations on that line.[1] Point B is an inefficient combination, as a country located in point B could - presumably - lower unemployment to the level in point A *without* sacrificing inflation. Hence, the distance between A and B is a measure of inefficiency.

To see how we can obtain empirical estimates of that measure, consider the follow-

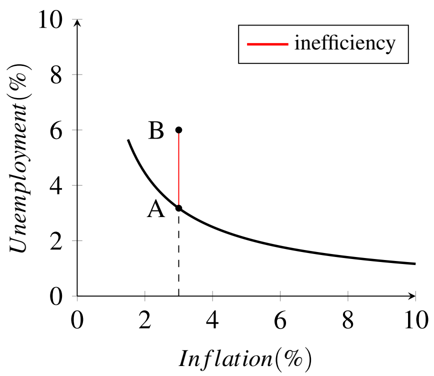
[1] Any combination lying under the Phillips curve is not feasible.

ing inverse Phillips curve frontier model:

$$u_{it} = \alpha_i - \beta\pi_{it} + \theta\pi_{it}^2 + \boldsymbol{\gamma}'\boldsymbol{x}_{it} + e_{it}, \tag{4.3a}$$
$$e_{it} = v_{it} + \varepsilon_{it}, \tag{4.3b}$$
$$v_{it} \sim N[0, \sigma_v^2], \tag{4.3c}$$
$$\varepsilon_i^* \sim N^+[\mu, \sigma_\varepsilon^2], \tag{4.3d}$$
$$\varepsilon_{it} = h_{it}\varepsilon_i^*, \tag{4.3e}$$
$$h_{it} = f(\boldsymbol{z}_{it}'\delta), \tag{4.3f}$$

where equation (4.3a) is the same as in our basic model. Contrary to that model, however, we now have a *composite* error term e_{it} (in equation (4.3a)), consisting of an i.i.d. noise term v_{it} in equation (4.3c) and a nonnegative inefficiency term ε_{it} in equation (4.3d). The noise term v_{it} is distributed as $N[0, \sigma_v^2]$, and captures uncertainty (unexpected shocks). The larger the uncertainty, the larger the variation along the Phillips curve. The inefficiency term ε_{it} is nonnegative, because it represents the gap between the best practice frontier and inefficient combinations of inflation and unemployment, as in Figure 4.1.

Figure 4.1: Inverse Phillips curve frontier and inefficiency



Notes: This figure illustrates the best attainable relationship between inflation and unemployment. B is the deviation from the frontier and the distance between B and the frontier is an inefficiency term.

Following Wang and Ho (2010), h_{it} in equation (4.3e) is a positive function of a vector of variables $\boldsymbol{z}_{it}$ explaining variations in inefficiency ε_{it} and ε_i^* is time-invariant inefficiency with a truncated normal distribution truncated at μ.[2] In order to bridge

[2]If $\mu = 0$, ε_i^* follows a half-normal distribution. Likewise, if $\delta = 0$, which means $\boldsymbol{z}_{it}$ has no explanatory power, the model is reduced to a time-invariant inefficiency model with a half-normal

the inefficiency gap, we are particularly interested in the vector of variables $\boldsymbol{z}_{it}$ in equation (4.3f). We therefore now turn to labor market frictions, as they provide our list of candidates for z_{it}.

4.2.3 A global Phillips curve frontier with labor market frictions

After we build a Phillips curve frontier, what remains to answer, is what affects inefficiency. Many factors could exert impacts on economic outcomes, for example, the status of the economy, monetary and fiscal policies to boost economic growth, financial crises, labor market regulations, and so on. A low inflation rate may mean that central banks have become credible at curbing inflation and hence become helpful to anchor inflation expectations. Meanwhile, a low unemployment rate reflects a promising labor market and economic development. Some best-performing countries, which have achieved economic and policy success, may have better policy-making than the rest. However, since there are frictions, the effectiveness of a policy can be influenced by many aspects, and policy-making is far more complicated. In particular, we pay close attention to labor market frictions. For the same level of inflation, countries with much higher levels of unemployment may have high labor market frictions. In this subsection, we analyze how labor market frictions influence inefficiency.

Labor market frictions can affect the Phillips curve and inefficiency due to the existence of nominal wage rigidity. Nominal wage rigidity can arise from fixed contracts, the presence of menu costs in the wage-setting process, and government regulations such as minimum wages or government pay systems (Fallick et al., 2016). The prevalence of nominal wage rigidity will lead to a higher level of unemployment (Goette et al., 2007). The Phillips curve includes only an abstract description of the labor market, which ignores the nature of continuing labor contracts, wage bargaining, and labor adjustment along the margins (Holden & Wulfsberg, 2008). Therefore, a more realistic framework with some degree of wage rigidity should be considered.

Akerlof et al. (1996) develop a model with an additive term to reflect the effects of DNWR. We follow Akerlof et al. (1996), with some modifications, we show how DNWR influences inefficiency. Under flexible wage settings, the nominal wage can be expressed as:

$$W_{it} = w_{it}^{r} p_{it}^{e}, \tag{4.4}$$

where W_{it} is the nominal wage in country i at time t, w_{it}^{r} is the notional real wage, and p_{it}^{e} is the expected price level. With a flexible adjustment of wages, the expected

distribution (Aigner et al., 1977).

real wage for this period will be the notional real wage. The current price level p_{it} is assumed to be the product of a markup factor m_{it} and the expected unit labor costs $p^e_{it}\frac{w^r_{it}}{A_{it}}$:

$$p_{it} = m_{it}p^e_{it}\frac{w^r_{it}}{A_{it}}, \tag{4.5}$$

where A_{it} is the aggregate labor productivity. Because the notional real wage is determined by workers' bargaining power and dependent on the level of unemployment, therefore it is assumed to be a nonlinear function for the unemployment rate u_{it}. Subtracting the natural log of the lagged price level from the natural log of equation (4.5), we can derive the Phillips curve without inefficiency:

$$\pi_{it} = \alpha_i - f(u_{it}) + \lambda\pi^e_{it} + \gamma\ln A_{it} + v_{it}. \tag{4.6}$$

If we reverse function $f(u_{it})$, we can arrive equation (4.2). It is worth noting that the error term is v_{it} instead of e_{it}.

On the other hand, when wage settings are subject to DNWR, the degree of DNWR could change the cost of wage adjustment and hence drive inefficiency. A higher degree of DNWR will result in higher inefficiency and higher social cost, namely further deviations from the Phillips curve. Conversely, a low degree of DNWR will alleviate the cost of wage adjustment and lead to less inefficient deviations. Inefficiency can be assumed as

$$\varepsilon_{it} = \frac{W_{it} - w^n_{it}}{A_{it}p^e_{it}}, \tag{4.7}$$

the gap between the nominal wage and the nominal notional wage deflated by labor productivity and the expected price level, where w^n_{it} is the nominal notional wage. As w^n_{it} is equal to $w^r_{it}p^e_{it}$, the augmented wage equation is

$$W_{it} = w^r_{it}p^e_{it}(1 + \frac{A_{it}}{w^r_{it}}\varepsilon_{it}). \tag{4.8}$$

The change in unit labor costs will also lead to a change in the price level, which is rearranged and reflected in equation (4.5):

$$p_{it} = m_{it}p^e_{it}\frac{w^r_{it}}{A_{it}}(1 + \frac{A_{it}}{w^r_{it}}\varepsilon_{it}). \tag{4.9}$$

After taking logs and rearrangement, we arrive at the augmented Phillips curve with an additional inefficiency term ε_{it} as equation (4.3a). In consequence, by the logic of equation (4.7), inefficiency depends on the effects of DNWR and can be a function of the degree of DNWR.

However, it is difficult to measure DNWR. Reitz and Slopek (2014) follow Akerlof et al. (1996)'s model and they suggest that expected inflation, output, growth in productivity, firms' profit, and unemployment will drive the change in the nominal notional wage and therefore cause inefficiency. In their model, they propose that inefficiency is a log-linear function of the change in firms' profit ratio, the growth in output, and the trend growth of labor productivity. Additionally, the degree of DNWR is determined by the wage bargaining process. The existence of labor market frictions will lead to a higher degree of DNWR. Holden and Wulfsberg (2008) illustrate that differences in the degree of DNWR across 19 OECD countries are associated with different labor market institutions. They find that stricter employment protection legislation (EPL) and higher union density give rise to stronger DNWR. Babecký et al. (2010) also find that the labor market institutional environment plays an important role in the determination of wage rigidity, based on the firm-level survey across 14 countries of the European Union (EU). Moreover, they indicate that workforce composition has a considerable impact on wage rigidity as well. They show that a high share of high-skilled white collars and employees' tenure is positively correlated with DNWR. What's more, firms with labor-intensive technologies are more likely to have rigidity. To estimate the effects of DNWR, we consider labor market institutional variables as explanatory variables z_{it}, and the estimated coefficients δ reflect the effect of each factor.

Furthermore, DNWR can not only affect inefficiency but also impact the slope of the Phillips curve. It can exert influence on two aspects: intensive and extensive margins. The former concerns how hard it is to adjust nominal wages for individual workers (the degree of DNWR), and the latter involves how many people cannot adjust their nominal wages. In a high inflation circumstance, prices are more likely to increase. The rise in the cost of living reduces real wages, which is more acceptable to workers than nominal wage cuts. Employers are less likely to cut wages. As a result, when the rate of inflation is high, fewer workers will be constrained by DNWR, whereas when the rate of inflation is low, more workers will be constrained and be unable to adjust their wages downward (Daly & Hobijn, 2014). Inefficiency is also correlated with inflation. Due to the omitted variable bias, if we do not take into account inefficiency, the slope of the Phillips curve could be biased. If the correlation between inefficiency and inflation is η, the estimated slope of the Phillips curve without accounting for inefficiency will be

$$-\hat{\beta} = -\beta + \eta, \tag{4.10}$$

If $\eta < 0$, which means a negative correlation, the slope of the inverse Phillips curve will be steeper. [3] Daly and Hobijn (2014) illustrate that both the slope and curvature of the Phillips curve depend on the level of inflation and the degree of DNWR.

