Essays on Inter-sectoral Labour Mobility and the Wage Gap

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Dedicated to

my parents,

and beloved Suin and Jeonghoo

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Abstract

Wage gaps between industries have increased over the past few decades in the US. Nevertheless, labour clusters in the low-wage sector, which is puzzling. This thesis explores a series of questions to seek the underlying factors: (i) Are there any frictions in inter-sectoral labour mobility? (ii) If so, can labour mobility frictions account for labour market distortions? (iii) What is the primary source of frictions?

Chapter 1 corroborates empirical evidence for the existence of labour mobility frictions using US micro-data: (i) The unexplained wage gap has increased, (ii) the flow of labour from the high- to the low-wage sector has risen but has declined in the reverse direction, (iii) the worker's wage significantly increases only by moving to the high-wage sector, but such mobility does not happen often, and (iv) the pecuniary cost of moving to a new sector has increased.

Chapter 2 evaluates the role of mobility frictions in labour market dynamics. While the neoclassical model without frictions cannot alone explain the labour market distortions, a multi-sector model embedded with frictions can illustrate that barriers to labour mobility act as a decisive factor in determining labour clustering and the wage gap. The main finding is that the degree of mobility frictions has increased, thus being much higher after 2000 than it was in the 1990s. As a result, the wage disparity and labour misallocation have worsened and non-trivial economic losses have occurred.

Chapter 3 demonstrates that differential job matching efficiency between sectors is a crucial source of labour mobility frictions. Importantly, differing matching efficiency stems from sectoral productivity gap. A two-sector search and matching model can satisfactorily explain the labour market distortions by showing that the productivity-driven matching efficiency gap triggers the wage gap and labour misallocation.

Declaration

I declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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Introduction

The sectoral wage gap is one of the most widely discussed issues today. Inter-sectoral labour mobility has been an extensively researched subject since Lewis's dual economy (1954). These two topics are inextricably linked because the wage gap functions as a driving factor in labour mobility between sectors. According to conventional neoclassical economic theory, sectoral wages will be equalised through the free movement of labour across sectors.

However, what do we really know about their dynamics and evolution in the labour market? Contrary to the theory, wage gaps between industries have been persistent and increasing over the past few decades in the US. Notwithstanding, labour tends to cluster in the low-wage sector in lieu of moving to the high-wage sector. Why does labour not flow in such a way as to make sectoral wages converge? Do these observations against the theory suggest the existence of frictions in labour mobility? What, if any, frictions exist in the labour market? The questions above have thus motivated this research to explore inter-sectoral labour mobility and the wage gap more deeply.

This is also a live issue, particularly for advanced labour markets where industries have experienced unbalanced growth and sectoral wage gaps are substantial. Barriers to labour mobility generate an inefficient allocation of labour and human capital in an economy and exacerbate wage differentials and, by extension, they could damage growth potential and raise inequality. Such barriers might additionally lead individuals to make sub-optimal choices in their economic activities since these barriers can act as significant constraints for them. This, in turn, implies that if labour mobility frictions are removed, labour reallocation results in efficiency gains.

With this emphasis on labour mobility, especially between high- and low-wage sectors, I focus on the link between inter-sectoral labour mobility and the wage gap and tailor my model to explain this relationship, which cannot be addressed by other studies. This thesis argues that labour mobility frictions can play a decisive role in influencing the dynamics of the labour market by hindering labour movement across sectors, and so aims to identify the source of these barriers in the labour market.

Chapter 1 draws attention to empirical evidence for labour mobility frictions that throws some light on the puzzling phenomenon in the labour market. The first piece of evidence is that the wage gaps are large and have widened during the last two decades, driven by a rise in unexplained factors. This increase in the unexplained wage gap suggests the presence of frictions preventing wage equalisation across sectors. Second, the dominant change in the US labour transition across sectors in the 2000s and beyond is that workers in the high-wage sectors tend to vertically move to the low-wage sectors whereas workers in the low-wage sectors primarily move horizontally within their sectors, which results in numbers of labourers clustering in the less productive sectors (henceforth referred to as 'labour clustering'). Third, even within a group, i.e. same characteristics, job and work experience, workers' wages will significantly increase when they move from the low- to the high-wage sector. Nonetheless, the downward labour flow has largely increased while the upward drift has decreased. Lastly, pecuniary costs of mobility, which exist as job search and moving costs, have increased. All of this evidence implies the existence and increase of frictions in upward labour mobility.

Chapter 2 evaluates the role of labour mobility frictions in labour market dynamics. I first verify that a standard canonical multi-sector model without labour mobility frictions is incapable of simultaneously explaining both the increase in the wage gap between the high- and the low-wage sectors, and labour concentration in the low-wage sector. The standard model also fails to fit the data regarding the wage gap and labour allocation in the US. I present a multi-sector general equilibrium model with the rigidity of labour mobility between sectors to see the effects of mobility frictions in the labour market. Introducing limited substitutability in labour supply across sectors can contribute to an explanation of why many workers get stuck in the low-wage sector despite higher potential wage options available in other career paths, as well as why sectoral wages are diverging. From my calibrated model using the US data, the degree of labour mobility frictions is estimated. The main finding is that the degree of mobility frictions has increased over the course of more than 25 years, thus being much higher after 2000 than it was in the 1990s. As a result of this, the wage disparity and labour misallocation have worsened, and non-trivial economic losses have occurred.

Chapter 3 shows that differential job matching efficiency between sectors is an important source of labour mobility frictions. I first provide stylised facts on job matching and its efficiency from the US labour market. The first fact is that filling a job vacancy takes much longer in the high-wage sector than in the low-wage sector. The second fact shows that this vacancy duration gap is largely attributed to the difference in matching efficiency between sectors rather than the difference in market tightness. The third fact is that sectoral matching efficiency has been inversely correlated with its productivity because increased productivity in a sector can cause skill mismatch between firms and job seekers. Based on these empirical facts, I develop a two-sector search and matching model whose key feature is the salient difference in matching efficiency between sectors originating from the gap in sector-specific productivity. The model illustrates that a productivity-driven matching efficiency gap exacerbates the matching frictions and impedes inter-sectoral labour mobility. Thus, this friction process impinges on the labour market negatively in a way that widens the wage gap and triggers labour misallocation across sectors, which cannot be explained by the productivity gap alone.

Chapter 1

Empirical Evidence on Labour Mobility Friction

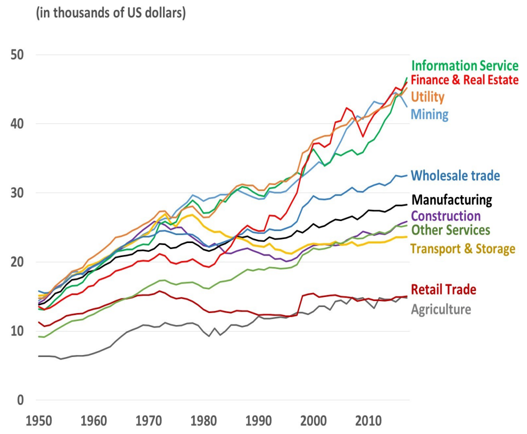
1.1 Introduction

Wages across industries have been diverging in the United States over the past few decades. Figure 1.1 shows the trend of real wages by industry for the US since 1950. Not only does the distribution of wage levels widen (Figure 1.1(a)),[1] but the growth rates of wages differ substantially across industries (Figure 1.1(b)). Figure 1.2 shows a positive relationship between the log of real wage in 1998 and its subsequent growth across 66 sub-industries in the US. This scatter diagram supports the notion of wage divergence. All these figures imply that there is no (unconditional or conditional) convergence in industrial wages in both level and growth rate.

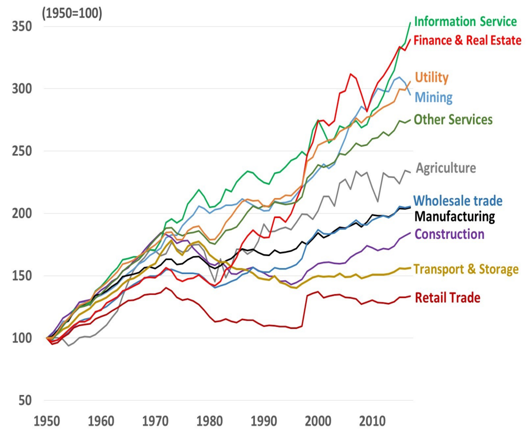
Notably, while wage gaps are increasing, the industries which account for a growing share of employment are mostly low-wage[2] services such as accommodation &

[1] The variance of logs of per capita real wages across industries in the US has increased from 0.125 in 2001 to 0.175 in 2017, or 39.6% (source: BEA).

[2] The classification of the high-wage and the low-wage sectors is different from the categorisation of the high-skilled and the low-skilled jobs. The former is associated with the average labour productivity in a sector or an industry while the latter is related to the qualifications required by a job. Thus, any sector can have both the high-skilled and the low-skilled jobs. In this research,



(a) real wage



(b) real wage index (1950=100)

Figure 1.1: Real wages per full-time employee by industry, US

Source: US Bureau of Economic Analysis (BEA) 'National Income and Product Accounts (NIPA) Tables 6.6 B-D'

Notes: Nominal wage is converted to real wage via US CPI (All items, 1982-84=100). The data for 'Finance & Real Estate' and 'Other Services' after 1998 are the arithmetic mean of their sub-industries. 'Other Services' include accommodation, education, health, etc. The government sector is excluded.

food services, retail trade, and educational services (Table 1.1). In contrast, the employment share in high-wage services (e.g. finance & insurance, information) has only slightly increased over the course of the last 20 years despite their high wage levels and growth rates. This indicates that structural transformation (or employment shift between sectors)[3] in the US has proceeded contrary to that in the ideal competitive labour market.

One possible explanation relates to technological changes such as automation and capital deepening (see, for example, Acemoglu and Guerrieri, 2008; Acemoglu and Autor, 2011). If technological progress complements labour, we would expect to see a rise in wages for the industries which employ high technology. Although

we focus on the former classification.

[3]Although the term 'sector' is the same as the term 'industry' in some literature defining both as an aggregate of firms with a similar business type, 'industry' is here defined as an individual sub-industry, e.g. construction, and 'sector' is defined as a group of sub-industries, e.g. high-wage sector.

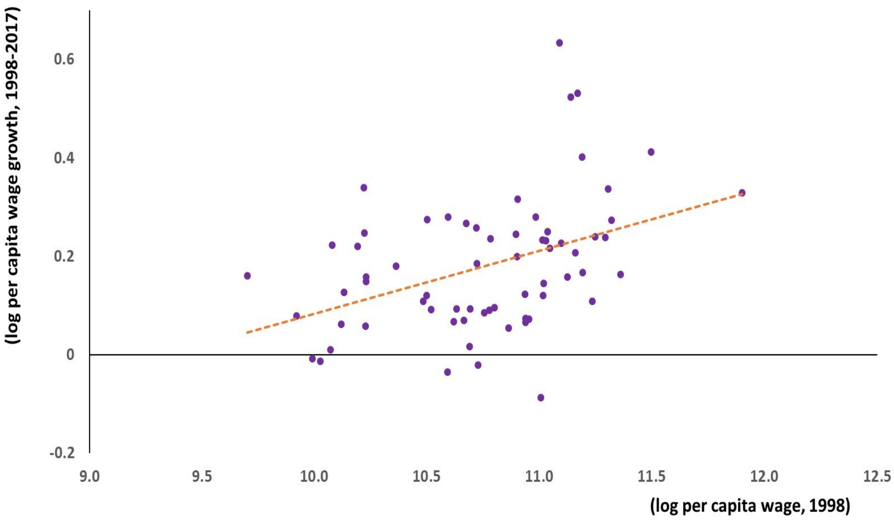


Figure 1.2: Per capita wage and its growth for 66 sub-industries, US

Source: BEA 'NIPA Tables 6.3D, 6.4D'

Notes: Variables are transformed by taking logarithms to observe the elasticity. The dashed line is the regression line by OLS ($Y = 0.13X - 1.20, R^2 = 0.17$). When dropping data points outside of the range between the 10th to 90th percentile in terms of wage growth to consider outliers, the regression also shows a positive relationship ($Y = 0.07X - 0.54, R^2 = 0.11$).

Table 1.1: Structural transformation and average wages by industry since 1998, US

industries	employment share (growth, %p)	real wage[a] level (thou.$)	real wage[a] growth (%)
total	-	46.26	0.83
agriculture	-0.10	26.46	0.68
mining	0.03	84.03	1.48
utilities	-0.12	87.05	1.27
construction	-0.11	49.39	0.98
manufacturing	-6.28	56.61	0.82
services[b]	6.63	44.27	0.93
high-wage ser.	0.28	70.28	1.26
low-wage ser.	**6.36**	**31.43**	**0.79**

Source: BEA 'NIPA Tables 6.3D, 6.4D'

Notes: [a]The real wage level is calculated as the sectoral mean of the nominal wage divided by US CPI (All items, 2010=100). The real wage growth is the annual growth rate between 1998-2017. [b]The low- (high-) wage service is the group of below- (above-) average wage service industries.

this story can explain what is happening to wages in the data, it cannot explain why workers are failing to move to the industries that offer higher wages. Alternatively, if the technology is labour displacing, we have a story about why workers are not moving to the high technology industries. However, the fall in labour demand in the industries cannot explain why wages in the industries increase.[4]

According to the standard neoclassical push and pull theory of labour mobility (Lewis, 1954; Ngai and Pissarides, 2007), no wage gap exists between sectors. With the assumptions of perfect labour mobility and competition, when sectoral wages diverge from each other due to, for example, changes in sectoral productivity or preference over goods, wages will be equalised by labour reallocation. If the wage in one sector (say sector 2) is higher than that in another (sector 1), workers move from sector 1 to sector 2 until both wages are the same.