[3] If there are correlations between explanatory variables and the omitted variable, the omitted variable bias will occur. With the objective of determining the effect of the omitted variable on the estimators, we illustrate the bias in the basic linear model and omit the subsets of variables from the model. The true model is supposed to be equation (4.3a)

$$u_{it} = \alpha_i - \beta\pi_{it} + \tau_t + v_{it} + \varepsilon_{it} \qquad (i = 1,\cdots,N; \quad t = 1,\cdots,T). \tag{4.11}$$

If we ignore inefficiency, then we will estimate

$$u_{it} = \alpha_i - \beta\pi_{it} + \tau_t + e_{it}. \tag{4.12}$$

The omitted variable inefficiency ε_{it} is assumed as a function of explanatory variable π_{it} in a conditional or auxiliary regression

$$\varepsilon_{it} = \eta\pi_{it} + \xi_{it}. \tag{4.13}$$

The POLS estimator $\hat{\beta}$ of parameter β is biased and inconsistent since it is correlated with ε_{it} and therefore with e_{it}. The variance-covariance matrix of π, denoted by Σ_π (which is $T \times T$), is the same across individuals but otherwise of general form over time. In vector form, the model becomes

$$\begin{aligned} u &= \alpha - \beta\pi + \tau + e, \\ e &= v + \varepsilon, \end{aligned} \tag{4.14}$$

where

$$\begin{aligned} v' &= (v_{11},\cdots,v_{N1},\cdots,v_{1T},\cdots,v_{NT}), \\ \varepsilon' &= (\varepsilon_{11},\cdots,\varepsilon_{N1},\cdots,\varepsilon_{1T},\cdots,\varepsilon_{NT}). \end{aligned}$$

Now consider any matrix P that eliminates the individual effects; P must satisfy $P\iota_T = 0$. For instance, one of such matrices is $P = I_T - (\iota_T\iota_T'/T)$ and the corresponding estimator is the within estimator. Let $Q = P'P$. Generally, for any Q, the estimator $\hat{\beta}$ is given by

$$\begin{aligned} -\hat{\beta} &= -\pi'(Q\otimes I_N)u/\pi'(Q\otimes I_N)\pi \\ &= -\beta + \pi'(Q\otimes I_N)(v+\varepsilon)/\pi'(Q\otimes I_N)\pi. \end{aligned} \tag{4.15}$$

For a fixed T, taking probability limits as the limit of expectations of the numerator and denominators as $N \to \infty$, we get

$$\begin{aligned} \frac{1}{N}\left[\pi'(Q\otimes I_N)(v+\varepsilon)\right] &= \frac{1}{N}\mathrm{tr}[(Q\otimes I_N)\mathrm{cov}(\pi'\varepsilon)] = \eta\,\mathrm{tr}(Q\Sigma_\pi), \\ \frac{1}{N}\left[\pi'(Q\otimes I_N)\pi\right] &= \frac{1}{N}\mathrm{tr}[(Q\otimes I_N)(\Sigma_\pi\otimes I_N)] = \mathrm{tr}(Q\Sigma_\pi), \end{aligned} \tag{4.16}$$

and

$$\begin{aligned} \mathrm{plim} - \hat{\beta} &= -\beta + \mathrm{tr}[(Q\mathrm{cov}(\pi'\varepsilon)]/\mathrm{tr}(Q\Sigma_\pi) \\ &= -\beta + \eta[\mathrm{tr}(Q\Sigma_\pi)/\mathrm{tr}(Q\Sigma_\pi)] \\ &= -\beta + \eta. \end{aligned} \tag{4.17}$$

The correlation η between u and ε determines the direction of the bias. If $\eta < 0$, which means they are negatively correlated, the slope will be steeper.

They show that the higher the inflation rate, the more workers can adjust their real wage downward, and on the other hand, when the rate of inflation is low, more workers are constrained by DNWR and not able to reduce their wages. This leads to a decline in total labor demand and output and increases in the unemployment rate, compared with what it would be at the high inflation rate. Since labor market frictions can increase DNWR, they can also exert influence on the slope of the Phillips curve.

Summing up, we have now developed an empirical model that allows us to explore the trade-off between inflation and unemployment, benchmark the efficiency of economic outcomes, and assess the factors that can reduce the inefficiency gap. We do not investigate how labor market institutions influence unemployment directly. Especially, when labor market policies do not change dramatically, it would not account for the dramatic change in unemployment over the years. More importantly, we focus on how labor market institutions have an impact on the way in which each of the economies of different countries responded to policy changes and shocks, notably balancing inflation and unemployment. In the next section, we introduce our data.

4.3 Data

4.3.1 Data Description

The empirical data is annual data retrieved from International Labor Organization (ILO). It covers 136 countries around the world during the period from 2000 to 2016. Our measure of inflation is the consumer price index (CPI), which is measured as the percentage change from the previous year. We use the ILO estimates of unemployment rates and labor productivity. Labor productivity is defined as output per worker and is calculated in constant 2011 international dollars in purchasing power parity (PPP). We re-scale labor productivity by dividing 10000 and taking the natural logarithm. Due to the availability of data, we use three indicators for labor market frictions: collective bargaining coverage rate (CBCR), trade union density (TUD), and minimum wage (MW). Forteza and Rama (2006) used minimum wages, mandated benefits, trade unions, and government employment to construct indicators of labor market rigidity. Collective bargaining coverage and trade union density can influence both the prices and the quantities of labor forces, and they may affect each individual worker, while minimum wage can only affect the prices of labor forces and the low end of the wage distribution (Boeri & van Ours, 2013). All the indicators are normalized between zero and one.[4] The higher

[4] $indicator = \frac{value - minimum(value)}{maximum(value) - minimum(value)}$

the indicator, the higher the rigidity, so the country with the highest level of rigidity gets a one, and the country with the lowest level gets a zero. It is worth mentioning that minimum wages are adjusted by labor productivity to control different wage levels across countries.

Following Forteza and Rama (2006), we also construct an average aggregate friction index, which is a weighted average of these three indicators. We calculate the average friction index for countries where information on at least one of the three indicators is available and adjust the denominator accordingly. Countries with missing or unreasonable values (such as the minimum wage being much higher than labor productivity) in the required variables are deleted. Since there is a large amount of missing data, in total, we have an unbalanced panel with 1616 observations. The details of the variables that are included can be found in Table 4.8 in Appendix 4.6. Table 4.1 presents the summary statistics of the variables. We can observe that the highest inflation rate in the sample is 54.92%, and the lowest is -6.81%, while the highest unemployment rate is 37.3%, and the lowest is 0.2%. All the friction indicators vary between zero and one, and there are enough variations.

Table 4.1: Summary Statistics

	N	Mean	St. Dev	Min	Max
Inflation rate	1616	0.0453	0.0539	-0.0681	0.5492
Inflation squared	1616	0.0050	0.0186	0.0000	0.3016
Unemployment rate	1616	0.0831	0.0633	0.0020	0.3730
Labor productivity	1616	1.0783	1.1182	-1.9255	3.1330
Collective bargaining coverage	560	0.4527	0.3234	0.0000	1.0000
Trade union density	749	0.2773	0.2099	0.0000	1.0000
Minimum wage	833	0.2081	0.1460	0.0000	1.0000
Average index	1187	0.2952	0.2166	0.0000	1.0000

Notes: This table shows summary statistics for the main variables used in the analysis. The data is annual data retrieved from International Labor Organization (ILO). It covers 136 countries around the world during the period from 2000 to 2016.

4.3.2 Empirical Evidence

In this section, we use simple statistics and graphs to look for some evidence of to what extent labor market frictions can influence unemployment and inflation. We start by summarizing the statistics of CPI and unemployment rates in low-friction and high-friction labor markets and then use a simple t-test to compare the differences.

As is in Table 4.2, we categorize low- and high-friction based on four labor market friction indicators separately. We use the median of the individual indicator to separate the higher half from the lower half of the data sample. The higher half indicates higher frictions, and the lower half shows relatively low frictions. Table 4.2 presents that according to collective bargaining coverage and trade union density, there is no significant difference between inflation rates in countries with high frictions and those in countries with low frictions. Meanwhile, countries with high collective bargaining coverage rates have significantly higher unemployment rates, whereas countries with higher trade union densities do not show higher unemployment rates. This is maybe because collective bargaining coverage can have an impact on more workers in the labor market than trade union density.

Moreover, regarding the price-based indicator of labor market frictions, the minimum wage, countries with relatively lower friction have significantly higher average inflation and unemployment rates than countries with higher friction. It suggests that countries with higher minimum wages may have achieved better economic progress than others. The lower bound of wages may have a smaller influence on developed countries. Besides, based on the average index, inflation rates are higher in low-friction countries, although there is no significant difference in unemployment rates. Apparently, labor market institutions may be effective and reduce inefficiency in some countries. Without controlling for country-specific characteristics, the statistics can only illustrate the compound effects on inflation and unemployment.

The comparison of the means can only show limited information. Even though there is no significant difference between the means of unemployment rates, the distributions are distinct. Figure 4.2 illustrates the distributions of unemployment rates in low and high average friction countries respectively. In the high-friction group, there are more observations with higher unemployment rates, especially when the unemployment rate is higher than 30%. It indicates that higher friction may deteriorate unemployment when unemployment rates are high, which supports that the effects of frictions can be amplified during recessions.

To further investigate the effects of labor market frictions, we plot more detailed scatter graphs of the relationship between unemployment rates and inflation rates distinguished by high and low average frictions as well. As is in Figure 4.3, the black dots represent the observations in high average friction countries, while the white dots represent low-friction countries. The relation between unemployment

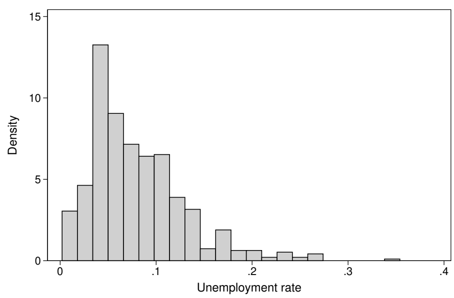
Table 4.2: Summary Statistics Based on Low and High Frictions

		Low			High			T-test	
Indicator	Variable	N	Mean	St. Dev	N	Mean	St. Dev	Difference	t-stat
Collective bargaining coverage	Inflation rate	282	0.0344	0.0335	278	0.0286	0.0395	0.0058	(1.8880)
	Unemployment rate	282	0.0746	0.0484	278	0.0848	0.0518	-0.0101*	(-2.3919)
Trade union density	Inflation rate	376	0.0302	0.0300	373	0.0341	0.0424	-0.0039	(-1.4389)
	Unemployment rate	376	0.0767	0.0480	373	0.0730	0.0449	0.0037	(1.0980)
Minimum wage	Inflation rate	417	0.0565	0.0686	416	0.0424	0.0475	0.0142***	(3.4626)
	Unemployment rate	417	0.0949	0.0528	416	0.0789	0.0603	0.0159***	(4.0602)
Average	Inflation rate	594	0.0502	0.0595	593	0.0371	0.0449	0.0131***	(4.2764)
	Unemployment rate	594	0.0800	0.0498	593	0.0791	0.0590	0.0010	(0.3048)

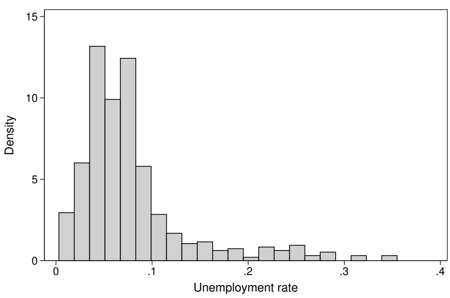
Notes: This table shows summary statistics for the CPI and unemployment rates in low-friction and high-friction labor markets and t-test statistics. Low and high frictions are based on four labor market friction indicators separately. High friction means sample values are above the median of the individual indicator and low friction means sample values are below the median. The t-test compares the differences in the mean of inflation and unemployment between low and high friction. The t statistics are in parentheses, and * p<0.05, ** p<0.01, *** p<0.001.

Figure 4.2: Distribution of unemployment

(a) Low average friction



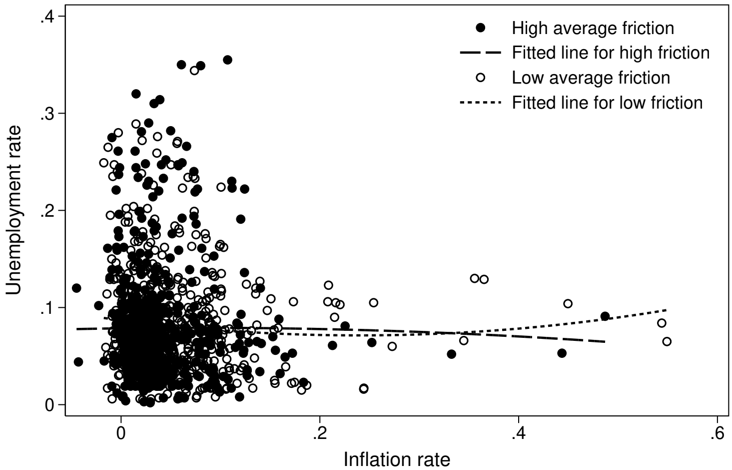
(b) High average friction



Notes: This figure illustrates the distributions of unemployment rates in low and high average friction countries respectively. High average friction means sample values are above the median of the average indicator and low friction means sample values are below the median.

and inflation can also be affected by frictions, according to the fitted lines. The high-friction group shows a concave line, and meanwhile, the low-friction group presents a convex line.

Figure 4.3: Relation between inflation and unemployment

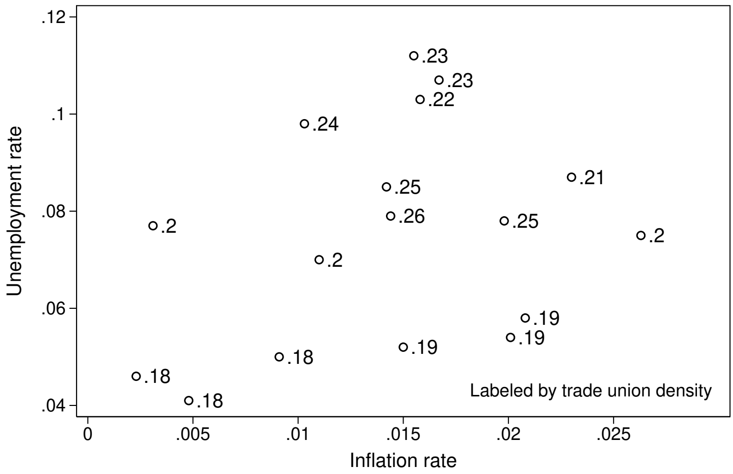


Notes: This figure plots the relation between inflation and unemployment in low and high average friction countries respectively. Black dots are in high average friction and white dots are in low average friction.

Additionally, it can provide more detailed evidence when we only plot the relation in one country. Figure 4.4 shows an example of the scatterplot of the relation in Germany. The observations are marked by the trade union density index. Within one country, it reveals that some observations, which have higher trade union densities, have higher unemployment rates than the ones that have lower trade union densities, even when the inflation rates are similar. This is more informative than the basic statistics.

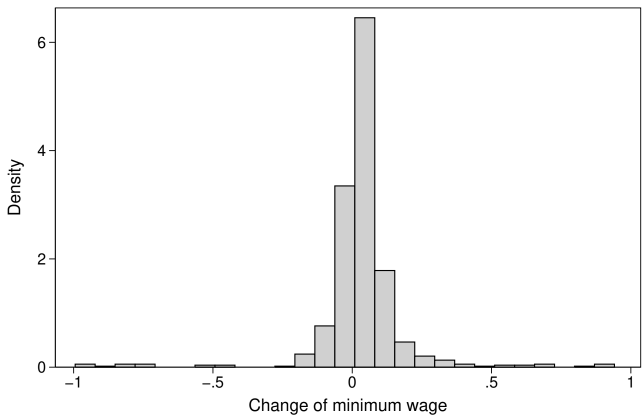
Last but not least, we also show some evidence of DNWR. Figure 4.5 depicts the distribution of the change in minimum wages in all countries, which is left-skewed. There are only 172 out of 753 observations that change the minimum wage downwards. In sum, the visual impression suggests labor market frictions can affect the combinations of inflation and unemployment, but a more thorough analysis is needed. In the next section, we will demonstrate the estimation results.

Figure 4.4: Relation between inflation and unemployment in Germany



Notes: This figure plots the relation between inflation and unemployment in Germany. The numbers show the trade union density, which is between 0 and 1.

Figure 4.5: Distribution of the percentage change of minimum wages



Notes: This figure shows the distribution of the percentage change of minimum wages to demonstrate that the wages are sticky.

4.4 Results

4.4.1 Estimation results

Before estimation, we first examine the stationarity of inflation and unemployment. The Fisher-type unit root tests provide evidence that both panels are stationary, as the null hypothesis that all panels contain unit roots can be rejected at a 0.1% significance level.

We begin with the estimation of the basic model without inefficiency as equation (4.2), which is presented in the first column of Table 4.3. The signs of the coefficients are as expected. As the coefficient of the inflation squared is significant at the 10% level, it verifies that there is a negative nonlinear relation between inflation and unemployment. Besides that, the increase in labor productivity can also reduce the unemployment rate. Then we use Greene (2005b)' true fixed-effects model to estimate the Phillips curve frontier. This model does not explain what determines and changes inefficiency. The result in the second column confirms the negative correlation. Part of the curvature of the relation can be explained by inefficiency since the coefficient of the inflation squared becomes insignificant. In order to verify the existence of inefficiency, we apply the likelihood ratio (LR) test (Coelli, 1995). We calculate the LR statistic as $LR = -2[L(H_0) - L(H_1)]$, where $L(H_0)$ and $L(H_1)$ are the log-likelihood values under the null (the fixed-effects model) and the alternative (the true fixed-effects frontier model) hypotheses. The LR test statistic (194.56) allows us to reject the null hypothesis that there are no one-sided effects of ε_{it}.