Although this neoclassical model provides a clear intuition for labour allocation and mobility, the real labour market dynamics have not been characterised satisfactorily by itself. Indeed, the observations from the US suggest the opposite. This research thus begins with the following question: Why has labour concentrated in the low-wage sector even though the wage gap between sectors has increased?

What is missing in the conventional theory is the role of various barriers to labour movements known as labour mobility frictions. In reality, just as most market transactions involve multiple types of frictions, barriers, or trading costs, there exist numerous frictions in the labour market, typically in the form of labour adjustment costs and time to move between sectors such as search costs. Even when all workers have equal skills and background and they are equally productive in all sectors, some workers would have trouble moving to better-paying industries in the presence of mobility frictions.

[4] Besides, we can leave this issue aside while analysing the disaggregated labour market between the high- and the low-wage sectors for the following reasons: The changes in skill distribution by sector is relatively constant since the 1990s, and technology changes, e.g. automation, occur not only in high-wage industries but also in low-wage industries. See the Appendix 1.A.1 for details.

Furthermore, obstacles to inter-sectoral labour mobility impinge on economic growth, theoretically and empirically. Hsieh and Klenow (2009) and Vollrath (2009a) stress that within-country labour misallocation caused by mobility frictions is the main reason for the differences in total factor productivity (henceforth, TFP) and income level across countries. Put differently, mobility frictions could generate inefficient allocation of labour and human capital in an economy, and damage growth potential. The constraints on labour mobility distort labour allocation, also causing individuals to take sub-optimal choices in their sector-switching decisions. This, in turn, implies that if the frictions are removed, labour reallocation results in efficiency gains. However, the research about frictions in inter-sectoral labour mobility is still in the initial stage. Existing studies are limited in accounting for the labour market distortions. This lack of explanation motivates me to identify the source and form of mobility frictions and the channel of linking it with the wage gap.

Throughout this thesis, great emphasis is placed on the key role of labour mobility frictions in explaining both the labour clustering and the widening wage gap. As a first and necessary step, this chapter examines the presence of mobility frictions from various angles such as sectoral wages, labour flow, and mobility costs. By analysing data from the US labour market, I find extensive empirical evidence for the existence and even the increase of labour mobility frictions between high- and low-wage sectors. Based on this evidence, we will further explore the effects of mobility frictions on labour market dynamics and the main source of frictions later in the following chapters.

This chapter is structured as follows. Standard neoclassical theories of the wage gap and labour mobility are revisited, and a literature review of the determinants of the wage gap and inter-sectoral labour mobility is included in section 1.2. Section 1.3 presents empirical evidence on the existence of labour mobility frictions from the US labour market. In section 1.4, a discussion about the source of frictions is presented and section 1.5 concludes. The Appendices provide further details about the empirical works.

1.2 Standard Theory and Literature Review

1.2.1 Neoclassical Theory of the Wage Gap and Labour Mobility: What It Can and Cannot Explain

This section introduces the standard neoclassical theory with a two-sector model which briefly explains how a dual economy works, and how the wage gap and labour allocation are determined in a frictionless framework.

We begin by assuming that, in the spirit of Acemoglu (2001), the technology for producing the unique final good is a form of the constant elasticity of substitution (henceforth, CES) between intermediate goods, meaning that the final output is produced by combining two sectors' goods.

$$Y = F(Y_1, Y_2) \equiv \left(Y_1^{\frac{\sigma-1}{\sigma}} + Y_2^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1.2.1}$$

where Y is the output of the final goods and Y_j is the output of the sector $j \in \{1, 2\}$. $\sigma \in (0, \infty)$ is the elasticity of substitution between two intermediate goods.[5]

Each sector uses labour inputs L_j to produce its output.

$$Y_j = Z_j \cdot L_j^{\alpha_j} \ , \quad j \in \{1, 2\} \tag{1.2.2}$$

where Z_j represents the sector-specific technology, and $\alpha_j \in (0, 1)$ is the labour income share. The total labour force N $(= L_1 + L_2)$ is normalised to one.

In perfect competition, sectoral wage W_j is the same as the value of marginal product of labour.

[5] The elasticity of substitution is the elasticity of the output ratio of two goods with respect to the ratio of their marginal products

$$\sigma = -\frac{\%\Delta\,(Y_2/Y_1)}{\%\Delta\,(MP_{Y,2}/MP_{Y,1})} = -\frac{\%\Delta\,(Y_2/Y_1)}{\%\Delta\,(P_2/P_1)}$$

where $MP_{Y,j}$ is the marginal product of sector j's goods and P_j is the real price of sector j's goods. The first order condition $MP_{Y,j} = P_j$ is used in the last equivalence.

$$W_j = VMP_{L,j} = MP_{L,j} \cdot P_j = \alpha_j \frac{P_j Y_j}{L_j} \tag{1.2.3}$$

where MP and VMP denote the marginal product and its value, and P_j is the real price of sector j's goods. The price of the final goods is assumed to be the numeraire, $P \equiv 1$.

Then, the wage gap between sector 1 and sector 2 can be defined as

$$\begin{aligned} \frac{W_2}{W_1} = \frac{\frac{\alpha_2 P_2 Y_2}{L_2}}{\frac{\alpha_1 P_1 Y_1}{L_1}} &= \frac{L_1}{L_2} \cdot \frac{\alpha_2}{\alpha_1} \cdot \frac{Y_2}{Y_1} \cdot \frac{P_2}{P_1} \\ &= \frac{L_1}{L_2} \cdot \frac{\alpha_2}{\alpha_1} \cdot \left(\frac{Y_2}{Y_1}\right)^{\frac{\sigma-1}{\sigma}} = \frac{\alpha_2}{\alpha_1} \cdot \left(\frac{Z_2}{Z_1}\right)^{\frac{\sigma-1}{\sigma}} \cdot \frac{L_1^{\tilde{\alpha}_1}}{L_2^{\tilde{\alpha}_2}} \end{aligned} \tag{1.2.4}$$

where $\tilde{\alpha}_j \equiv 1 - \alpha_j(\sigma - 1)/\sigma$. The first equivalence in the second line is justified by the first order condition, $P_j = MP_{Y,j}$, from the profit maximisation of the final good firm,[6] and the sectoral production functions are used in the second equivalence. The wage gap is eventually affected by two factors given the labour income shares[7] and the elasticity of substitution: (i) the productivity gap and (ii) labour allocation. However, if the conditions of *perfect labour mobility* and homogeneous workers are satisfied, the wage gap will disappear by labour reallocation between sectors, which is analogous to an arbitrage process, and thus the *law of one wage* holds. It implies that if both wages are different from one another, workers have an incentive to move from the low-wage sector to the high-wage sector, which in turn leads to wage equalisation between sectors.

This equation can describe the processes of labour reallocation and the wage equalisation between the two sectors following changes in the labour demand side, i.e.

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[6]From the final good firm's profit maximisation ($\Pi = Y - P_1 Y_1 - P_2 Y_2$), the marginal product of sector j's goods can be derived as $P_1 = MP_{Y,j} = (Y_j/Y)^{-1/\sigma}$.

[7]One of Kaldor's facts is that the capital and labour income shares are roughly constant over a long time span. However, Alvarez-Cuadrado, Long, and Poschke (2018) demonstrate that the labour income share in manufacturing has declined much more than the one in services in the US since the 1980s, and therefore both labour income shares have converged to around 0.64.

sector-biased technological change. We start from the law of one wage ($W_2/W_1 = 1$). Now, suppose that technological progress takes place in sector 2, denoted by an increase of Z_2. The following three cases lend themselves to variations in the value of σ.

Case 1. When the two goods are substitutes, or $\sigma \in (1, \infty)$,

$$\frac{W_2}{W_1} = \frac{\alpha_2}{\alpha_1} \cdot \left(\frac{Z_2}{Z_1}\right)^{\frac{\sigma-1}{\sigma}>0} \cdot \frac{{L_1}^{\tilde{\alpha}_1 \in (0,1)}}{{L_2}^{\tilde{\alpha}_2 \in (0,1)}} \tag{1.2.5}$$

If Z_2 rises, *ceteris paribus*, the wage gap grows. Then, labour moves from sector 1 to sector 2 to bring the wage gap back to unity.[8] This reflects the 'labour pull' theory since technological progress in sector 2 consequently pulls labour out of sector 1, which is described by Lewis (1954).[9]

Case 2. When the two goods are complements, or $\sigma \in (0, 1)$,

$$\frac{W_2}{W_1} = \frac{\alpha_2}{\alpha_1} \cdot \left(\frac{Z_2}{Z_1}\right)^{\frac{\sigma-1}{\sigma}<0} \cdot \frac{{L_1}^{\tilde{\alpha}_1 \in (1,\infty)}}{{L_2}^{\tilde{\alpha}_2 \in (1,\infty)}} \tag{1.2.6}$$

When Z_2 increases, *ceteris paribus*, the wage gap goes down. To equalise both wages, labour moves from sector 2 to sector 1. This represents the 'labour push' theory because technology development in sector 2 pushes labour out of sector 2, which is shown by Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008).[10]

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[8]If ${L_1}^{\tilde{\alpha}_1}/{L_2}^{\tilde{\alpha}_2}$ decreases (increases), if and only if $\alpha_j \in (0, 1)$ and $L_1 + L_2 = N(\equiv 1)$, L_1/L_2 decreases (increases). The proof is as follows:

$$\frac{{L_1}^{\tilde{\alpha}_1}}{{L_2}^{\tilde{\alpha}_2}} \downarrow \iff d\ln\frac{{L_1}^{\tilde{\alpha}_1}}{{L_2}^{\tilde{\alpha}_2}} < 0 \iff \frac{\tilde{\alpha}_1}{\tilde{\alpha}_2} d\ln L_1 < d\ln L_2$$

where $\tilde{\alpha}_1/\tilde{\alpha}_2$ is a positive number. Since the total labour force N is normalised, $d\ln L_1$ and $d\ln L_2$ must have different signs. To make the above inequality hold, $d\ln L_1 < 0$ and $d\ln L_2 > 0$. This guarantees that L_1/L_2 decreases.

[9]Lewis (1954) presents a dual economy where technological progress and physical capital accumulation in the modern sector attracts labour out of the traditional sector.

[10]Ngai and Pissarides (2007) highlight that if the substitutability between industrial goods is low, structural transformation occurs in such a way that labour moves from the high TFP growth sectors to the low ones. Likewise, Acemoglu and Guerrieri (2008) emphasise that technological advancement in the capital-intensive sector causes its share of production factors to fall with the

Case 3. When the elasticity of substitution between two goods is unity, or $\sigma = 1$,

$$\frac{W_2}{W_1} = \frac{\alpha_2}{\alpha_1} \cdot \frac{L_1}{L_2} \tag{1.2.7}$$

where technological progress has no effect on the wage gap and labour allocation.

In summary, when $\sigma \neq 1$, technological changes make the wage gap deviate from unity in the absence of any labour mobility. The neoclassical theories *can* explain that in a world of perfect labour mobility, labour will move between sectors in a direction that brings the wage gap back to unity to make the law of one wage hold. As in Table 1.2(a), in response to changes in the productivity gap (Z_2/Z_1), labour allocation (L_2/L_1) changes in the same direction as the wage gap (W_2/W_1) in the neoclassical framework. What these theories *cannot* explain is the previously mentioned stylised fact that labour has clustered in the low-wage sector even though the wage gap has widened, which poses a puzzle as illustrated in Table 1.2(b).

Table 1.2: Neoclassical theory and labour market puzzle

(a) neoclasscial theory

$\frac{Z_2}{Z_1}\uparrow$	case 1. $\sigma \in (1, \infty)$	$\frac{\boldsymbol{W}_2}{\boldsymbol{W}_1}\uparrow$ $\frac{\boldsymbol{L}_2}{\boldsymbol{L}_1}\uparrow$
	case 2. $\sigma \in (0, 1)$	$\frac{\boldsymbol{W}_2}{\boldsymbol{W}_1}\downarrow$ $\frac{\boldsymbol{L}_2}{\boldsymbol{L}_1}\downarrow$
	case 3. $\sigma = 1$	$\frac{\boldsymbol{W}_2}{\boldsymbol{W}_1}$ - $\frac{\boldsymbol{L}_2}{\boldsymbol{L}_1}$ -

(b) labour market puzzle

$\frac{\boldsymbol{W}_2}{\boldsymbol{W}_1}\uparrow$ $\frac{\boldsymbol{L}_2}{\boldsymbol{L}_1}\downarrow$

1.2.2 Literature Review

The relationship between inter-sectoral labour mobility and the wage gap is a topical issue, especially for advanced labour markets. While much progress has been made to explain structural transformation and the wage gap, most existing studies on the

assumption of less-than-one elasticity of substitution between products.

topic have dealt with the migration between agriculture and non-agriculture (so-called 'rural-urban migration') in developing economies (Harris and Todaro, 1970; Gollin, Lagakos, and Waugh, 2014; Restuccia and Rogerson, 2013). However, in advanced economies, the employment share in agriculture is low and constant.[11] Indeed, these countries have experienced the divergence of sectoral wages and unbalanced growth within non-agriculture industries which adversely affect sustainable growth.

Theoretically, wage disparity and inter-sectoral labour mobility are inextricably linked. The Lewis model (1954) suggests that the central process in a dual economy consists of labour flow from a traditional, or low-wage, sector into an expanding modern, or high-wage, sector positing the assumption of free labour mobility. However, this ideal labour mobility does not happen; instead considerable wage differentials between sectors exist.

No consensus has emerged in the literature as to why the wage gap has been widening, and whether or not labour is efficiently allocated between sectors. Here, we shall explore the issues posed by the wage gap and inter-sectoral labour mobility and seek to find evidence for labour mobility frictions.