Subsequently, our main focus is the question of whether labor market frictions can affect inefficiency. In order to answer that, we estimate equation (4.3a) with different labor market friction indicators. From the third to the sixth column in Table 4.3, we consider each of the indicators as the determinant of inefficiency. The reported coefficients of labor market frictions can only imply the signs of their effects but not the levels. As is shown, collective bargaining coverage ratios tend to have a negative effect on inefficiency, although the effect is not significant. It indicates that expanding the collective bargaining coverage ratio is likely to reduce deviations from the frontier. On the other hand, the results suggest that increasing trade union densities and minimum wages can give rise to more inefficiency. The average index may positively influence inefficiency but the effect is not statistically significant. The last column presents that if one country has all three labor market friction indicators, we can observe that a higher collective bargaining coverage ratio may decrease inefficiency, and meanwhile, a higher trade union density and minimum wage can raise inefficiency. This result is consistent with the results of the models with only one determinant of inefficiency. And the insignificant impact of the average index may be explained by the mixing effects of different indicators. It is worth mentioning that due to the data constraint, we have different sample sizes for each model and therefore different best attainable combinations of inflation and unemployment (frontiers).

In addition, we also consider alternative models to investigate how sensitive the estimated results are to different model specifications. Particularly, we examine two alternative model specifications. For the first one, we include time-specific effects, which are captured by time dummy variables. The results are reported in Table 4.9 in Appendix 4.6. As is presented, there is still a negative relation between inflation and unemployment, however, the relation is not significant in the models without labor market frictions. This may be attributed to the fact that time-specific effects capture the economic fluctuations, which are presented in inflation as well. On top of that, it can also absorb some time-specific inefficiency. The frontier models suggest that the labor market friction indicators have similar effects on inefficiency except for minimum wages. However, because of the limitation of this model specification, we prefer the model without time effects.

Another model specification is that we take into account the effect of inflation expectations on inefficiency. According to equation (4.7), inefficiency can also be affected by the expected inflation rate. However, we can not observe the expected inflation directly. The simplest and most common implementation is to use the realized inflation rate (Mavroeidis et al., 2014). Since this is not our main interest, we use the one-year-ahead realized inflation rate as the inflation expectation. The estimation results are given in Table 4.10 in Appendix 4.6. The estimated relation between inflation and unemployment is not significant in those models with the determinants of inefficiency. Because our main purpose is to explain inefficiency, the shape of the Phillips curve is inconsequential. As a determinant, the expected inflation can significantly reduce inefficiency in four models, which is consistent with the theory (Akerlof et al., 1996). It also illustrates that the signs of the effects of the labor market frictions are consistent with the results of previous models. In sum, this shows that the previously estimated results are less likely to be significantly altered if different model specifications are employed.

4.4.2 Analysis

In this section, we analyze the estimated results from the original models in Table 4.3. We start our analysis of the trade-off between inflation and unemployment. Next, we examine whether the level of inflation can affect inefficiency and uncertainty. More importantly, we investigate how labor market frictions drive ineffi-

Table 4.3: Estimation Results of Different Models

VARIABLES	(1) Fixed-effects	(2) True fixed-effects	(3) Wang&Ho2010	(4) Wang&Ho2010	(5) Wang&Ho2010	(6) Wang&Ho2010	(7) Wang&Ho2010
Phillips curve							
Inflation rate	-0.0786***	-0.0695***	-0.2539***	-0.3569***	-0.0480	-0.1415***	-0.2175**
	(0.0253)	(0.0205)	(0.0638)	(0.0517)	(0.0387)	(0.0329)	(0.0918)
Inflation squared	0.1190*	0.0719	0.4845***	0.8030***	0.0506	0.2127***	0.6210**
	(0.0614)	(0.0470)	(0.1644)	(0.1585)	(0.0880)	(0.0770)	(0.3014)
Labor productivity	-0.0193***	-0.0145***	-0.0170	-0.0041	-0.0394***	-0.0243***	-0.0335
	(0.0050)	(0.0044)	(0.0119)	(0.0134)	(0.0078)	(0.0064)	(0.0284)
Inefficiency determinants							
Collective bargaining coverage			-0.1612				-0.0674*
			(0.1069)				(0.0379)
Trade union density				0.2221*			0.4078*
				(0.1297)			(0.2226)
Minimium wage					0.3977**		0.5160*
					(0.1557)		(0.2749)
Average index						0.0193	
						(0.0440)	
$Constant_u$		-9.7298***	-1.2786	0.1816	-0.4152	0.2155	0.1924
		(0.2013)	(1.3235)	(1.3082)	(0.8868)	(5.0662)	(1.2368)
Symmetric error term parameter							
$Constant_v$		-6.9818***	-7.6879***	-7.7656***	-7.5999***	-7.6585***	-7.6601***
		(0.0700)	(0.0644)	(0.0578)	(0.0547)	(0.0440)	(0.0945)
Observations	1,616	1,616	560	749	833	1,187	293
R-squared	0.0149						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood value	4050	4147	1168	1602	1703	2539	577.7

Notes: This table compares the estimates of the association between inflation and unemployment among different models. The dependent variable is the unemployment rate. The determinants of inefficiency and variance are examined based on equation (4.3f). Model (3) to (6) include one friction indicator to explain inefficiency and model (7) include three friction indicators together to explain inefficiency. Because not all the observations have values for all the indicators, the sample sizes are different for each model. The standard errors are in parentheses. */**/*** signifies statistical significance at the 10/5/1% level.

ciency. Our final question is whether countries converge. The results can provide advice to bridge the gap among countries.

What is the best practice for curbing inflation and unemployment? Is there a trade-off?

The results in subsection 4.4.1 provide evidence of the significant negative relationship between inflation and unemployment. The coefficients reported in Table 4.3 are not the marginal effects due to the nonlinearity of the model. Thus we calculate the marginal effects of inflation and compute the standard errors by using the Delta method.

Table 4.4 reports the point estimates of the marginal effects at the 5th percentile, the median, and the 95th percentile of CPI. It advocates that the level of inflation influences the association between inflation and unemployment. The effects of inflation are larger when inflation rates are low, and on the contrary, the effects are smaller when inflation rates are high. This result can support Daly and Hobijn (2014)' s conclusion that the curvature of a Phillips curve hinges on the level of inflation. Empirically, the original Phillips curve discovered by Phillips (1958) was not linear. Smyth (1971) also found that a cross-country Phillips curve was remarkably convex towards the origin. Moreover, this result is also similar to what Ball (1994) found in his cross-country study. He finds that the trade-off between output and inflation was decreasing at the speed of disinflation. Our result is consistent among all the models. Except in model (5) and (7), all the marginal effects are significant at the 1% level. As model (1) and model (2) have the same sample, we can compare the average Phillips curve and the Phillips curve frontier. The marginal effect of CPI at the 5th percentile indicates that CPI rises 1% is correlated with the 0.0791% decline in the unemployment rate on the average Phillips curve and 0.0698% on the frontier. Apparently, on the frontier, the trade-off between inflation and unemployment is smaller than the average. The best-performing countries have achieved lower unemployment while keeping low inflation. On the other hand, it is harder to curb unemployment by adjusting monetary policies. This may be due to that some countries have a more flexible labor market. Similarly, Ball (1994) provide cross-country evidence that the trade-off between output and inflation is smaller in countries with more flexible labor contracts.

Table 4.4: Marginal Effects of Inflation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Marginal effects	Fixed-effects	True fixed-effects	Wang&Ho2010	Wang&Ho2010	Wang&Ho2010	Wang&Ho2010	Wang&Ho2010
CPI at 5th percentile	-0.0791***	-0.0698***	-0.2558***	-0.3591***	-0.0481	-0.1420***	-0.2206**
	(0.0255)	(0.0206)	(0.0643)	(0.0521)	(0.0389)	(0.0331)	(0.0929)
CPI at 50th percentile	-0.0748***	-0.0672***	-0.2420***	-0.3371***	-0.0463	-0.1352***	-0.2018**
	(0.0237)	(0.0192)	(0.0607)	(0.0488)	(0.0361)	(0.0310)	(0.0865)
CPI at 95th percentile	-0.0635***	-0.0604***	-0.2118***	-0.2844***	-0.0411	-0.1151***	-0.1616**
	(0.0192)	(0.0158)	(0.0533)	(0.0419)	(0.0290)	(0.0253)	(0.0750)

Notes: This table reports the point estimates of the marginal effects at the 5th percentile, the median, and the 95th percentile of inflation based on the estimation results in Table 4.3. The standard errors are in parentheses. */**/*** signifies statistical significance at the 10/5/1% level.

Does the level of inflation affect inefficiency and uncertainty?

Now that we have established the frontier for the best achievable combinations of inflation and unemployment, we can examine whether inefficient unemployment is affected by the level of inflation. To do so, we plot inefficiency against inflation in Figure 4.6a. The estimated inefficiency is from the estimation of model (2), the true fixed effect (Greene, 2005b). The graph indicates that when inflation is lower than 20%, inefficiency is higher and more dispersed. This conforms to Daly and Hobijn (2014)'s theory that in a low inflationary environment, DNWR is more binding for workers who are not able to adjust their wages downward, so it affects the extensive margin. Therefore, this reduces total labor demand and raises unemployment relative to what it would be at the higher inflation rate, which means higher inefficiency in our model. As a result, inefficiency could result from the asymmetric adjustment of nominal price due to DNWR (Abbritti & Fahr, 2013).

Additionally, one feature of our model is that we can distinguish asymmetric inefficiency ε_{it} from symmetric uncertainty v_{it}. Uncertainty could be the result of symmetric shocks or macroeconomic volatility. In the same vein, we plot uncertainty against inflation in Figure 4.6b. It presents larger uncertainty and more volatility at lower inflation rates. This is consistent with Ball and Mankiw (1994)'s model that inflation is correlated with relative price shocks. Apparently, in a low inflationary environment, the responses to shocks are more volatile, which in turn may magnify inefficiency (Blanchard & Galí, 2007; Daly & Hobijn, 2014).

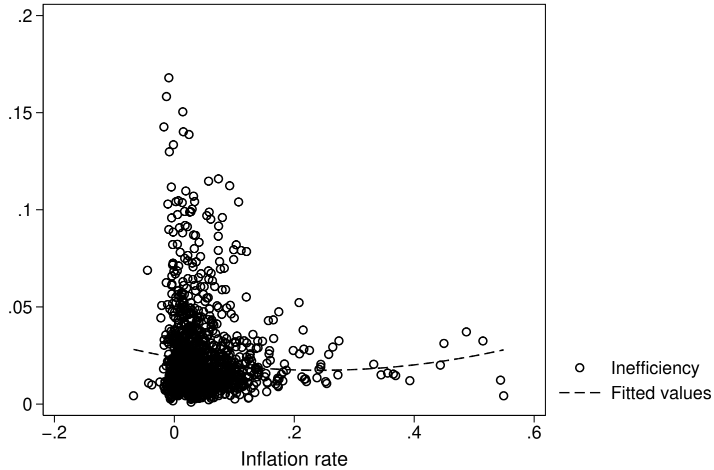
As a further exploration, we would like to investigate how DNWR affects inefficiency. Since it is difficult to measure DNWR, we examine the effects of labor market friction indicators, which can determine the degree of DNWR. Our next section proceeds with such an investigation.

Do labor market frictions drive inefficiency?

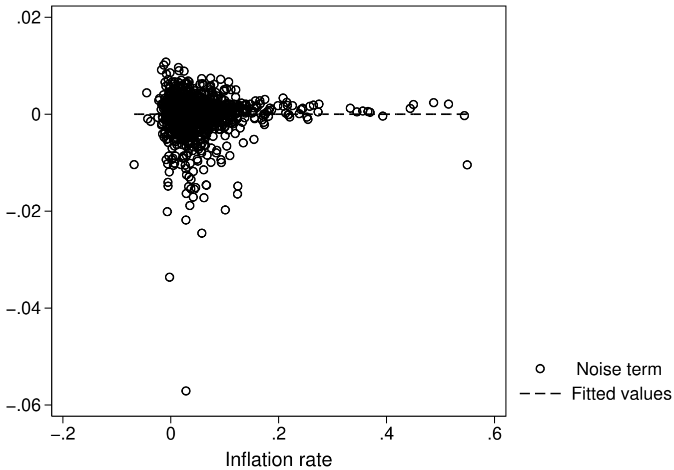
The next question we ask is, therefore, to what extent labor market frictions can affect inefficiency. The corresponding estimation results of model (3) to (6) in Table 4.3 have already given us a hint about the signs of the effects, however, we can not measure the effects of labor market frictions directly from the reported coefficients. We can derive the marginal effects based on Wang and Schmidt (2002). Figure 4.7 displays the point estimates of the marginal effects of four indicators from model (3) to (6). As demonstrated, the marginal effects of all the indicators are positive except for collective bargaining coverage. The negative marginal effect of collective bargaining coverage shrinks with the increase of the coverage level, while for

Figure 4.6: Does the level of inflation affect inefficiency and uncertainty?

(a) Inefficiency



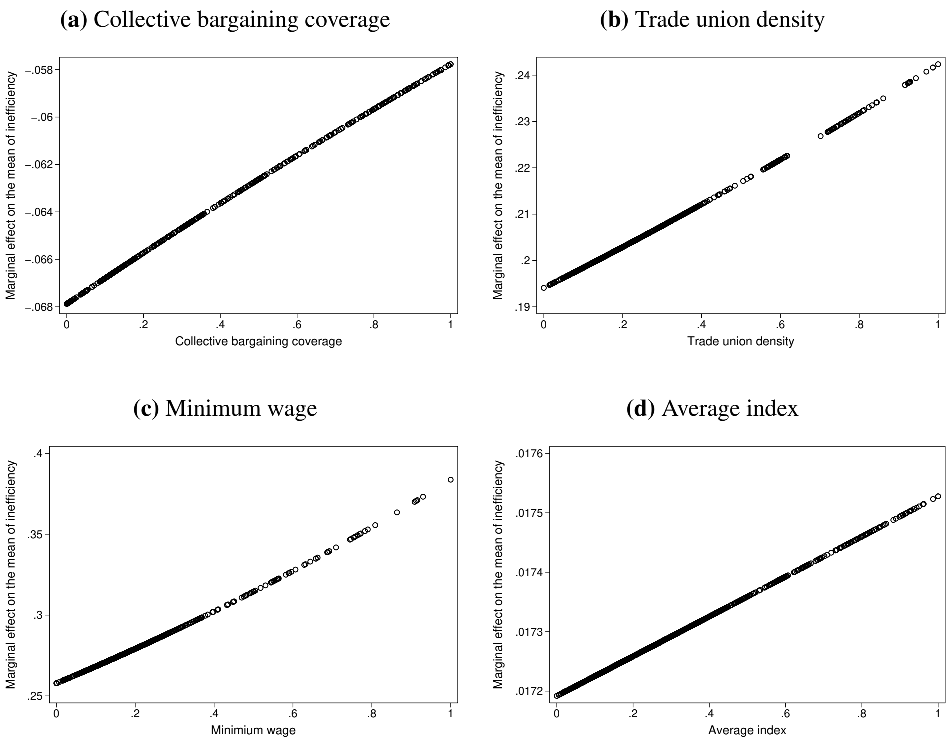
(b) Uncertainty



Notes: Figure (a) shows the relationship between inflation and inefficiency. The horizontal axis is the inflation rate and the vertical axis is the inefficiency rate. Figure (b) shows the relationship between inflation and uncertainty. The horizontal axis is the inflation rate and the vertical axis is the noise term. The estimated inefficiency and noise term are from the estimation of model (2), the true fixed effect (Greene, 2005b).

other indicators, a higher level can have a larger marginal effect. The minimum wage has the largest size of the marginal effect, which can increase unemployment rates from more than 25% to around 38%.

Figure 4.7: Marginal effects of labor market frictions on the unconditional mean of inefficiency



(a) Collective bargaining coverage **(b)** Trade union density **(c)** Minimum wage **(d)** Average index

Notes: This figure illustrates the marginal effects of labor market friction indicators on the unconditional mean of inefficiency. It shows the point estimates of the marginal effects of four indicators based on the estimations of model (3) to (6). Figure (a) shows collective bargaining coverage, Figure (b) shows trade union density, Figure (c) shows minimum wage, and Figure (d) shows the average. The horizontal axis is the indicator and the vertical axis is the marginal effects on inefficiency.

In addition, we calculate the marginal effects of labor market frictions at mean values and bootstrap the standard errors from 100 replications. The results are shown in Table 4.5. We focus on the marginal effects on both the mean and the variance of inefficiency. Particularly, the marginal effects of collective bargaining coverage are negative on both the mean and the variance. It indicates that increasing collective bargaining coverage ratios can not only narrow the gap between the best attainable and inefficient economic performances but also decrease the uncertainty of inefficiency. The underlying reason may be that collective bargaining coverage can increase market efficiency and therefore reduce some frictions in the imperfect competitive labor markets (Boeri & van Ours, 2013). However, the marginal effects of trade union density and minimum wage are positive on both the mean and the variance. A rising trade union density or minimum wage can not only increase inefficiency but also induce more uncertainty. This results in worse economic performance. In the last column, labor market frictions can raise 1.73% of the unemployment rate on average. Overall, the average index can measure a mixed effect of all labor market frictions. Nevertheless, all the marginal effects are not significant, except the marginal effect of trade union density on the variance.

Table 4.5: Marginal Effects of Labor Market Frictions

	(1) CBCR	(2) TUD	(3) MW	(4) Average
Marginal effects on $E(\varepsilon_{it})$	-0.0631	0.2218	0.2920	0.0173
	(0.1149)	(0.2262)	(0.2389)	(0.0538)
Marginal effects on $V(\varepsilon_{it})$	-0.0282	2.2467***	0.3033	0.0176
	(0.2994)	(0.5513)	(0.7781)	(0.2053)

Notes: This table reports the point estimates of the marginal effects of labor market frictions at mean values and the standard errors from 100 bootstrap replications. It shows the marginal effects on both the mean and the variance of inefficiency based on the estimation results from model (3) to (6). The standard errors are in parentheses. */**/*** signifies statistical significance at the 10/5/1% level.

Our findings provide additional empirical evidence to the hotly debated topic regarding labor market institutions. An early perspective believed that there is a positive link between institutions and macroeconomic outcomes (Flanagan, 1999). However, empirical literature found equivocal results. Researchers have considered trade unions as twofold organizations (Boeri & van Ours, 2013). Calmfors and Driffill (1988) postulated that large and all-encompassing trade unions would recognize their market power and take into account both the inflationary and unemployment effects of wage increases, and there is a hump-shaped relationship between bargaining coordination and economic performance. It is interesting to compare their result with our results on bargaining coverage and union density, because it may be easier to achieve high coordination when coverage and union density are higher (Holden & Raaum, 1991). The positive effect of collective bargaining coverage may be due to the high coordination at the national level. Conversely, even though a country has a higher trade union density, it could be the case that those unions are operating at the individual firm or plant level and have less market power. Our result about trade union density can also support Holden and Wulfsberg (2008)'s finding that DNWR is more extensive when union density is high. On the other hand, our result runs counter to the lack of (little) evidence of the negative impact of minimum wages in literature (e.g., Dolado et al., 1996; Machin and Manning, 1997). It is possibly because minimum wages can only influence the lower bound of wages, and we can not observe the impact on economic performance directly if the percentage of minimum-wage workers is small. Avouyi-Dovi et al. (2013) indeed found evidence that the higher the percentage of minimum-wage workers, the higher the impact on the wage bargaining process.