1.2.2.1 Wage Gap

Krueger and Summers (1988) establish a stepping stone on the literature of the sectoral wage gap by highlighting the role of the 'efficiency wage', i.e. above the competitive wage, in explaining the reason for the wage gap. They argue that some firms pay more than the value of the marginal product to employees in order to avoid turnover costs. Subsequent research focuses on the worker's skill premium (e.g. schooling, experience, or unobserved ability) to account for the wage gap. Since the increase in observed characteristic premium accounts for a small part of the increase

[11] The employment share in agriculture, forestry, fishing, and hunting in the US has been merely below 1% since 2000 (source: BEA).

in the wage gap, the theories rely on *ex-ante* differences in workers' unobserved abilities for uncovering a large unexplained part of the wage gap (Gibbons and Katz, 1992; Katz and Autor, 1999). According to this hypothesis, labour is efficiently allocated in an economy on the basis of its unobserved ability, called 'self-selection'. Young (2013) shows that the urban-rural wage gap can be well explained by this view. He discovers that workers migrate in both directions between urban and rural areas, demonstrating that workers sort themselves into sectors depending on their ability. Herrendorf and Schoellman (2015, 2018) support the impact of a worker's ability on the wage gap by empirically showing that the difference in human capital mostly accounts for the inter-industry wage gap in the US. They find that different returns to human capital between workers are mainly attributed to the differences in unobserved abilities.

In contrast to the arguments outlined above, many studies suggest that frictions or barriers to labour mobility, which do not exist in the Walrasian equilibrium, are crucial factors for the wage gap between sectors. Mortensen (2003, pp.6) states that "Wage dispersion is largely the consequence of search friction and cross-firm differences in factor productivity". Manning (2011) points out job search frictions as a primary source of imperfect competition in the labour market, which may violate the law of one wage. Gollin, Lagakos, and Waugh (2014) claim that a puzzle of the large labour productivity gap between agriculture and non-agriculture remains even after adjustment for measurement error and human capital. They propose that one of the main culprits is a restriction on labour mobility within a country. Martins (2004) and Ferreira (2009) show that inter-industry wage gaps in Portugal are still sizable and persistent after controlling for both observed and unobserved heterogeneities. The authors argue that there are non-competitive forces which account for wage differentials, but they do not examine what these forces or frictions are. Plasman, Rycx, and Tojerow (2006) find similar results using data from Belgium. According to Restuccia, Yang, and Zhu (2008), the wage gap and structural change of employment can be affected by indirect barriers to labour movements into the industry sector. McMillan and Rodrik (2011) maintain that large labour productivity gaps between sectors in Latin America and Africa are caused by abnormal labour flows from high productivity sectors to low productivity ones. Barth et al. (2016) find that the increase in the earnings gap between individuals in the US after the 1970s is mostly attributed to changes in earnings among establishments. They suggest a new analysis of introducing a policy on promoting labour movements between firms by conjecturing that imperfect labour mobility could be a primary source of the earnings gap. The role of occupation-specific skills in labour mobility and the wage gap is discussed in Kambourov and Manovskii (2009) who examine the relationship between occupational mobility and the wage gap. The authors assert that less mobile occupation-specific skills impinge on the distribution of workers' skills and thus end up increasing wage gaps across occupations.

1.2.2.2 Labour Mobility Frictions

Empirical studies have demonstrated the existence of imperfect labour mobility across sectors. Horvath (2000) estimates a relatively low elasticity of substitution of labour between industries in the US using data based on the number of hours worked. Beaudry and Portier (2011) assume that labour mobility between sectors is insufficient to equalise the returns to labour across sectors by showing a sizable difference between labour income growth and employment growth by industry in the US. Such observations have naturally led to the research on what causes labour mobility frictions and why mobility frictions exist and persist in the labour market. However, no consensus yet exists (Restuccia and Rogerson, 2013).

Since Lewis's seminal work on the dual economy (1954), many studies have explored the determinants of labour reallocation and its dynamics between sectors. Harris and Todaro (1970) maintain that the flow of labour between agriculture and non-agriculture takes place when expected wages are unequal in both sectors. According to their theory, uncertainty in getting a job in urban area acts as a barrier to labour migration, and thus in equilibrium actual wages may not be the same in both sectors. Gollin, Parente, and Rogerson (2007) argue that labour mobility from agriculture to industry is restricted by subsistence needs for food in line with the Schultz's food problem.[12] Hayashi and Prescott (2008) regard a non-economic force in labour supply side as a primary source for explaining unchanged employment share in the agricultural sector despite a substantial wage gap between agriculture and non-agriculture during prewar Japan. They point out that the contemporary patriarchal social system is a dominant barrier to rural-to-urban labour mobility. Restuccia, Yang, and Zhu (2008) put an invisible cost of labour movements between industries into their model as an indirect barrier. The mobility cost leads to a relatively low wage in agriculture and the overuse of labour in the sector.

Search and matching models also provide some idea of the source of labour mobility frictions. McCall (1970) find matching frictions in the process of job search on the basis of the presence of involuntary unemployment. Diamond, Mortensen, and Pissarides propose a general equilibrium search and matching model, named 'DMP model' (Pissarides, 2000) which demonstrates that matching between workers and firms is costly since job seekers pay a search cost to find a better job and each employer is faced with a recruitment cost. In line with this, Phelan and Trejos (2000) show that even a small search and matching type cost in labour reallocation significantly slows inter-sectoral labour mobility.

Acquisition of sector-specific skills can act as mobility friction. Caselli and Coleman (2001) suggest that workers need to acquire related skills to switch sectors, and stress that the US structural transformation, or labour movements out of agriculture, is due to the declining cost of acquiring manufacturing-specific skills over time. Elliott and Lindley (2006) find that in the UK labour market workers who have industry-specific skills are less mobile across industries, while low skilled workers tend to be mobile, supporting the Jones' (1971) specific factor model. Hsieh et

[12] Schultz (1953) argues that less productive countries devote a large proportion of production factors to producing food to satisfy subsistence needs (cited in Gollin, Parente, and Rogerson, 2007).

al. (2013) model heterogeneous costs of acquiring human capital and discrimination by employers as frictions to occupational labour mobility, which drive the difference between a worker's wage and marginal product. Thus, it is assumed that the degree of mobility frictions varies based on personal characteristics and current occupation.

Finally, how does labour misallocation caused by mobility frictions affect an economy? Hsieh and Klenow (2009) argue that misallocation of capital and labour inputs lowers aggregate TFP in a country, and evaluate that manufacturing TFPs in China and India could increase by a third through the reallocation of production inputs. Jovanovic and Moffitt (1990) estimate that the availability of job mobility options increases a worker's expected earning and boosts aggregate output. Similarly, Vollrath (2009a) points out that since similar production factors receive different earnings in a misallocated labour market, a policy of enhancing inter-sectoral factor mobility significantly raises levels of aggregate income and TFP within a country. Hayashi and Prescott (2008) claim that labour misallocation between urban and rural sectors is the main cause of prewar Japan's stagnation. Likewise, Graham and Temple (2006) create a two-sector model in which labour reallocation between sectors has substantial positive impacts on the income level. According to Restuccia, Yang, and Zhu (2008), the removal of barriers to labour movements could reallocate previously misallocated labour and improve overall labour productivity in a country. Hsieh et al. (2013) place greater importance on efficient labour allocation by showing that the improved allocation of human capital accounts for 15 to 20 percent of the growth in output per worker in the US between 1960 and 2008.

Despite the numerous research on the wage gap and inter-sectoral labour mobility, little is still known about their interactive relationship and the source of mobility frictions, especially within non-agricultural sectors. Furthermore, existing studies are not satisfactory in explaining the labour market puzzle; that is, the labour clustering into the low-wage sector despite the widening wage gap. This thesis could thus shed light on the link between the wage gap and labour mobility by identifying the role and source of labour mobility frictions.

1.3 Empirical Evidence on Labour Mobility Frictions from the US

This section presents extensive evidence on the presence and increase of labour mobility frictions from the US labour market.

1.3.1 Overview and Data

The US labour market is generally evaluated as the most flexible market which follows market economy principles.[13] Hence, a closer observation on the US labour market through micro-data could reveal the underlying root of labour market distortions in advanced economies.

This section begins with a measure of the magnitude of the unexplained wage gap in the US as estimated by sectoral Mincerian earning equations. Next, the degree of inter-sectoral labour mobility is measured at both aggregate and sectoral levels. We also look at the changes in the average wage level of workers who move to the high-wage sector. Lastly, how a worker's mobility cost changes over time is discussed. These analyses can determine whether labour mobility frictions exist and if they are relevant to the wage gap.

The primary database for the US labour market used in this section is the Current Population Surveys from the US Census Bureau (IPUMS-CPS).[14] It provides personal information on demographic characteristics (e.g. age, gender, race, and person-level weight), years of schooling, employment status (e.g. employed or unemployed, full-time or part-time), previous year's wage, previous & current industries, and so forth. For assessing wage gaps between sectors, I restrict the attention to the

[13]The US union density (number of union members/total number of employment) is 12.4% in 2003 much lower than most of the other advanced economies, e.g. UK 29.3%, Germany 22.6% in 2003 (Blanchflower, 2006). The US ranked the lowest on employment protection among OECD countries in 2015 (source: OECD employment protection indicators).

[14]IPUMS-CPS is a rearranged dataset of the US 'Current Population Survey' (CPS) which is a monthly household survey.

period 1991-2015 (last 25 years) and the age between 16 and 70. In some analyses, the sample is limited to white male full-time, full-year employees in order to control for workers' demographic characteristics (i.e. race and gender) and hours worked. Nominal wages are converted to real wages by deflating them with the consumer price index (CPI) for all items.

To scrutinise the labour flow, I calculate indices representing the aggregate level of inter-sectoral labour mobility using the EU KLEMS database which provides the number of employees on the level of 72 industries in the US between 1978 and 2007. Labour transitions across sectors are also measured using the information of an individual's previous and current industries in the IPUMS-CPS database during the period 1991-2015. The sample here is restricted to persons who switch sectors.

Meanwhile, 146 sub-industries in the IPUMS-CPS database are classified into five sectors: high-wage manufacturing (or HM, for short), low-wage manufacturing (LM), high-wage services (HS), low-wage services (LS), and other production industries (OI) including agriculture, mining, construction, utility, and public administration.[15] If a sub-industry is either a top 20 percent in terms of mean wage level since 1991, or shows both above-average wage level and growth rate in its upper category industry since 1991, it is classified as a high-wage sector.[16] Otherwise, it is assigned to a low-wage sector.

1.3.2 Evidence 1: The Increasing Unexplained Wage Gap

We test the hypothesis that wage gaps between sectors are large and increasing even after controlling for workers' observed characteristics. To test this, sectoral

[15]See the Appendix 1.A.2 'Sector classification' for details.

[16]The first criterion (top 20% industries in the wage level) is arbitrary, but the sector classification is little changed with different cutoffs such as 10% or 30%. Regarding the second criterion, the reason to consider both wage level and growth rate is that when workers make decisions about a sector switch, they maximise the expected present value, which is consistent with dynamic sector choice models (e.g. Artuç, Chaudhuri, and McLaren, 2010). Thus, workers take account of the current wage as well as the future wage level or its expected growth when switching sectors.

Mincerian earning equations for full-time, full-year white male workers is estimated as

$$\ln W_{i,j} = \alpha_j + \beta_{1,j} SCH_{i,j} + \beta_{2,j} EXP_{i,j} + \beta_{3,j} EXP^2_{i,j} + \varepsilon_{i,j} \tag{1.3.1}$$

where the dependent variable is the natural log of the real wage of individual i in sector j, $\ln W_{i,j}$. $SCH_{i,j}$ is years of schooling, $EXP_{i,j}$ is work experience, and $\varepsilon_{i,j}$ is an i.i.d. error term with zero mean. Here, the work experience is calculated by the Mincer's way (= age - years of schooling - 6). The concave pattern of lifetime earnings is captured by its squared term, $EXP^2_{i,j}$.

For comparing sectoral wages, it is necessary to control different qualifications between workers. This is known as the 'Blinder-Oaxaca decomposition'. Through this procedure, the mean wage difference between two sectors is decomposed to *explained* and *unexplained* parts. For keeping the notation clean, after estimating equation (1.3.1), the mean wage of sector j can be rewritten in vector notation as

$$\widehat{\ln W_j} = \widehat{\alpha}_j + \bar{X}_j \widehat{b}'_j \tag{1.3.2}$$

where $\bar{X}_j$ (=[$\overline{SCH}_j, \overline{EXP}_j, \overline{EXP^2}_j$]) is a row vector of the averaged independent variables in sector j, and $\widehat{b}'_j$ (=[$\widehat{\beta}_{1j}, \widehat{\beta}_{2j}, \widehat{\beta}_{3j}$]$'$) is a column vector of their coefficients. Now, suppose two sectors, 1 and 2.

$$\text{sector 1} : \widehat{\ln W_1} = \widehat{\alpha}_1 + \bar{X}_1 \widehat{b}'_1$$
$$\text{sector 2} : \widehat{\ln W_2} = \widehat{\alpha}_2 + \bar{X}_2 \widehat{b}'_2$$

By subtracting one from the other, explained and unexplained components of the wage differential between both sectors are derived as

$$
\begin{aligned}
\widehat{\ln W_2} - \widehat{\ln W_1} &= (\widehat{\alpha}_2 - \widehat{\alpha}_1) + (\bar{X}_2\widehat{b}_2' - \bar{X}_1\widehat{b}_1') \\
&= (\widehat{\alpha}_2 - \widehat{\alpha}_1) + (\bar{X}_2\widehat{b}_2' - \bar{X}_1\widehat{b}_1') + \bar{X}_1\widehat{b}_2' - \bar{X}_1\widehat{b}_2' \\
&= \underbrace{(\bar{X}_2 - \bar{X}_1)\widehat{b}_2'}_{explained} + \underbrace{(\widehat{\alpha}_2 - \widehat{\alpha}_1) + \bar{X}_1(\widehat{b}_2' - \widehat{b}_1')}_{unexplained} \qquad (1.3.3)
\end{aligned}
$$

The 'explained' component reflects a portion caused by different schooling and experience between two comparison groups. In other words, if two workers from different sectors have the same skill, or $\bar{X}_2 = \bar{X}_1$, there exists no explained wage gap. However, even given the same skill between workers, the 'unexplained' wage gap remains owing to unobserved factors. This quantifies the difference in intercepts between sectors plus the difference in the returns to workers' qualifications.