In order to further explore how frictions can explain the differences in the levels of inefficiency, we investigate whether high-friction labor markets are less efficient than their lower counterparts. We start, in Table 4.6, with a comparison of the inefficiency of high and low friction labor markets. As previously discussed in Table 4.2 in Section 4.3.2, we separate high-friction from low-friction labor markets in regard to the median of each labor market friction indicator. As inefficiency is not normally distributed, we use a Kruskal-Wallis (KW) rank test to compare differences in levels. In comparison with the statistics in Table 4.2, the differences in inefficiency present how frictions can influence the differences in economic performance after controlling for other factors. From the KW test statistics, we find that the level of friction and the level of inefficiency are related. On average, countries with higher collective bargaining coverage and trade union density are more efficient than their lower counterparts. Although the marginal effect of trade union density can increase inefficiency, in general, the level of inefficiency is lower when trade union density is higher. In contrast, countries with relatively higher minimum wages have higher inefficiency than their lower counterparts. A country that has a higher average friction index, has higher inefficiency as well. Combined with the results in Table 4.2, this can illustrate that lower unemployment rates in the countries with higher minimum wages and higher average frictions can be explained by the higher inflation rates. Apart from the differences in levels, we can also detect significant distinctions in the variation of inefficiency. The reported p-values of the F test for homogeneity of variances imply that labor market frictions can also affect the uncertainty of inefficiency.

So far, our results show that different friction indicators can influence the average level of inefficiency distinctly. Earlier, we plotted the relationship between inflation and unemployment in Germany in Figure 4.4 and found visual evidence that higher trade union density may lead to higher unemployment rates. The analysis would be more accurate after we considered other factors. Therefore, we plot the relationship between trade union density index and inefficiency in Figure 4.8.

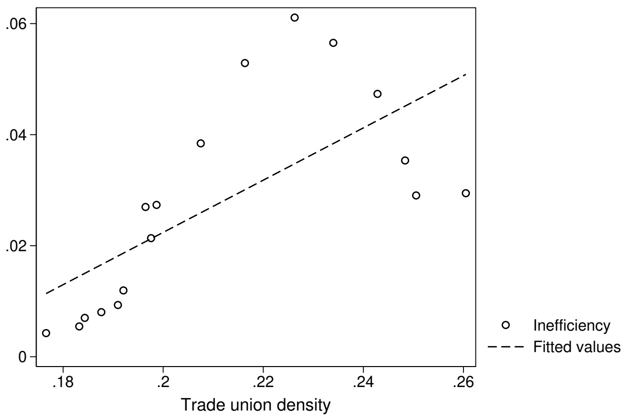
The graph demonstrates that when trade union density is lower and inefficiency is lower, although in general, Germany has low inefficiency and higher trade union density.

Table 4.6: Level of Frictions and Differences in Inefficiency

		Low			High			Test	
Indicator	Variable	N	Mean	St. Dev	N	Mean	St. Dev	KW	F
Collective bargaining Coverage	Inefficiency	81	0.4040	0.0642	80	0.2906	0.0694	0.0000	0.0010
Trade union density	Inefficiency	135	1.2303	1.1689	165	0.7726	0.4431	0.0256	0.0000
Minimum wage	Inefficiency	193	0.7401	0.8211	192	1.1005	0.9230	0.0000	0.0053
Average	Inefficiency	312	0.8799	0.1398	311	0.9018	0.1435	0.4186	0.8866

Notes: This table displays the differences in inefficiency between low and high-friction observations. KW is the Kruskal-Wallis rank test and the relative p-values are reported. F is the F test for the homogeneity of variance and the relative p-values are reported. Inefficiency is estimated based on model (3) to (6).

Figure 4.8: Relation between friction and inefficiency in Germany



Notes: This figure illustrates the relation between trade union density and inefficiency. The horizontal axis is the trade union density and the vertical axis is inefficiency.

Is there convergence across countries?

The final question we are interested in is whether there is convergence across countries. We start with testing the convergence hypothesis, then go one step further, and test the convergence hypothesis in different labor markets.

The convergence in the economic growth literature (Baumol, 1986) means whether there is a closing gap between inefficient and efficient countries over time. To test the convergence across countries, we first calculate the efficiency index TE_{it} as $exp(-\varepsilon_{it})$, which is commonly used in productivity literature (e.g., Aigner et al., 1977). We then follow Bos et al. (2016) and run a simple regression of time-average efficiency growth rates on the initial level of efficiency:

$$\Delta TE_i = \beta_0 + \beta_1 TE_{i,2000} + \nu_i, \tag{4.18}$$

where ΔTE_i is the annual average growth rate of the efficiency index level of country i during the period from 2000 to 2016, $TE_{i,2000}$ is the initial efficiency level in the year 2000, and ν_i is an error term. A negative and statistically significant coefficient β_1 can indicate the convergence of efficiency levels (Bos et al., 2016). The underlying reasoning is that the higher the initial level of efficiency is, the slower the level of efficiency grows, as inefficient countries can learn from efficient countries. We start by estimating equation (4.18) across all the countries in the sample. Our next step is, to divide countries into high- and low-friction groups and to estimate the same equation based on sub-samples. Table 4.7 reports the corresponding estimation results of coefficients. Generally, the convergence coefficient β_1 is negative in the full sample and sub-samples, providing evidence of convergence across countries. It appears that the convergence is strong at the pace of 2% in the full sample. The low-friction countries experience strong convergence at the pace of 2% as well. On the contrary, the convergence across high-friction countries is not significant. It also indicates that countries with high labor market frictions have a low speed of convergence. This is in line with Carmeci and Mauro' finding that labor market rigidity does lower the long-run growth rate.

In sum, our findings show significant convergence across countries and different speeds of convergence between high- and low-friction countries. It suggests that high labor market frictions could lower the speed of convergence and make it harder to improve macroeconomic performance.

Table 4.7: Convergence across Countries

Variables	(1) Full sample	(2) Low-friction	(3) High-friction
β_1	-0.0202***	-0.0199***	-0.0085
	(0.0021)	(0.0021)	(0.0069)
Constant	0.0195***	0.0194***	0.0075
	(0.0020)	(0.0020)	(0.0067)
Observations	849	492	272

Notes: Efficiency is calculated based on the estimation of the true fixed-effects model. Low- and high-friction countries are separated based on the average index indicator. Standard errors in parentheses, *** p<0.01, ** p<0.05, and * p<0.1.

4.5 Conclusion

The relationship between inflation and unemployment, known as the Phillips curve, has long been discussed both in the theoretical and empirical literature. Regardless of the shape of the Phillips curve, some advanced economies have achieved better economic performance by lowering the level of unemployment while keeping low inflation. Closing the gap between those economies and others is far from easy. In this paper, we benchmark the extent to which countries are able to minimize inflation and unemployment. In order to do so, we build a global best practice frontier, that describes the optimal attainable combinations of low unemployment and inflation. We distinguish asymmetric inefficiency (the deviations from the frontier) from symmetric uncertainty (shocks). Then we explore how inefficiency can be driven by labor market frictions, in particular, minimum wage, trade union density, and collective bargaining coverage.

Our results provide sufficient evidence that there is a negative nonlinear relation between inflation and unemployment. It is harder to balance both in a low inflationary environment. However, some countries have achieved better practices to curb inflation and unemployment, so the trade-off is smaller than the average. It may be that some countries have more flexible labor contracts.

Moreover, one feature of our model is that we can distinguish asymmetric inefficiency from symmetric uncertainty. We find that inefficiency and uncertainty are larger at lower inflation rates, and at the same time, the volatility is higher. In a low inflationary environment, the responses to shocks are more volatile, leading to higher inefficiency.

As a further exploration, we find that labor market frictions can drive the gap between efficient performance and inefficient performance. In particular, increasing collective bargaining coverage ratios can not only narrow the gap but also decrease the uncertainty of inefficiency. In contrast, the rising trade union density or minimum wage can not only increase inefficiency but also induce more uncertainty, which results in worse economic performance. On average, countries with higher collective bargaining coverage and trade union density are more efficient than their lower counterparts, whereas countries with relatively higher minimum wages have higher inefficiency.

We also find strong convergence across countries. However, the extent to which this has happened differs. In low-friction countries, the pace of convergence is 2%, and meanwhile, the pace is 0.85% in high-friction countries. It suggests that high labor market frictions can hinder the improvement of macroeconomic performance.

Our analysis has important consequences for policymakers. Our results suggest that institutional labor market reforms can help close the gap between the best-performing countries and the rest. Well-designed labor market institutions are needed to reduce labor market frictions and therefore diminish DNWR. When collective bargaining coverage and union density are higher, it is better to take into account both the inflationary and unemployment effects of wage increases and achieve high coordination at the national level. Additionally, policymakers need careful thoughts to adjust minimum wages. Future research could focus on how matching and searching frictions in the labor market influence macroeconomic performance.

4.6 Appendix

Table 4.8: Data Description

Variable	Description
Consumer price index (CPI)	National consumer price index (CPI) by COICOP, percentage change from the previous year.
Unemployment rate	The unemployment rate is the number of persons who are unemployed as a percent of the total number of employed and unemployed persons (i.e., the labor force).
Collective bargaining coverage rate (CBCR)	The number of employees whose pay and/or conditions of employment are determined by one or more collective agreements as a percentage of the total number of employees.
Trade union density rate (TUD)	A trade union is defined as a workers' organization constituted for the purpose of furthering and defending the interests of workers. This trade union density rate conveys the number of employees. Trade union membership excludes union members who are not in paid employment (self-employed, unemployed, retired, etc.).
Minimum wage (MW)	Data refer to the minimum monthly earnings of all employees as of December 31st of each year. Minimum wages are not reported for countries for which collective bargaining is in place for minimum wages. In cases where a national minimum wage is not mandated, the minimum wage in place in the capital or major city is used. In some cases, an average of multiple regional minimum wages is used. In countries where the minimum wage is set at the sectoral level or occupational level, the minimum wage for manufacturing or unskilled workers is generally applied. This is a harmonized series: (1) data reported as hourly, weekly, and yearly are converted to monthly, using data on average weekly hours if available; and (2) data are converted to a common currency, using exchange rates for the series in U.S. dollars and using 2011 purchasing power parity (PPP) rates for the series in constant 2011 PPP dollar.
labor productivity	This is defined as output per worker. It is calculated using data on GDP (in constant 2011 international dollars in PPP) derived from the World Development Indicators database of the World Bank.

Notes: The definitions are from International Labor Organization.

Table 4.9: Estimation Results of Models with Time Effects

VARIABLES	(1) Fixed-effects	(2) True fixed-effects	(3) Wang&Ho2010	(4) Wang&Ho2010	(5) Wang&Ho2010	(6) Wang&Ho2010	(7) Wang&Ho2010
Phillips curve							
Inflation rate	-0.0205	-0.0063	-0.1769**	-0.2646***	-0.1090***	-0.0604*	-0.2869***
	(0.0288)	(0.0278)	(0.0717)	(0.0564)	(0.0420)	(0.0362)	(0.1084)
Inflation squared	0.0164	-0.0155	0.4064**	0.6301***	0.1392	0.0699	0.9935***
	(0.0660)	(0.0453)	(0.1750)	(0.1633)	(0.0912)	(0.0808)	(0.3483)
Labor productivity	-0.0277***	-0.0238***	-0.0410***	-0.0684***	-0.0599***	-0.0463***	-0.0318
	(0.0061)	(0.0069)	(0.0148)	(0.0160)	(0.0114)	(0.0081)	(0.0379)
Inefficiency determinants							
Collective bargaining coverage			-0.1741				-0.1124
			(0.2030)				(0.0926)
Trade union density				0.2629**			0.7038
				(0.1281)			(0.5597)
Minimium wage					-5.7099***		-0.2354
					(2.0437)		(0.1981)
Average index						0.0163	
						(0.1532)	
$Constant_u$		-38.5764	-1.4618	0.4883	-4.2228***	-1.0721	0.1879
		(78.3628)	(2.2081)	(1.0828)	(0.4081)	(19.4368)	(1.7880)
Symmetric error term parameter							
$Constant_v$		-6.7875***	-7.8426***	-7.9774***	-7.7307***	-7.7364***	-8.0635***
		(0.0352)	(0.0645)	(0.0574)	(0.0543)	(0.0437)	(0.0975)
Observations	1,616	1,616	560	749	833	1,187	293
R-squared	0.0576						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood value	4086	4311	1205	1666	1761	2584	623.5

Notes: This table compares the estimates of the association between inflation and unemployment among different models. The dependent variable is the unemployment rate. All the models include time-specific effects, which are captured by time dummy variables. The estimated parameters of time dummies are not reported. The standard errors are in parentheses. */**/*** signifies statistical significance at the 10/5/1% level.

Table 4.10: Estimation Results of Models with Inflation Expectation

VARIABLES	(1) Wang&Ho2010	(2) Wang&Ho2010	(3) Wang&Ho2010	(4) Wang&Ho2010	(5) Wang&Ho2010
Phillips curve					
Inflation rate	-0.0918	-0.1904***	-0.0274	-0.0470	0.0098
	(0.0643)	(0.0495)	(0.0396)	(0.0317)	(0.0951)
Inflation squared	0.2541	0.4241***	0.0976	0.0502	0.1652
	(0.1553)	(0.1369)	(0.1108)	(0.0720)	(0.2301)
Labor productivity	-0.0090	0.0064	-0.0389***	-0.0270***	-0.0694***
	(0.0108)	(0.0121)	(0.0073)	(0.0058)	(0.0231)
Inefficiency determinants					
Expected inflation	-1.2870***	-0.2812**	-1.4589	-25.6014***	-0.0089*
	(0.3191)	(0.1370)	(1.1842)	(7.6994)	(0.0054)
Collective bargaining coverage	-0.1310***				-0.0011
	(0.0475)				(0.0008)
Trade union density		0.2840**			0.0060
		(0.1347)			(0.0045)
Minimium wage			0.6933		0.0094*
			(0.4921)		(0.0054)
Average index				0.0803	
				(0.3309)	
$Constant_u$	-1.9197***	0.6634	-2.6028	-6.9554***	7.8822***
	(0.5215)	(1.0259)	(1.6819)	(0.5399)	(1.1736)
Symmetric error term parameter					
$Constant_v$	-7.9351***	-7.9858***	-7.7687***	-7.8964***	-7.7344***
	(0.0695)	(0.0582)	(0.0556)	(0.0458)	(0.0984)
Observations	538	728	812	1,153	284
Country FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood value	1146	1588	1703	2553	566.5

Notes: This table compares the estimates of the association between inflation and unemployment among different models. The dependent variable is the unemployment rate. The determinants of inefficiency and variance are examined based on equation (4.3f). The one-year-ahead realized inflation rate as the inflation expectation is included to explain inefficiency in all the frontier models. Because not all the observations have values for all the indicators, the sample sizes are different for each model. The standard errors are in parentheses. */**/*** signifies statistical significance at the 10/5/1% level.

5 Conclusions

Because of the fast developments in technologies, our lives have been constantly changing and the impact of changes on labor markets is essential for economic growth and inequality. This dissertation explores how labor adjustment costs influence aggregate dynamics and policy-making.

Chapter 2 and 3 focus on labor adjustment costs of labor inputs. Both chapters try to model the effect of on-the-job learning on productivity change and how this effect interacts with technical change and wage dynamics. Chapter 2 finds that labor of different skill levels has different costs of on-the-job learning and those different costs reduce productivity at different rates. Compared with low-skilled labor, high-skilled labor has higher costs of on-the-job learning and higher decreases in their productivity. This effect of on-the-job learning impairs the contribution of technical change to economic growth. Chapter 3 extends this finding to theoretically show that the higher costs of on-the-job learning of high-skilled labor can hinder technological development in skill-intensive industries. Chapter 4 focuses on labor adjustment costs of labor market policies. It adopts a similar empirical framework as Chapter 2 and finds that labor market frictions can affect the distance from the frontier of the best combinations of inflation and unemployment.

In particular, I begin with the adjustment costs of changes in the skill composition. In Chapter 2, I build a simple model to explain how the increase of newly hired workers causes efficiency loss. It illustrates that the rising newly hired high-skilled labor can slow down the productivity increases, and thus SBTC can be underestimated. Then I theoretically derive the bias in the measurement of technical change, which is due to inefficient labor. Based on that model, I conduct an empirical analysis of panel data covering 40 countries and 31 industries during the period from 1995 to 2009. The results show that the increase in high-skilled labor can decrease efficiency at a higher rate than low-skilled labor, and this effect offsets the effect of SBTC. I also find that after accounting for adjustment costs, the estimation demonstrates higher rates of SBTC. This estimation provides evidence that SBTC can increase the wage differential between high- and relatively lower-skilled labor. Moreover, the empirical findings also provide evidence that the skill intensity and institutional effects can also influence wage differentials and thus contribute to the overcompensation or undercompensation of high-skilled labor.

Chapter 3 focuses on the adjustment costs of inter-industry labor mobility. Many economies put emphasis on technologically emerging industries. Because technological progress will change the demand for skills, it will inevitably affect labor reallocation across industries. Chapter 3 theoretically studies how the labor market adjusts to industry-specific technology shocks. I compare the outcomes with perfect and imperfect inter-industry labor mobility and in the partial and general equilibrium. My analysis illustrates that in the partial equilibrium of a competitive labor market, the expanding industry, after a technology shock, attracts both high- and low-skilled labor and more high-skilled labor will switch industries. This is called the mobility effect. In the general equilibrium, the elasticity of substitution between two goods plays a crucial role in labor mobility. When products are more substitutable, there will be more labor mobility. This is called the price effect. The price effect mitigates the mobility effect. In the partial equilibrium of an imperfect labor market, when high-skilled labor has more specific human capital than low-skilled labor, the wage differential will be higher in the expanding industry than in the contracting one. In addition, wage compression assists skill upgrading, especially when high-skilled labor has higher specific human capital than low-skilled labor. In the general equilibrium, the price effect and the effect of specificity mitigate the reaction of the labor market to technology shocks and make inter-industry labor mobility and skill upgrading difficult. Overall, the results suggest that policymakers should consider four factors: the competitiveness of product markets, the specificity of human capital, the bargaining power of firms, and education costs.