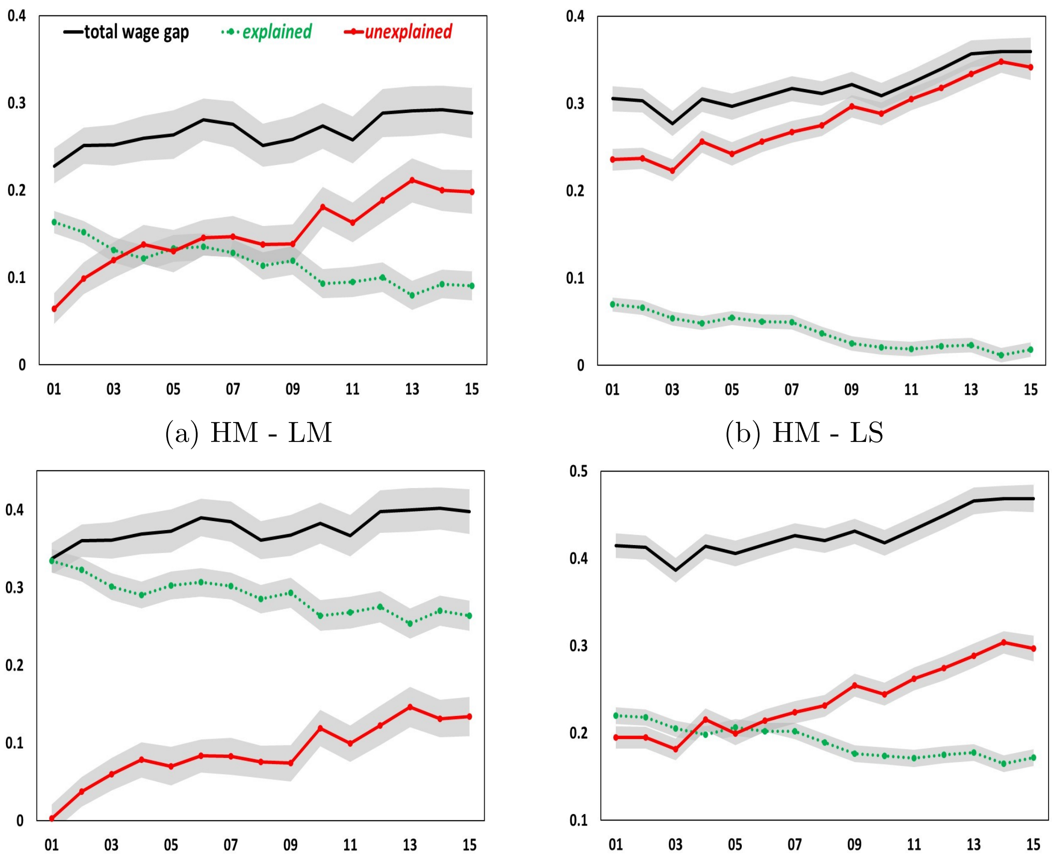
The origin of the first term in the unexplained part, $(\widehat{\alpha}_2 - \widehat{\alpha}_1)$, is unknown. This term means that workers with zero schooling and experience get paid $\widehat{\alpha}_1$ in sector 1 or $\widehat{\alpha}_2$ in sector 2. The difference may be caused by a difference in TFPs between sectors and consumers' preferences for the goods, or by the existence of labour mobility frictions.

In the second term, $(\widehat{b}_2' - \widehat{b}_1')$ reflects the difference in the return to workers' schooling and experience between sectors. Regarding this term, there are two conflicting views in the literature (Herrendorf and Schoellman, 2018). According to the 'selection view', the difference in the returns is attributable to the difference in workers' unobserved abilities so that a worker with high ability can earn more per schooling or per experience than those with low ability. In contrast, the 'sectoral view' attributes the difference in the returns to the different technologies between sectors. Embedded within this view is the existence of labour mobility frictions because the wage gap caused by the different technologies should reduce through labour reallocation provided that mobility frictions do not exist. Under the sectoral view, the persistent and widening wage gap implies the existence of labour mobility frictions. For example, Lee and Wolpin (2006), Artuç, Chaudhuri, and McLaren (2010), and Dix-Carneiro (2014) associate continuing divergence in wages with large mobility costs. Romer (2012, pp.501-504) points out that only the former hypothesis cannot convincingly explain all the findings of the entire wage gap. He refers to four counter-evidences on the selection view: (i) a large portion of the wage gap is inexplicable by workers' unmeasured abilities (Katz and Summers, 1989), (ii) the large wage cuts at new jobs for the labourers, who worked in high-wage firms but lost jobs because of the firms' shutdown, cannot be explained (Gibbons and Katz, 1992), (iii) high-profit industries typically have a high wage premium, and (iv) all occupations including janitors and cleaners in high-wage industries earn high wages.

Figure 1.3 presents year-by-year estimations of the explained and unexplained parts in the Blinder-Oaxaca decomposition on the wage gaps between sectors. A striking feature of the graphs is that the unexplained variations between high- and low-wage sectors have increased since the early- and mid-2000s albeit some fluctuations during the global financial crisis. The unexplained wage gap between the high-wage manufacturing (HM) and the low-wage manufacturing (LM) rose from 7 percent ($\exp(0.064) - 1 \simeq 0.066$) in 2001 to over 20 percent after 2012. That part between the high-wage manufacturing (HM) and the low-wage services (LS) rose by approximately 14 percentage points between 2001 and 2015. Similarly, the unexplained variations between the high-wage services (HS) and the low-wage manufacturing (LM), and the high-wage services (HS) and the low-wage services (LS) increased by 14 percentage points and 13 percentage points during the period, respectively. All these estimates are statistically significantly different from zero at the 1 percent level.[17]

Table 1.3 shows that the proportion of the unexplained part in the total wage gap has increased since 2000. The increases in the proportions between the high-wage sector and the low-wage sector range from 16.4 percentage points (HS-LS) to

[17]See the Appendix 1.A.3 for the measurement of standard error.



(a) HM - LM

(b) HM - LS

(c) HS - LM

(d) HS - LS

Figure 1.3: Decomposition of wage gaps, full-time full-year white male, US

Source: Author's own, from IPUMS-CPS

Notes: All estimates are statistically significantly different from zero at the 1% level. The grey shaded areas represent the 95% confidence intervals.

40.4 percentage points (HM-LM) over the period.

In summary, the wage gaps have been large and increasing for a long period of time, driven by a rise in unexplained factors. Therefore, labour mobility frictions seem a promising avenue to explain the large and long-lasting wage differentials, partly or mostly.

Table 1.3: Proportion of unexplained part in wage gap, US

		2001 (A)	2006	2011	2015 (B)	(B-A)
HM-LM	total wage gap	0.228	0.281	0.258	0.288	0.061
	unexplained	0.064	0.145	0.163	0.198	0.134
	percentage	28.3%	51.8%	63.2%	68.6%	40.4%p
HM-LS	total wage gap	0.305	0.307	0.324	0.359	0.054
	unexplained	0.236	0.257	0.305	0.341	0.106
	percentage	77.2%	83.6%	94.2%	95.0%	17.8%p
HS-LM	total wage gap	0.337	0.390	0.367	0.398	0.061
	unexplained	0.003	0.083	0.099	0.134	0.131
	percentage	0.8%	21.4%	27.0%	33.7%	32.8%p
HS-LS	total wage gap	0.415	0.416	0.433	0.469	0.054
	unexplained	0.195	0.214	0.262	0.297	0.102
	percentage	47.0%	51.5%	60.5%	63.3%	16.4%p

Source: Author's own, from IPUMS-CPS

Notes: The percentage is calculated as (unexplained part)/(total wage gap)×100.

1.3.3 Evidence 2: Downward Inter-sectoral Labour Mobility

In this part, we first examine the aggregate level of inter-sectoral labour mobility in the US using macro-data. Then, the direction of labour transition is measured using micro-data. The main finding here is that although aggregate labour mobility has increased since the 2000s, labour flows from high- to low-wage industries or labour tends to move within low-wage industries.

1.3.3.1 Aggregate inter-sectoral labour mobility

Several methods have been introduced in previous research to measure the extent of inter-sectoral labour mobility. We follow two approaches. The first is the method introduced by Davis et al. (1996, cited in Wacziarg and Wallack, 2004) called *industry reallocation* of employment (henceforth, IR index, for short).

$$IR_{t,t-\tau} = \frac{\sum_{j=1}^{J} |E_j^t - E_j^{t-\tau}| - |\sum_{j=1}^{J} E_j^t - \sum_{j=1}^{J} E_j^{t-\tau}|}{0.5 \sum_{j=1}^{J} (E_j^t + E_j^{t-\tau})} \tag{1.3.4}$$

where E_j^t is the number of employees in sector j at time t, τ is a time lag, and J is the total number of sectors. This method captures the fraction of workers who move between sectors, which is independent of the change in the overall employment. The first term in the numerator ($\sum_{j=1}^{J} |E_j^t - E_j^{t-\tau}|$) of equation (1.3.4) represents the sum of the absolute values of the changes in individual sector's employment between time $t - \tau$ and time t, and the second term ($|\sum_{j=1}^{J} E_j^t - \sum_{j=1}^{J} E_j^{t-\tau}|$) refers to the absolute value of the total change in the country's employment between two points of time. Hence, the numerator demonstrates net labour reallocation between sectors independent of total employment changes. For example, if the sum of the changes in each sector's employment is bigger than the change in total employment, the level of inter-sectoral labour mobility goes up; otherwise, it drops.[18]

The second method to measure the degree of aggregate labour mobility is to use each sector's employment share, called *structural adjustment* in employment (henceforth, SA index). Charette et al. (1986, cited in Wacziarg and Wallack, 2004) apply this way to assess the long-term change in employment patterns within a country.

$$SA_{t,t-\tau} = \frac{1}{2} \sum_{j=1}^{J} |S_j^t - S_j^{t-\tau}| \tag{1.3.5}$$

where S_j^t is the proportion of sector j's employees in all sectors at time t. By summing the absolute difference values of the employment share in each sector between time t and time $t - \tau$, it measures the magnitude of the structural employment changes in an economy. Thus, a high value of the SA index can be interpreted as a high degree of inter-sectoral labour mobility.[19]

Table 1.4 describes the trends of the indices for aggregate inter-sectoral labour mobility in the US since the 1990s. Although the levels of both indices are different from each other, the patterns are similar. In particular, the increase in labour

[18] The upper bound of the IR index rises as the number of sectors (J) increases. Its lower bound is zero when employment changes in the same direction in all sectors.

[19] The upper bound of the SA index is 100 and its lower bound is zero.

mobility since the 2000s is noticeable. Taking account of its link to sectoral wage gaps, it tells us that despite the increased level of labour mobility since the 2000s, the wage differentials puzzlingly have been persistent and increasing over the same period. Why have wage gaps widened even in the high degree of labour mobility?

Table 1.4: Indices of aggregate inter-sectoral labour mobility, US

index	early 1990s-late 1990s	late 1990s-early 2000s	early 2000s-late 2000s
IR	0.71	2.46	3.26
SA	1.70	2.37	2.82

Source: Author's own, from EU KLEMS ('number of persons engaged', 1990-2007, US)
Notes: 'early' ('late') denotes the first (second) half of each decade.

1.3.3.2 Direction of labour transition

Labour transition across sectors can be calculated as the fraction of switchers from one sector to another sector, $\mathcal{M}_{jj'}/\sum_{j'}\mathcal{M}_{jj'}$.[20] Here, $\mathcal{M}_{jj'}$ is the number of movers from sector j at time t to sector j' at time $t+1$.[21] Table 1.5 shows the matrices of labour transition rates by sector in the US pre- and post-2000. Each cell of the table presents the fraction of switchers from the row sector to the column sector in any given period. For example, in the 1990s, if a full-time white male worker in the high-wage manufacturing (HM) current year (t) intends to switch industries, her transition probability to the low-wage services (LS) next year ($t+1$) is 15.5 percent, statistically. The diagonal cell shows the fraction of workers who change their industries within the sector. Comparing both periods, the rate of switching from LM to HM dropped (19.5% $\rightarrow$ 16.6%) whereas that in the reverse direction jumped (16.4% $\rightarrow$ 32.8%). Likewise, the transition rate from HS to LS substantially increased (34.4% $\rightarrow$ 44.8%) as opposed to a reduction in moving from LS to HS

[20] See the Appendix 1.A.4 for the statistics on switchers' demographic characteristics.
[21] When $j = j'$, $\mathcal{M}_{jj'}$ indicates the number of movers within sector j.