Chapter 4 examines the adjustment costs of labor market policies and provides some implications for policy-making. Labor market policies may affect the relationship between inflation and unemployment, the Phillips curve. Disregarding the shape of the Phillips curve, some advanced economies have achieved better economic performance by lowering unemployment while keeping low inflation. In this chapter, I benchmark the extent to which countries can manage inflation and unemployment and explore how labor market policies can drive the gaps between those economies. The results provide sufficient evidence that there is a negative nonlinear relation between inflation and unemployment. It is harder to manage both in a low inflationary environment because inefficiency and uncertainty are larger, and the volatility is higher. Subsequently, the results further demonstrate that labor market policies can drive the gap between efficient performance and inefficient performance. In particular, increasing collective bargaining coverage ratios can not only narrow the gap but also decrease the uncertainty of inefficiency. On the contrary, the rising trade union density or minimum wage can not only widen the gap but also induce more uncertainty, resulting in worse economic performance. On average, countries with higher collective bargaining coverage and trade union density are more efficient than their lower counterparts, whereas countries with relatively higher minimum wages are less efficient. Finally, the findings suggest a strong convergence across countries and a negative impact of high labor market frictions on macroeconomic performance. Therefore, well-designed labor market institutions are needed to reduce labor market frictions and hence diminish DNWR. When collective bargaining coverage and union density are higher, it is better to consider both the inflationary and unemployment effects of wage increases and achieve high coordination at the national level. Additionally, policymakers need careful thoughts to adjust minimum wages.

Since on the aggregate level, it is difficult to control other factors that may influence adjustment costs, I propose to use firm-level data and dive into the specificity of different jobs or tasks for future research. It is of vital importance to develop a measure for the specificity of human capital. It is worth trying to combine micro-economic and macro-economic analyses. As a further matter, other labor market frictions can be considered, for example, matching and searching frictions in the labor market.

6
Impact Paragraph

This dissertation contributes to the understanding of the impact of adjustment costs on aggregate dynamics and provides implications for policy-making in the fast-changing world. Adjustment costs matter because constant technological developments bring about enormous changes, and adjustments often encounter obstacles. Economic growth is thus subject to changes, and the future is hard to predict. It is the change that would cause, consequently, changes in policies.

Frontier technologies like artificial intelligence, robotics, big data, and networks are expected to revolutionize production processes. They can have a crucial impact on economic growth and inequality because technologies increase productivity and favor skilled labor, high-tech industries, and countries. It goes without saying that the pie is larger, but not everyone gets a bigger slice. It means that although an economy‘s GDP is growing, not everyone‘s income is increasing. The contradiction between economic growth and equality has never been fully resolved, even though policymakers always put both topics at the center of their agenda and attempt to reconcile this contradiction. Technological progress makes this issue even more complicated. This dissertation analyzes the effects of adjustment costs on these topics at the skill level, industry level, and country level. The key takeaway is that adjustment costs curtail the advantages of those who benefit from technical change and impair economic growth. Policymakers should place attention to minimizing adjustment costs and aiding those disadvantaged groups.

Chapter 2 emphasizes the effects of skill-biased technical change on labor markets. It contributes to the debate on SBTC by applying a novel measure of SBTC that considers the effects of adjustment costs. It shows that the adjustment costs of changes in the skill composition diminish the effects of SBTC on economic growth in the short term. Therefore, the influences of adjustment costs on SBTC can help explain the widening wage skill premium. It provides evidence that technical change has the attribute of skill bias, and this attribute drives the shift in the structure of wages toward high-skilled workers against the low-skilled. Consequentially, this chapter provides implications for the changing demand for knowledge and skills because of technological innovation. Research shows that most OECD countries have experienced a remarkable increase in educational attainment, which is commonly used as a proxy for human capital and skill levels (OECD, 2021). Chapter 2 suggests that SBTC may be the reason for the educational expansion, and investing in education is of vital importance. To adapt to fast-developing technology, individuals have incentives to pursue more education, and governments need to provide more education infrastructure and incentivize higher levels of educational attainment across the population. Especially, policymakers should consider providing assistance for the less fortunate to receive a better education, which can help them obtain higher wages and better adaptability to changes. Offering everyone a fair chance to receive a high-quality education can contribute to economic growth and equality. Another major finding of this chapter is that high-skilled labor may have higher adjustment costs. This indicates that investing in higher education may also engender higher adjustment costs, which makes education investments risky.

Although education investments are indispensable, not all of them have good returns. Another question worth pondering is where those investments should concentrate. For example, it is more favorable to support someone to study computer science than library science. Chapter 3 attempts to answer this question and provide more thoughtful advice on adjustments to industry-specific technical change. Technical change is often industry-specific, and specific industries require certain skills. Technological breakthroughs can disrupt the labor market when they increase the returns to related skills while making others less obsolete (Fillmore & Hall, 2021). They change the demand for skills and make current human capital investment risky, especially investment in non-transferable (specific) human capital. As a result, we can not examine education investment individually. Policymakers need to use a multifaceted approach, taking industrial strategies, labor market policies, and education policies altogether into consideration. To achieve that, policymakers should consider different factors and economic contexts to coordinate distinct policies. Chapter 3 illustrates four prime factors to bear in mind: the competitiveness of product markets, the specificity of human capital, the bargaining power of firms, and education costs.

In Chapter 3, I theoretically explore how adjustment costs affect labor market adjustments to industry-specific technology shocks. I bridge the gap in understanding how the interaction between education and building skills on the job will influence switching jobs and human capital dynamics. I consider on-the-job learning as specific and non-transferable human capital, which causes adjustment costs. Based on the findings of Chapter 2, high-skilled labor has higher adjustment costs than low-skilled labor, implying a higher specific human capital. In Chapter 3, I find that when this is the case, the skill premium will be higher in the expanding industry than in the contracting one. There will be relatively fewer high-skilled workers switching industries but more skill upgrading in the expanding industry. The results show that in the responses to technology shocks, the specificity of human capital can impair inter-industry labor mobility but stimulate skill upgrading. In addition, firms with more bargaining power can compress the wages of high-skilled labor and invest in upgrading the skills of low-skilled labor. This promotes equality, especially when high-skilled labor has higher specific human capital than low-skilled labor. However, the previous situation changes when product markets are competitive, meaning products are highly substitutable. In that case, the expanding industry will barely attract high-skilled labor and upgrade skills.

Those findings offer an overview of various situations to consider to policymakers and help them make better policy options. To identify and evaluate their policy options, they should study the following questions. What is the objective of policy-making? How specialized is the economy? Do firms in target industries have bargaining power? How expensive are education investments? How specific are skills? When they perceive the particular situation, they can adjust labor market policies and education investment policies accordingly. Labor market policies need to help lower adjustment costs, reallocate labor of different skill levels, and enhance human capital. Besides that, governments can make a profound impact on education and training by cutting costs for individuals to invest in human capital. Investing in more transferable skills is essential for human capital accumulation and economic growth, and investing in on-the-job training is imperative for technological progress.

Even though taking various options into consideration, policymakers often face painful trade-offs between different policy objectives. Chapter 4 contributes to our understanding of achieving the optimal trade-off between two distinct goals: managing inflation and maintaining low unemployment. This trade-off, well known as the Phillips curve, is often used in macroeconomic models and monetary policies. First, this chapter finds the optimal attainable combinations of low inflation and unemployment across countries and distinguishes inefficient drifts from the best practice frontier. Whereas most studies estimate a Phillips curve for an individual country and subsequently compare curves across countries, I build a single frontier for all countries given the data at hand. Second, I discover how the mix of inflation and unemployment can influence inefficiency and uncertainty, meaning how hard to achieve both goals. The results illustrate that it is harder to manage both in a low inflationary environment. Third, I investigate whether labor market policies can drive the gap between the best-performing countries on the frontier and the rest. I discover that in general, countries with higher collective bargaining coverage and trade union density are more efficient than their lower counterparts, whereas countries with relatively higher minimum wages are less efficient. I propose that to narrow the gap and decrease the uncertainty of inefficiency, policymakers can increase collective bargaining coverage ratios and decrease trade union density or minimum wage. When collective bargaining coverage and union density are high, policymakers should contemplate both the inflationary and unemployment effects of wage increases and achieve high coordination at the national level. Additionally, policymakers need careful thoughts to adjust minimum wages. In consequence, this chapter calls for well-designed labor market institutions to reduce labor market frictions and hence to well balance two contrary policy goals.

In summary, policy-making is far from easy. The conclusions of this dissertation provide advice for education policies and labor market policies. I hope this dissertation offers valuable insights to develop well-designed programs and policies and helps policymakers make the right decisions.

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About the author

Ming Li was born on the 27th of May, 1989, in Jinan, Shandong, China. She obtained a Bachelor's degree in E-commerce and a Bachelor's degree in Finance from Qingdao University in 2012. In 2013, she joined a pre-master program in economics at Erasmus University Rotterdam. After that, she was motivated to do research and obtained her Research Master's degree in Economic and Financial Research at Maastricht University in 2016.

In October 2016, she started her Ph.D. at the Finance Department at Maastricht University under the supervision of Prof. Jaap Bos and Prof. Pierre Mohnen. Ming's fields of research are economic growth, macro labor economics, and productivity analysis. Her research focuses on empirical and theoretical analyses of what drives inequality in labor markets, especially a reallocation of different types of skilled labor. Her joined work with Dr. Hang Sun and Prof. Jichuan Zong has been published in the Journal of Banking and Finance. She has also presented her work at international conferences and seminars such as the European Workshop on Efficiency and Productivity Analysis (London, 2017 and 2019), the 12th Asia-Pacific Productivity Conference (Seoul,2018), the Workshop on Dynamics of Skills Supply and Demand in Maastricht in 2018, and the 2019 China Meeting of the Econometric Society in Guangzhou. Furthermore, Ming has taught undergraduate courses Corporate Finance and Corporate Governance and supervised bachelor and master theses.

In April 2022, Ming joined Nationale-Nederlanden Bank as a model validator in the model validation team.