Table 1.5: Labour transition rate by sector, full-time full-year white male, US

(a) 1991-2000

(%)

t+1 / t	high-wage manu.	low-wage manu.	high-wage ser.	low-wage ser.	other industries[a]
high-wage manu.	44.4	16.4	13.5	15.5	10.1
low-wage manu.	19.5	28.0	13.0	25.6	13.7
high-wage ser.	9.6	8.2	31.4	34.4	16.1
low-wage ser.	6.4	9.3	20.9	48.8	14.3
other industries[a]	10.4	12.8	20.2	35.1	21.4
total	15.3	13.2	20.8	35.6	15.0

(b) 2001-2015 (excl.2007-2010)

(%, %p)

t+1 / t	high-wage manu.	low-wage manu.	high-wage ser.	low-wage ser.	other industries[a]
high-wage manu.	27.9	32.8	14.1	15.2	10.0
	(−16.5)	(+16.4)	(+0.6)	(−0.3)	(−0.1)
low-wage manu.	16.6	32.0	12.8	24.8	13.9
	(−3.0)	(+3.9)	(−0.2)	(−0.9)	(+0.2)
high-wage ser.	6.8	6.1	29.6	44.8	12.6
	(−2.9)	(−2.0)	(−1.8)	(+10.3)	(−3.5)
low-wage ser.	4.9	6.7	19.7	55.8	12.9
	(−1.5)	(−2.7)	(−1.2)	(+7.0)	(−1.4)
other industries[a]	7.3	8.4	19.3	44.9	20.1
	(−3.1)	(−4.4)	(−0.9)	(+9.8)	(−1.3)
total	9.9	12.7	20.6	42.8	13.8
	(−5.3)	(−0.5)	(−0.1)	(+7.2)	(−1.2)

Source: Author's own, from IPUMS-CPS

Notes: [a]Other industries include agriculture, mining, construction, utility, and public administration. [b]The numbers in brackets are the differences in transition rates between pre- and post-2000 periods. [c]The sum of each row in the two tables is not 100% because some workers flow into unemployment. See the Appendix 1.A.5 for the full tables.

(20.9% → 19.7%). Compared to the period prior to 2000, a person who worked in the low-wage sector (LM and LS) is more likely to be stuck in the same sector over the period between 2001 and 2015 (28.0% → 32.0% and 48.8% → 55.8%, respectively). In contrast, the probability of moving within the high-wage sector (HM and HS) dropped (44.4% → 27.9% and 31.4% → 29.6%, respectively). Particularly, the labour transition into the low-wage services (LS) considerably increased in most sectors since 2001 (35.6% → 42.8%).

Table 1.6 shows the modified labour transition rate by removing the effect of the labour demand shift. Here, sectoral market size and each worker's occupation are additionally controlled. To put it concretely, the modified rate is calculated by

Table 1.6: Market size-adjusted labour transition rate by sector, full-time full-year white male with controlling for occupation, US

(a) 1991-2000

(%)

t \ t+1	high-wage manu.	low-wage manu.	high-wage ser.	low-wage ser.	other industries
high-wage manu.	67.5	18.0	4.7	2.7	7.0
low-wage manu.	33.1	44.2	6.2	5.6	11.0
high-wage ser.	23.7	16.2	23.5	12.6	24.1
low-wage ser.	15.1	19.1	17.1	26.6	22.1
other industries	22.4	22.6	14.1	12.0	28.9
total	36.3	23.3	12.2	11.6	16.7

(b) 2001-2015 (excl.2007-2010)

(%, %p)

t \ t+1	high-wage manu.	low-wage manu.	high-wage ser.	low-wage ser.	other industries
high-wage manu.	44.6	42.2	4.7	2.1	6.4
	(−22.9)	(+24.1)	(-)	(−0.6)	(−0.6)
low-wage manu.	30.0	49.8	5.4	4.2	10.6
	(−3.1)	(+5.6)	(−0.8)	(−1.4)	(−0.3)
high-wage ser.	22.8	17.0	24.2	17.5	18.5
	(−0.8)	(+0.8)	(+0.7)	(+4.9)	(−5.6)
low-wage ser.	17.5	17.4	17.4	27.7	19.9
	(+2.4)	(−1.6)	(+0.3)	(+1.1)	(−2.2)
other industries	20.1	18.1	14.4	18.4	29.1
	(−2.3)	(−4.5)	(+0.2)	(+6.4)	(+0.2)
total	28.4	29.2	13.1	13.7	15.7
	(−7.9)	(+6.0)	(+0.9)	(+2.0)	(−1.0)

Source: Author's own, from IPUMS-CPS

multiplying a weight to the fraction of switchers as $\mathcal{M}_{jj'}/\sum_{j'}(\mathcal{M}_{jj'}) \times \lambda_{j'}$ and by restricting the sample to workers who switch sectors but keep the same occupation. $\lambda_{j'}$ is the inverse of the share of persons engaged at sector j' which reflects the sector's labour market size. This table proves that labour still tends to cluster in the low-wage sector even after controlling for the change in labour demand. When compared to the period of pre-2000, the labour transition rates from HM to LM and from HS to LS sharply rose (18.0% → 42.2%, 12.6% → 17.5%, respectively), and the rates of staying within the low-wage sector (LM and LS) goes up (44.2% → 49.8%, 26.6% → 27.7%). As a result, labour has concentrated in the low-wage sector.

In conclusion, the dominant change in the US labour transition after the 2000s, is that workers in the high-wage sector tend to vertically move to the low-wage sector whereas workers in the low-wage sector primarily move horizontally within their sector, which results in labour clustering in the low-wage or less productive sector. This suggests that there exist frictions in low-to-high sectoral labour mobility.

1.3.4 Evidence 3: A Large Change in Wage from Sector Switch

I measure the average wage change from vertical movement between sectors. If a worker's wage significantly increases when she moves in the direction of low-to-high given that all other conditions are the same, this with previous facts supports the existence of labour mobility frictions. Put differently, despite this strong incentive to move to the high-wage sector, the observation of labour flowing in the opposite direction suggests that there exist some barriers which hinder workers from switching sectors. However, if the previously discussed selection view on the wage gap is true, there should be little change in wage when a worker switches sectors.

For the measurement of the wage change, the ideal data is workers' wages before and after switching sectors, but the IPUMS-CPS database only provides a worker's previous year's wage. I alternatively measure the difference in mean wages between former and current industries. To see the wage change purely caused by the sector switch, worker's characteristics, occupation and work experience are controlled.

$$\begin{aligned}&\triangle\mathbb{E}\big[\ln w^i_{t,t+1}(j,j') \mid \overline{occ},\ \overline{exp}\big] \qquad (1.3.6)\\ &\qquad \equiv \mathbb{E}\big[\ln w^i_{t+1}(j') \mid \overline{occ},\ \overline{exp}\big] - \mathbb{E}\big[\ln w^i_t(j) \mid \overline{occ},\ \overline{exp}\big]\end{aligned}$$

where $w^i_t(j)$ is the wage level of individual i who works in the sector j at time t, and $\mathbb{E}[\ln w^i_t(j) \mid \overline{occ}, \overline{exp}]$ is the mean of the logged wage of workers in sector j given a fixed occupation, $\overline{occ}$ and work experience, $\overline{exp}$. Thus, $\triangle\mathbb{E}[\,\cdot\,]$ measures the average wage change of a worker who switches sectors without changing the occupation, for example, when an accountant with a 10-year career at an apparel firm (a low-wage industry) moves to a shipbuilding company (a high-wage industry) and works as an accountant as before.

Table 1.7 shows the average wage change by switching sectors. When a worker moves from the low- to the high-wage sector, her wage increases by 13.3 percent ($\exp(0.125) - 1 \simeq 0.133$) on average during the period after 2001. In particular, the increase in wage is substantial when a worker in the low-wage services switches to the high-wage sector (LS $\rightarrow$ HM: 14.5%, LS $\rightarrow$ HS: 15.6%). This result is in line with Krueger and Summers (1988) who find that the wages of switchers from one industry to another averagely change by as much as the wage gaps between both industries. Contrarily, when a worker moves from the high- to the low-wage sector, her wage is likely to decrease averagely by about 8 percent after the 2000s. Doubtless, the worker's incentive from the low-to-high sectoral movement is far more than the reverse. Nevertheless, the US labour market has shown that the downward labour flow has largely increased while the upward drift has decreased as previously found. Were the theory of perfect labour mobility valid, this kind of labour flow should not happen.

Table 1.7: Average wage change from sectoral switch, full-time full-year white male with controlling for occupation and work experience, US

	1991-2000			2001-2015 (excl.2007-10)		
	$\triangle E[\ln(w)]$	std.err.	obs.	$\triangle E[\ln(w)]$	std.err.	obs.
$LM_t \rightarrow HM_{t+1}$	0.075**	(0.015)	471	0.116**	(0.015)	498
$LM_t \rightarrow HS_{t+1}$	-0.039*	(0.023)	247	0.039*	(0.023)	351
$LS_t \rightarrow HM_{t+1}$	0.113**	(0.021)	288	0.135**	(0.020)	397
$LS_t \rightarrow HS_{t+1}$	0.092**	(0.016)	836	0.145**	(0.011)	1,521
$Low_t \rightarrow High_{t+1}$	**0.073****	(0.009)	1,842	**0.125****	(0.008)	2,767
$HM_t \rightarrow LM_{t+1}$	-0.068**	(0.014)	485	-0.033**	(0.007)	1,682
$HM_t \rightarrow LS_{t+1}$	-0.163**	(0.020)	333	-0.135**	(0.017)	515
$HS_t \rightarrow LM_{t+1}$	-0.030	(0.022)	247	-0.038**	(0.018)	462
$HS_t \rightarrow LS_{t+1}$	-0.114**	(0.016)	846	-0.099**	(0.007)	3,090
$High_t \rightarrow Low_{t+1}$	**-1.000****	(0.009)	1,911	**-0.078****	(0.005)	5,749

Source: Author's own, from IPUMS-CPS

Notes: '$**$', '$*$' indicate that the $\triangle E[\ln(w)]$ is not zero with a significance level of 5%, 10%, respectively, using t-test. The t-statistic is defined as $t = (\ln \bar{w}_{t+1} - \ln \bar{w}_t)\sqrt{n}/s.e.$, where $s.e.$ is standard error and n is the size of sample.

1.3.5 Evidence 4: The Increasing Mobility Cost

Artuç, Chaudhuri, and McLaren (2010, henceforth, ACM) propose a method of estimating the pecuniary loss from a sector switch, the so-called labour mobility cost by setting up a dynamic model of workers' sector switches.[22] They use the data of sectoral wages and the fraction of sector switchers for the period before 2000 from the US CPS database. Following this method, I estimate the inter-sectoral labour mobility cost and its trend to see how the mobility cost changes since the 2000s.

As in ACM, a worker maximises her utility in the sector choice problem by choosing to remain at her current sector (j) or move to another sector (j'). The worker's optimisation problem can be written as

[22] Artuç, Chaudhuri, and McLaren (2010) postulate that the labour mobility cost has two parts: a common and an idiosyncratic (worker-specific) component. They define the common component as the pecuniary loss in switching sectors which does not vary across individuals and estimate it to examine the economy-wide level of mobility cost.

$$U^j(L_t, s_t, \varepsilon_t) = W_{j,t} + \max_{j'} \left\{ \varepsilon_{j',t} - \phi_{jj'} + \beta \mathbb{E}_t[V^{j'}(L_{t+1}, s_{t+1})] \right\} \tag{1.3.7}$$

where $U^j(\cdot)$ is the value to a worker in sector j which is a function of the labour supply L_t, a state s_t such as technology shock, and an idiosyncratic benefit ε_t. $W_{j,t}$ is the sector j's wage, $\phi_{jj'} > 0$ is a pecuniary mobility cost when a worker moves from sector j to sector j'. $V^j(\cdot)$ denotes the average value of $U^j(\cdot)$ across all workers, or the expected value of being in sector j. β is the discount factor.

By optimising a worker's choice in switching sectors, a Euler equation can be derived as[23]

$$\begin{aligned} &\phi_{jj'} + \bar{\varepsilon}_{jj',t} \qquad\qquad (1.3.8)\\ &\quad = \beta \mathbb{E}_t \left[(W_{j',t+1} - W_{j,t+1}) + (\phi_{jj'} + \bar{\varepsilon}_{jj',t+1}) + (\Omega(\bar{\varepsilon}_{j',t+1}) - \Omega(\bar{\varepsilon}_{j,t+1})) \right] \\ &\text{where } \bar{\varepsilon}_{jj',t} \equiv \beta \mathbb{E}_t \left[V^{j'}(L_{t+1}, s_{t+1}) - V^j(L_{t+1}, s_{t+1}) \right] - \phi_{jj'} \ , \\ &\quad \bar{\varepsilon}_{j,t} = (\bar{\varepsilon}_{j1,t}, \cdots, \bar{\varepsilon}_{jJ,t}) \\ &\quad \Omega(\bar{\varepsilon}_{j,t}) = \sum_{j'=1}^{J} \int_{-\infty}^{\infty} (\varepsilon_{j'} + \bar{\varepsilon}_{jj',t}) f(\varepsilon_{j'}) \prod_{k' \neq j'} F(\varepsilon_{j'} + \bar{\varepsilon}_{jj',t} - \bar{\varepsilon}_{jk',t}) d\varepsilon_{j'} \end{aligned}$$

$\bar{\varepsilon}_{jj',t}$ is the net value when switching sectors and $\Omega(\cdot)$ is the additional value which is the option to move to another sector. $f(\cdot)$ is the probability density function and $F(\cdot)$ is the cumulative distribution function. Thus, this Euler equation shows that the expected change in the future value by moving from sector j to sector j' has three components: (i) the wage gap, (ii) the expected value of being in sector j' in lieu of sector j, (iii) the difference in additional values.

With the assumption that idiosyncratic shocks follow an extreme value distribution, (1.3.8) gives the following linear regression equation as[24]

[23]See the Appendix 1.A.6 for the derivation.
[24]See the Appendix 1.A.6 for the derivation.

$$(\ln m_{jj',t} - \ln m_{jj,t}) - \beta(\ln m_{jj',t+1} - \ln m_{j'j',t+1}) = \qquad (1.3.9)$$
$$-\frac{(1-\beta)}{\nu}\phi_{jj'} + \frac{\beta}{\nu}(W_{j',t+1} - W_{j,t+1}) + u_{t+1}$$

where $m_{jj',t}$ denotes the faction of the labour force in sector j that moves to sector j', which indicates the gross labour flow from sector j to j'. β is set to 0.96 as in the standard literature. ν is a parameter which is related to the variance of idiosyncratic shocks and u_{t+1} is news revealed at $t+1$.

The data used in this estimation are the same as before. By using IPUMS-CPS database, I construct the fraction of sector switchers, $m_{jj',t}$, and sector j's real wage $W_{j,t}$. Here, sectoral wages are normalised in such a way that each wage is deflated by the average wage of the whole sample. The sample is restricted to the full-time white males aged 16 to 70 and the period covers 26 years (1991-2015). The sector classification follows ACM who aggregate sub-industries to six sectors: agriculture & mining, construction, manufacturing, transportation, communication & utilities, trade, and all other services.[25]

By running a panel regression, the average mobility cost $\hat{\phi}$ in inter-sectoral labour movements is estimated.[26] Table 1.8 shows the results from the panel data regression. Panel 1 shows the results of the generalised linear squares (GLS) regressions by period. The generalised two-stage linear squares (G2SLS) regressions are also conducted as in Panel 2 where instrumental variables are used because the error term is likely to be correlated with the wages as the error term contains news at time $t+1$. ACM use lagged endogenous variables, $(W_{j',t-1} - W_{j,t-1})$ and $(\ln m_{jj',t-1} - \ln m_{j'j',t-1})$, as instrumental variables which are uncorrelated with the

[25] Artuç, Chaudhuri, and McLaren (2010) point out that classifying samples into many sub-industries makes them close to zero observations since the number of directions for labour flows grows fast as the number of sectors increases. These six sectors are the same as the major sector classification in the CPS database.

[26] This panel data regressions estimate the average moving cost across sectors as in ACM.

wages at time $t+1$.

Table 1.8: Estimations on labour mobility cost using panel data, US

	Panel 1. GLS			Panel 2. G2SLS (IV)		
	Total	1991-2000	2001-2015	Total	1991-2000	2001-2015
$\hat{\phi}$	27.968	19.438	34.168	29.022	24.206	31.294
	(27.971)***	(19.435)***	(34.167)***	(29.026)***	(24.202)***	(31.283)***
$\hat{\nu}$	6.417	5.330	7.069	6.382	5.946	6.475
	(6.409)***	(5.338)**	(7.070)**	(6.389)***	(5.953)***	(6.470)***
$Wald\ \chi^2$	11.67***	6.02**	6.30**	18.02***	15.25***	12.02***
No. obs	750	300	450	720	270	450

Source: Author's own, from IPUMS-CPS, based on Artuç et al. (2010)

Notes: The White robust variance estimator is used. Values within parenthesis indicate t-statistics. Based on the Hausman test (p-value is 0.7399 for Panel 1 and 0.7969 for Panel 2.), the random effects model is applied.

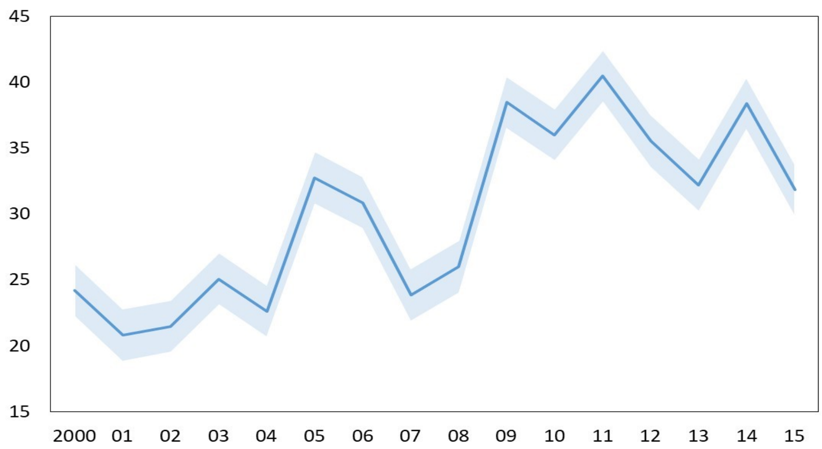


Figure 1.4: Average mobility cost ($\hat{\phi}$), 10-year window rolling regressions, US

Source: Author's own, from IPUMS-CPS, based on Artuç et al. (2010)

Notes: The shaded area is the 95% confidence interval. The value is the coefficient $\hat{\phi}$ from 10-year window rolling regressions (G2SLS); e.g. the value in 2000 is the coefficient $\hat{\phi}$ from the regression for the period 1991-2000.

The results show that the average cost for workers to switch sectors, or $\hat{\phi}$, has been much higher in the period after 2001 than before.[27] The estimates of $\hat{\phi}$ indicate that the inter-sectoral mobility cost increased from 19 - 24 times the average wage

[27] A rise in $\hat{\nu}$ means that the tails of the shock distribution fatten and thus a given worker is more likely to change sectors due to idiosyncratic reasons such as nonpecuniary factors.

in the 1990s to 31 - 34 times after 2000.[28] Figure 1.4 is the plot of time-varying coefficient $\hat{\phi}$ estimated by 10-year window rolling regressions. The plot also describes that the labour mobility cost has risen since the early 2000s except for the period of the global financial crisis.

1.4 Sources of Labour Mobility Frictions

So far, we have observed a puzzling phenomenon of the increasing wage gap and downward labour mobility. To offer an explanation of this puzzle, I have shown evidence from the US labour market which suggests the existence of increasing labour mobility frictions. This implies that workers now pay higher costs, in terms of time and money, to move to other sectors than in the past. Such mobility frictions thus distort labour allocation across sectors and further widen the wage gap.

We now discuss changes in the process of switching sectors. This discussion provides potential avenues for opening the black box, the source of mobility frictions, and for addressing what drives the frictions to increase over time.

1.4.1 Worker's Sector Switch Process

There have been some studies on labour mobility frictions which encompass observable costs, for example, job search costs and training costs, as well as shadow mobility costs such as uncertainty in matching. In general, when a worker tries to switch sectors, she needs to pass through a series of steps as delineated in Table 1.9. The first step is to train transferable or specific skills required in the desired industry.[29] After that, the worker searches for better workplaces and applies for as

[28]These estimates are similar to ACM's which is 22.065 in the baseline model for the period 1975 - 2000. According to ACM, the estimates of moving cost in the literature usually show a very high cost (e.g. Kennan and Walker, 2003).

[29]The skills required in switching jobs are divided into firm-specific, industry-specific, occupation-specific, and transferable (or general) skills. The first two skills are normally acquired by the on-the-job training in a firm, and the others are obtained at schools or vocational training institutions (off-the-job training).

many jobs as possible, but faces constraints in terms of time and information cost. Some applicants succeed in switching sectors, and others fail. The workers who fail to change sectors try the first or second step again by extending their list of desired jobs, or stay in their original places, while successful workers move to new places. In this process, various types of costs and uncertainties are involved.

Table 1.9: Worker's sector switching process

process		**mobility costs or frictions**
step 1	getting transferable skills	training costs and period
step 2	searching & applying for jobs	costs, time, and efforts in searching, networking, and applying for jobs
step 3	matching	uncertainties (possibility of failure) in switching sectors
step 4	moving	moving costs, and geographical constraints, opportunity costs

Many studies find a lack of skills or training to be an important impediment for a worker who is trying to shift to other sectors. Papers by Sicherman and Galor (1990) and Dolton and Kidd (1998) suggest that workers need to invest in skills for changing sectors or jobs and obtaining a superior wage option. Dolton and Kidd (1998) theoretically and empirically show that investment in transferable skills promotes inter-sectoral labour mobility, inferring that an individual needs to spend money and time in order to enter a preferred sector. Likewise, Lynch (1991) reveals, using training data from the US, that young workers, who participated in off-the-job training to get transferable skills, were more likely to switch sectors so that they would have better chances to find higher wage firms. This paper also shows that people who earn a low income tend to move to a better workplace by investing in human capital.

Even if individuals become equally productive and have the same skills through training, different types of mobility frictions prevent some of them from switching sectors. When attempting to move to other sectors, workers face frictions related to search, moving, and opportunity costs (Bartel, 1979; Diamond, 1981). Further, according to the job search and matching theory, information about a better job and job's nature is costly and not easy to acquire so that workers pay costs in terms of time and money while trying to shift to other sectors (Lippman and McCall, 1976).

Lastly, in the matching process, mobility frictions can come in the form of uncertainty. Harris and Todaro (1970) point out that workers who try to change sectors face the uncertainty of risking unemployment during the switching process.

Based on the sector switching process, three types of *inter-sectoral labour mobility frictions* can be defined:

1. Training cost: To acquire skills (transferable and occupation-specific skills) required by a sector, workers need to invest in training.

2. Search & Moving cost: This is a certain amount of time, effort, and money for job search, application, and moving to switch sectors.

3. Matching uncertainty: Many, although not all, workers have the possibility of failure in changing sectors.

1.4.2 Discussion: Sources of Mobility Frictions

Several hypotheses lend themselves as candidate explanations for the source of mobility frictions which trigger anomalous labour allocation. These will be discussed individually by type of frictions.

1.4.2.1 Training Cost

Workers consider what skills are required when thinking about a career change to a different sector. Employers, of course, look for workers who can demonstrate a good set of occupation-specific and transferable skills. Thus, training costs are a form of affecting a worker's acquisition cost of skills, and a levy imposed by employers according to Hsieh et al. (2013). They assume that a worker's consumption is set as income less expenditure on human capital as

$$c = w - \underbrace{e \cdot (1 + \tau)}_{\text{training cost}}$$

where w is an individual's wage, and e is her expenditure on skills. τ is the additional cost for human capital investment depending on a worker's ability, demographics, and current sector. Hence, the agent's sector switch choice depends largely on how much they pay for training.

As shown in Figure 1.5, the share of movers from the low- to the high-wage sector is directly proportional to the share of vocational trainees in the previous year, and this observation is consistent with empirical evidence in Veum (1997) that self-paid job training raises the likelihood of leaving a job. He argues that skill acquisition from training serves to improve job matches.

Importantly, it is observed that as the participation rate in vocational training

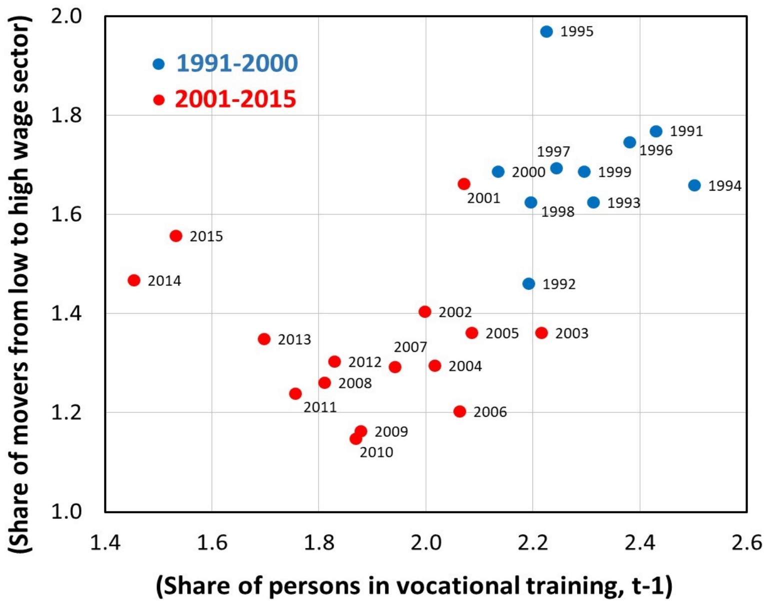


Figure 1.5: Training and upward labour mobility, US

Source: Author's own, from IPUMS-CPS

Notes: Each share is measured against the total labour force. Vocational training is a training program including business, technical, trade, or correspondence courses, other than regular school or on-the-job training. The sample is restricted to persons aged 16-70 years.

has decreased since the 2000s, so has the share of switchers to the high-wage sector. In the relation to this, Cappelli (2012) emphasises that many good workers fail to get a decent job in the US mainly due to a lack of training. Chang (2010) argues that little public support for workers' retraining and job search in the US renders them less open to change their current jobs.

The reason for the decrease in training could be the change in training costs. The statistics of education institution fees suggest the possibility of an increase in training costs. The real tuition fee in the US public 4-year universities has increased at an annual rate of 4.35 percent on average after the 2000s (3.33% in the 1990s) while the real GDP per capita has increased just at an annual rate of 0.91 percent for the same period (2.19% in the 1990s), meaning that the relative cost of training has risen (source: The College Board, IMF). Furthermore, the US public expenditure in labour market training programmes has dwindled markedly from 0.10 percent in 1990 to 0.03 percent in 2015 in terms of a percentage of GDP as in Table 1.10.[30]

Table 1.10: Public expenditure on training programmes, US

1990	2000	2010	2015
0.10%	0.06%	0.04%	0.03%

Source: OECD
Note: a percentage of GDP

1.4.2.2 Search and Moving Cost

Alvarez and Shimer (2011) defines job search as a costly activity that enables workers to move to a new sector. According to Mortensen (2011), job search costs are an investment in information to find job opportunities, and they act as an impediment to the process of efficient labour allocation.

[30] The training programmes include institutional training, workplace training, integrated training, and special support for apprenticeship.

Recently, with high accessibility to information, the time needed to search for a job has become shorter, and the commission paid for job information has decreased. For individual job seekers, however, input effort level on searching and applying for a preferred job is higher since the supply of well-prepared competitors, e.g. university leavers, has increased rapidly for these good jobs, meaning that the supply of skills would exceed the demand for those skills (Acemoglu and Autor, 2011). In the US, the number of Bachelor's degrees increased at an annual rate of 3.1 percent since 2001 which is more than twice as high as the rate (1.3%) in the 1990s (source: US Department of Education). In particular, graduates with a Bachelor's degree in the fields of study related to the high-wage sector have increased much faster than employment in that sector. As shown in Table 1.11, the number of graduates with a Bachelor's degree in an ICT-related field increased by 42.8 percent since the 2000s while employment in the ICT industry decreased by 14.8 percent. This congestion pressure also exists in the other high-wage industries including legal services (employment: 2.1% vs. graduates: 122.0%), finance & insurance (8.9% vs. 38.1%), and bio-industry (15.8% vs. 138.9%). Therefore, the degree of competition for the high-wage sector is likely to increase in abundance of those high-educated candidates who are well equipped with good general or occupation-specific skills, and thus workers in the low-wage sector compete with more people to enter the high-wage sector.

Table 1.11: Employment in high-wage sector and college graduates, 2001-2015, US

employment		graduates with Bachelor degree	
sector	growth (%)	major	growth (%)
High-wage sector	0.2	Total	52.3
ICT industry[a]	-14.8	ICT[b]	42.8
Legal services	2.1	Legal	122.0
Finance & Insurance	8.9	Business	38.1
Bio-industry[c]	15.8	Bio-science[d]	138.9

Source: US Department of Education 'HEGIS', BEA 'NIPA Table 6.5D'

Notes: [a]computer and electronic products, Information and computer systems design and related services, [b]communications technologies, computer and information sciences, [c]chemical products, hospitals, [d]biological and biomedical sciences, health professions and related programmes

Another reason for the high degree of congestion in the job search is associated with an increase of the skilled elderly in the labour force, especially after the 2000s. In the US, the compulsory retirement age was abolished in 1986, causing the labour force participation rate of persons aged over 65 to increase from 12.4 percent in 1994 to 18.6 percent in 2014 (source: BLS).

In the last step of switching sectors, direct moving costs and indirect opportunity costs are generated. The moving costs are a spatial constraint to labour mobility. Some research shows that the housing market affects inter-sectoral labour mobility via higher moving costs. Oswald (1997) claims that home ownership negatively influences the worker's geographical movement. According to Hyatt and Spletzer (2013), workers worry about losing health insurance coverage, called 'job-lock', and homeowners take their housing price into account, called 'house-lock', when they consider transferring to other firms. The authors point out that the intensity of job- and house-lock has increased during the past 10 to 15 years due to economic crises. Likewise, Brown (2016) argues that the housing market recession in the US during the 2000s discouraged workers from migrating to other regions as the decline of house value led to a liquidity constraint. According to Bartel (1979), the moving costs involve the loss of the spouse's income and the cost of uprooting their residence which are opportunity costs. The US family income data lend more weight to the view of the increased opportunity costs. In the US, the gender wage gap fell about 5 percentage points since the 2000s over the 1990s (source: OECD) while the share of dual-income families remained high around 70 percent (source: BLS). These observations indicate that sector switches of male workers generate higher opportunity costs than in the past.

1.4.2.3 Matching Uncertainty

The uncertainty or the probability of failure in matching makes people hesitate to attempt to switch sectors. There have been some studies aimed at revealing the source of matching uncertainty in the labour market. Harris and Todaro (1970) regard the possibility of unemployment as the uncertainty for workers in shifting from the rural sector to the urban sector. Since the 1990s, the Diamond-Mortensen-Pissarides (DMP) type matching technology has been widespread in research on matching frictions. In the DMP matching function, new job-worker matches (H_t) depend on not only the number of job seekers (U_t) and vacancy postings (V_t) but also matching efficiency (μ) which is an uncertain factor.

$$H_t = \mu \cdot M(U_t, V_t)$$

Relatedly, Petrongolo and Pissarides (2001) indicate that skill mismatch, or the gap in skill sets possessed by job seekers and skills required by industries, is one possible determinant for the extent of matching efficiency. As a sector achieves faster progress in technology, the sector requires a higher skill set from candidates so that matching uncertainty or skill mismatch increases in the sector.[31] For instance, with the advent of the ICT (Information & Communication Technology) revolution, the skills required by firms have changed. In the past, transferable skills were defined as generic skills such as communication and collaboration skills, fundamental numeracy, and literacy and computing skills, but these days many firms place more emphasis on specific IT skills, critical thinking, foreign languages and sense of entrepreneurship (Hart and Howieson, 2008). Not only does the change in skills required by firms make workers train for a longer time, but it also entails an increase in the skill mismatch between workers and firms. As a consequence, transferring to another sector is more uncertain for workers.

Besides, asymmetric information between job seekers and firms should be considered. Firms prefer qualified workers to avoid adverse selection. However, the rising number of highly educated candidates makes it difficult for firms to select the best candidate for the job.

[31] We will discuss the effect of unbalanced productivity between sectors on matching efficiency in Chapter 3.

1.5 Conclusion

Frictional inter-sectoral labour mobility and the widening wage gap exacerbate income inequality and hurt economic growth by creating inefficiencies in the labour market. From the viewpoint of labour market dynamics, the increasing inflow of labour into less productive sectors could trigger labour misallocation within an economy. Since barriers to labour mobility act as a significant constraint on economic agents, it is hard to achieve the first-best equilibrium in the economy. Therefore, labour mobility could be the key to improving economic disparity and promoting economic growth. All these imply that the removal of labour mobility frictions leads to a Pareto improvement.

The puzzling phenomenon of the low-wage sector clustering despite the increase in the wage gap, cannot be explained by labour supply and demand in the competitive market where labour moves freely across sectors. As a foundational step to identify what makes this distortion, we have found multiple evidence of the existence of labour mobility frictions from the US labour market: (i) The part of the wage gap unexplained by variables in the standard wage equation has increased. This implies that labour mobility frictions have increased since the unexplained wage gap is caused by the mobility frictions, partly or mostly. (ii) Labour flows from the high- to the low-wage sector increased, but labour flows in the reverse direction declined, indicating that there exist barriers to upward labour mobility. (iii) Even within a group, i.e. same characteristics, job and work experience, workers' wages significantly increase when they move from the low- to the high-wage sector. Put differently, while the incentive to move to the high-wage sector is strong enough, upward labour mobility does not happen often. (iv) Mobility costs from switching sectors have gone up since the 2000s.

There are three types of frictions in the process of a worker's sector switch. The first one is the training costs. Participation in skill training has decreased due to the increasing training costs. The second type of frictions is job search and moving costs which have risen because of the congestion in job search and the constraints on geographical movement. Lastly, matching uncertainty is growing since technology changes so fast that skill mismatch between job seekers and firms is larger.

By providing evidence of the existence and even the increase of labour mobility frictions, and by identifying the source of frictions, this study motivates us to do further research to examine the role of labour mobility frictions and its ripple effects on the labour market, as well as on the whole economy.

1.A Appendix

1.A.1 Skill distribution by sector, US

Table 1A.1: Occupation distribution by sector, full-time full-year white male, US

sector	period	occupation (skill)[a]		
		low-skill	*middle-skill*	*high-skill*
Low	1991 – 2000 (%)	19.1	53.8	27.1
Wage	2001 – 2015[b](%)	19.2	53.2	27.6
	change (%p)	0.1	-0.6	0.5
High	1991 – 2000 (%)	7.5	43.5	49.0
Wage	2001 – 2015[b](%)	6.8	40.7	52.4
	change (%p)	-0.6	-2.8	3.4

Source: Author's own, from IPUMS-CPS

Notes: [a]Occupations are classified by percentile of mean wage in 2000. I classifies 0-30 percentile occupations as 'low-skill', 30-70 percentile as 'middle-skill', 70-100 percentile as 'high-skill'. [b]Except 2007-2010

Table 1A.2: Degree of automation potential by industry, US

sectors	automation potential		sectors	automation potential
accom. & food services	73%		finance & insurance	43%
manufacturing	60%		arts, entertain. & recreation	41%
agriculture	58%		real estate	40%
transport. & warehousing	57%		administrative	39%
retail trade	53%		health care & social work	36%
mining	51%		information	36%
other services	49%		professionals	35%
construction	47%		management	35%
utilities	44%		educational service	27%
wholesale trade	44%			

Source: McKinsey Global Institute Analysis "A Future that Works: Automation, Employment, and Productivity", Executive Summary, 2017

Notes: Automation potential is defined according to occupations or work activities within a sector that can be automated by adapting currently demonstrated technology. McKinsey measures this using BLS database.

1.A.2 Sector classification

IPUMS-CPS provides each worker's industry data based on the industry classification in the year 1950 (code label: IND1950) or 1990 (IND1990). I use IND1950 for period comparison because it provides a consistent set of industry codes in the historical samples. Total 146 sub-industries are classified into five sectors: high-wage manufacturing (HM), low-wage manufacturing (LM), high-wage services (HS), low-wage services (LS), and other production industries (OI). If a sub-industry meets either one of two following criteria, it is classified into the high-wage sector; otherwise, it is assigned to the low-wage sector.

1. Top 20% sub-industries in terms of mean wage level since 1991

2. Sub-industries which satisfy both conditions: (i) above-average wage level, (ii) above-average wage growth rate in its upper category since 1991

Table 1A.3: Sector classification, US

sector (No.)	sub-industries (code)
HM (18)	Blast furnaces, steel works, & rolling mills(336), Fabricated steel products(346), Agricultural machinery & tractors(356), Office & store machines & devices(357), Electrical machinery, equipment, & supplies(367), Motor vehicles & motor vehicle equipment(376), Aircraft & parts(377), Ship & boat building & repairing(378), Professional equipment & supplies(386), Photographic equipment & supplies(387), Tobacco manufactures(429), Pulp, paper, & paperboard mills(456), Drugs & medicines(467), Paints, varnishes, & related products(468), Miscellaneous chemicals & allied products(469), Petroleum refining(476), Miscellaneous petroleum & coal products(477), Rubber products(478)

sector (No.)	sub-industries (code)
LM (41)	Logging(306), Sawmills, planing mills, & millwork(307), Misc wood products(308), Furniture & fixtures(309), Glass & glass products(316), Cement, concrete, gypsum & plaster products(317), Structural clay products(318), Pottery & related products(319), Miscellaneous nonmetallic mineral & stone products(326), Other primary iron & steel industries(337), Primary nonferrous industries(338), Fabricated nonferrous metal products(347), Not specified metal industries(348), Miscellaneous machinery(358), Railroad & miscellaneous transportation equipment(379), Watches, clocks, & clockwork-operated devices(388), Miscellaneous manufacturing industries(399), Meat products(406), Dairy products(407), Canning & preserving fruits, vegetables, & seafoods(408), Grain-mill products(409), Bakery products(416), Confectionery & related products(417), Beverage industries(418), Miscellaneous food preparations & kindred products(419), Not specified food industries(426), Knitting mills(436), Dyeing & finishing textiles, excl. knit goods(437), Carpets, rugs, & other floor coverings(438), Yarn, thread, & fabric mills(439), Miscellaneous textile mill products(446), Apparel & accessories(448), Miscellaneous fabricated textile products(449), Paperboard containers & boxes(457), Miscellaneous paper & pulp products(458), Printing, publishing, & allied industries(459), Synthetic fibers(466), Leather: tanned, curried, & finished(487), Footwear, excl. rubber(488) Leather products, excl. footwear(489), Not specified manufacturing industries(499)
HS (24)	Railroads & railway express service(506), Taxicab service(536), Water transportation(546), Air transportation(556), Petroleum & gasoline pipe lines(567), Telephone(578), Telegraph(579), Drugs, chemicals, & allied products(607), Electrical goods, hardware, & plumbing equipment(616), Machinery, equipment, & supplies(617), Petroleum products(618), Farm products-raw materials(619), Drug stores(669), Banking & credit agencies(716), Security & commodity brokerage & investment companies(726), Insurance(736), Advertising(806), Accounting, auditing, & bookkeeping services(807), Miscellaneous business services(808), Radio broadcasting & television(856), Medical & other health services, excl. hospitals(868), Hospitals(869), Legal services(879), Engineering & architectural services(898)

sector (No.)	sub-industries (code)
LS (44)	Street railways & bus lines(516), Trucking service(526), Warehousing & storage(527), Services incidental to transportation(568), Motor vehicles & equipment(606), Dry goods apparel(608), Food & related products(609), Miscellaneous wholesale trade(626), Not specified wholesale trade(627), Food stores, excl. dairy products(636), Dairy products stores & milk retailing(637), General merchandise stores(646), Five & ten cent stores(647), Apparel & accessories stores, excl. shoe(656), Shoe stores(657), Furniture & house furnishing stores(658), Household appliance & radio stores(659), Motor vehicles & accessories retailing(667), Gasoline service stations(668), Eating & drinking places(679), Hardware & farm implement stores(686), Lumber & building material retailing(687), Liquor stores(688), Retail florists(689), Jewelry stores(696), Fuel & ice retailing(697), Miscellaneous retail stores(698), Not specified retail trade(699), Real estate(746), Auto repair services & garages(816), Miscellaneous repair services(817), Private households(826), Hotels & lodging places(836), Laundering, cleaning, & dyeing services(846), Dressmaking shops(847), Shoe repair shops(848), Miscellaneous personal services(849), Theaters & motion pictures(857), Bowling alleys, & billiard & pool parlors(858), Miscellaneous entertainment & recreation services(859), Educational services(888), Welfare & religious services(896), Nonprofit membership organizations(897), Miscellaneous professional & related services(899), Postal service(906), Federal public administration(916), State public administration(926), Local public administration(936)
OI (19)	Agriculture(105), Forestry(116), Fisheries(126), Metal mining(206), Coal mining(216), Crude petroleum & natural gas extraction(226), Nonmetallic mining & quarrying, excl. fuel(236), Mining not specified(239), Construction(246), Electric light & power(586), Gas & steam supply systems(587), Electric-gas utilities(588), Water supply(596), Sanitary services(597), Other & not specified utilities(598), Postal service(906), Federal public administration(916), State public administration(926), Local public administration(936)

Source: IPUMS-CPS

1.A.3 Estimation of standard error in the Blinder-Oaxaca decomposition (Jann, 2008)

The formula of variance for product of two independent random variables, X and Y, is

$$V(X \cdot Y) = V(X)\{E(Y)\}^2 + V(Y)\{E(X)\}^2 + V(X)V(Y)$$

where $V(X)$ and $E(X)$ denote the variance and the expected value of X, respectively. Analogously, the variance of the unexplained part in the Blinder-Oaxaca decomposition can be calculated. The unexplained part in equation (1.3.3) can be simply written as $\bar{X}_1(\hat{b}_2' - \hat{b}_1')$. Taking the randomness of the regressors into account[32] and assuming that two groups are independent, and coefficients and regressors are uncorrelated, the variance estimator for this term is

$$\begin{aligned}\hat{V}(\bar{X}_1[\hat{b}_2' - \hat{b}_1']) =& \bar{X}_1[\hat{V}(\hat{b}_2') + \hat{V}(\hat{b}_1')]\bar{X}_1' + (\hat{b}_2 - \hat{b}_1)\hat{V}(\bar{X}_1')(\hat{b}_2' - \hat{b}_1') \\ &+ trace[\hat{V}(\bar{X}_1')\hat{V}(\hat{b}_2 - \hat{b}_1)]\end{aligned}$$

where $\hat{V}(\hat{b}')$ is the variance-covariance matrix obtained from the regressions, and $\hat{V}(\bar{X}') = \tilde{X}'\tilde{X}/[n(n-1)]$ where $\tilde{X} = \mathbf{X} - \mathbf{1}\bar{X}'$ and n is the sample size. $\mathbf{X}$ is the observed data matrix and $\mathbf{1}$ is the column vector of ones. Since the last term on the right-hand side is asymptotically zero, the approximate variance of the unexplained part is

$$\hat{V}(\bar{X}_1[\hat{b}_2' - \hat{b}_1']) \approx \bar{X}_1[\hat{V}(\hat{b}_2') + \hat{V}(\hat{b}_1')]\bar{X}_1' + (\hat{b}_2 - \hat{b}_1)\hat{V}(\bar{X}_1')(\hat{b}_2' - \hat{b}_1')$$

[32] Most variables in survey data such as CPS are random variables.

1.A.4 Demographic characteristics on sector switchers

Table 1A.4: Summary statistics on switchers, US

(%)

	period	gender		race		age[c]		full/part		college edu.	
		M	F	white	o/w	15-49	50-70	full	part	Y	N
total sample[a]	1991-2000	48.1	51.9	85.4	14.6	73.4	26.6	79.3	20.7	46.0	54.0
	2001-2015	48.2	51.8	79.5	20.5	70.6	29.4	79.7	20.3	53.4	46.6
	change(%p)	0.1	-0.1	-5.9	5.9	-2.8	2.8	0.3	-0.3	7.4	-7.4
total movers	1991-2000	50.9	49.1	83.2	16.8	84.6	15.4	77.9	22.1	47.1	52.9
	2001-2015	50.1	49.9	77.2	22.8	78.3	21.7	79.6	20.4	54.1	45.9
	change(%p)	-0.7	0.7	-5.9	5.9	-6.4	6.4	1.7	-1.7	7.0	-7.0
movers H to L[b]	1991-2000	46.7	53.3	83.3	16.7	83.0	17.0	82.1	17.9	52.5	47.5
	2001-2015	49.7	50.3	77.4	22.6	76.3	23.7	83.2	16.8	57.9	42.1
	change(%p)	3.0	-3.0	-5.9	5.9	-6.7	6.7	1.1	-1.1	5.4	-5.4
movers L to H[b]	1991-2000	45.9	54.1	83.5	16.5	84.9	15.1	75.9	24.1	53.4	46.6
	2001-2015	45.5	54.5	78.0	22.0	79.0	21.0	76.9	23.1	61.4	38.6
	change(%p)	-0.5	0.5	-5.5	5.5	-5.9	5.9	1.0	-1.0	8.0	-8.0

Source: IPUMS-CPS

Notes: [a]Total sample is workers aged 16-70 years during 1991-2015, except for the period 2007-2010, [b]The number of movers between the high-wage sector (HM, HS) and the low-wage sector (LM, LS)., [c]The UK ONS (Office for National Statistics) defines older workers as those aged over 50.

1.A.5 Labour transition matrices

Table 1A.5: Labour transition rate by sector, all switchers, US

(a) 1991-2000

(%)

t+1 / t	HM	LM	HS	LS	OI	UN	total	observations (thou.)	observations (%)
HM	38.9	16.8	16.3	19.4	8.4	0.1	100	9.3	7.5
LM	15.8	25.7	16.4	30.7	11.2	0.3	100	10.5	8.4
HS	5.9	6.8	35.6	40.1	11.3	0.3	100	24.1	19.3
LS	4.2	6.8	24.0	54.1	9.8	0.9	100	46.3	37.2
OI	7.6	10.3	24.1	40.6	16.3	1.0	100	12.3	9.9
UN	4.2	7.7	18.9	54.8	14.4	-	100	22.0	17.7
total	8.5	9.7	24.2	45.6	11.5	0.5	100	124.6	100.0

(b) 2001-2015 (except 2007-2010)

(%)

t+1 / t	HM	LM	HS	LS	OI	UN	total	observations (thou.)	observations (%)
HM	27.2	28.9	15.8	19.3	8.7	0.1	100	12.9	6.2
LM	14.1	28.0	15.4	30.5	11.8	0.1	100	11.2	5.4
HS	4.3	4.7	32.1	49.2	9.7	0.1	100	44.7	21.6
LS	3.2	4.5	21.8	61.6	8.7	0.3	100	73.4	35.5
OI	6.2	7.2	23.2	46.7	16.3	0.4	100	20.8	10.1
UN	3.7	5.5	19.5	56.2	15.2	-	100	43.7	21.1
total	5.9	7.8	23.0	52.0	11.2	0.2	100	206.8	100.0

Source: Author's own, from IPUMS-CPS

Notes: The acronyms denote sectors: HM = high-wage manufacturing, LM = low-wage manufacturing, HS = high-wage services, LS = low-wage services, OI = other industries, UN = unemployment.

Table 1A.6: Labour transition rate by sector, full-time full-year white male, US

(a) 1991-2000

(%)

t+1 / t	HM	LM	HS	LS	OI	UN	total	observations (thou.)	observations (%)
HM	44.4	16.4	13.5	15.5	10.1	0.1	100	4.1	15.4
LM	19.5	28.0	13.0	25.6	13.7	0.2	100	3.5	13.3
HS	9.6	8.2	31.4	34.4	16.1	0.2	100	5.3	20.0
LS	6.4	9.3	20.9	48.8	14.3	0.2	100	9.4	35.5
OI	10.4	12.8	20.2	35.1	21.4	0.1	100	3.9	14.7
UN	7.2	11.7	22.0	40.8	18.2	0.0	100	0.3	1.1
total	15.3	13.2	20.8	35.6	15.0	0.2	100	26.5	100.0

(b) 2001-2015 (except 2007-2010)

(%)

t+1 / t	HM	LM	HS	LS	OI	UN	total	observations (thou.)	observations (%)
HM	27.9	32.8	14.1	15.2	10.0	0.0	100	6.0	13.6
LM	16.6	32.0	12.8	24.8	13.9	0.0	100	4.4	9.9
HS	6.8	6.1	29.6	44.8	12.6	0.0	100	10.3	23.4
LS	4.9	6.7	19.7	55.8	12.9	0.0	100	15.3	34.8
OI	7.3	8.4	19.3	44.9	20.1	0.1	100	8.0	18.1
UN	16.1	10.3	19.9	36.7	16.9	0.0	100	0.0	0.1
total	9.9	12.7	20.6	42.8	13.8	0.0	100	43.9	100.0

Source: Author's own, from IPUMS-CPS

Notes: The acronyms denote sectors: HM = high-wage manufacturing, LM = low-wage manufacturing, HS = high-wage services, LS = low-wage services, OI = other industries, UN = unemployment.

Table 1A.7: Market size-adjusted labour transition rate by sector, full-time full-year white male with controlling for occupation, US

(a) 1991-2000

(%)

t+1 / t	HM	LM	HS	LS	OI	total	observations (thou.)	observations (%)
HM	67.5	18.0	4.7	2.7	7.0	100	3.0	20.5
LM	33.1	44.2	6.2	5.6	11.0	100	2.1	14.4
HS	23.7	16.2	23.5	12.6	24.1	100	2.8	19.5
LS	15.1	19.1	17.1	26.6	22.1	100	4.9	33.7
OI	22.4	22.6	14.1	12.0	28.9	100	1.7	11.8
total	36.3	23.3	12.2	11.6	16.7	100	14.5	100.0

(b) 2001-2015 (except 2007-2010)

(%)

t+1 / t	HM	LM	HS	LS	OI	total	observations (thou.)	observations (%)
HM	44.6	42.2	4.7	2.1	6.4	100	5.4	15.7
LM	30.0	49.8	5.4	4.2	10.6	100	3.5	10.3
HS	22.8	17.0	24.2	17.5	18.5	100	8.5	24.8
LS	17.5	17.4	17.4	27.7	19.9	100	11.4	32.9
OI	20.1	18.1	14.4	18.4	29.1	100	5.6	16.3
total	28.4	29.2	13.1	13.7	15.7	100	34.5	100.0

Source: Author's own, from IPUMS-CPS

Notes: The acronyms denote sectors: HM = high-wage manufacturing, LM = low-wage manufacturing, HS = high-wage services, LS = low-wage services, OI = other industries.

1.A.6 Derivation of the linear equation of mobility cost (Artuç, Chaudhuri, and McLaren, 2010)

A worker's optimisation problem in switching sectors can be written as

$$\begin{aligned} U^j(L_t, s_t, \varepsilon_t) &= W_{j,t} + \max_{j'} \left\{ \varepsilon_{j',t} - \phi_{jj'} + \beta \mathbb{E}_t [V^{j'}(L_{t+1}, s_{t+1})] \right\} \\ &= W_{j,t} + \beta \mathbb{E}_t [V^j(L_{t+1}, s_{t+1})] + \max_{j'} \left\{ \varepsilon_{j',t} + \bar{\varepsilon}_{jj',t} \right\} \end{aligned} \tag{1.A.1}$$

where $U^j(\cdot)$ is the value to a worker in sector j which is a function of the labour supply L_t, a state s_t, and an idiosyncratic benefit ε_t. $W_{j,t}$ is the sector j's wage, $\phi_{jj'} > 0$ is a pecuniary mobility cost when a worker moves from sector j to sector j'. $V^j(\cdot)$ denotes the expected value of $U^j(\cdot)$. β is the discount factor. $\bar{\varepsilon}_{jj',t}$ is the net value when switching sectors as

$$\bar{\varepsilon}_{jj',t} \equiv \beta \mathbb{E}_t \left[V^{j'}(L_{t+1}, s_{t+1}) - V^j(L_{t+1}, s_{t+1}) \right] - \phi_{jj'} \tag{1.A.2}$$

By taking the expectation of (1.A.1) with respect to ε,

$$\begin{aligned} & V^j(L_t, s_t) = W_{j,t} + \beta \mathbb{E}_t [V^j(L_{t+1}, s_{t+1})] + \Omega(\bar{\varepsilon}_{j,t}) \\ & \text{where } \; \Omega(\bar{\varepsilon}_{j,t}) = \sum_{j'=1}^{J} \int_{-\infty}^{\infty} (\varepsilon_{j'} + \bar{\varepsilon}_{jj',t}) f(\varepsilon_{j'}) \prod_{k' \neq j'} F(\varepsilon_{j'} + \bar{\varepsilon}_{jj',t} - \bar{\varepsilon}_{jk',t}) d\varepsilon_{j'} \\ & \qquad \bar{\varepsilon}_{j,t} \equiv (\bar{\varepsilon}_{j1,t}, \cdots, \bar{\varepsilon}_{jJ,t}) \end{aligned} \tag{1.A.3}$$

where $\Omega(\cdot)$ is the additional value which is the option to move to another sector. $f(\cdot)$ is the probability density function and $F(\cdot)$ is the cumulative distribution function.

By substituting (1.A.3) into (1.A.2), a Euler equation can be derived as

$$\begin{aligned}\phi_{jj'} + \bar{\varepsilon}_{jj',t} &= \beta \mathbb{E}_t \Big[W_{j',t+1} - W_{j,t+1} + \beta \mathbb{E}_{t+1} \big(V^{j'}(L_{t+2}, s_{t+2}) - V^{j}(L_{t+2}, s_{t+2}) \big) \\ &\qquad + \Omega(\bar{\varepsilon}_{j',t+1}) - \Omega(\bar{\varepsilon}_{j,t+1}) \Big] \\ &= \beta \mathbb{E}_t \Big[(W_{j',t+1} - W_{j,t+1}) + (\phi_{jj'} + \bar{\varepsilon}_{jj',t+1}) + (\Omega(\bar{\varepsilon}_{j',t+1}) - \Omega(\bar{\varepsilon}_{j,t+1})) \Big]\end{aligned} \tag{1.A.4}$$

Now, define $m_{jj',t}$ as the faction of the labour force in sector j that moves to sector j'. Assume that ε follows an extreme-value distribution with zero mean as

$$\begin{aligned} f(\varepsilon) &= \frac{1}{\nu} \exp \Big(-\frac{\varepsilon}{\nu} - \gamma - \exp \Big(-\frac{\varepsilon}{\nu} - \gamma \Big) \Big) \\ F(\varepsilon) &= \exp \Big(- \exp \Big(-\frac{\varepsilon}{\nu} - \gamma \Big) \Big) \end{aligned}$$

where ν is a parameter which is related to the variance of idiosyncratic shocks and γ is the Euler's constant. With this distribution, $\bar{\varepsilon}_{jj',t}$ and $\Omega(\bar{\varepsilon}_{j,t})$ can be rewritten as[33]

$$\bar{\varepsilon}_{jj',t} = \nu \left(\ln m_{jj',t} - \ln m_{jj,t} \right) \tag{1.A.5}$$

$$\Omega(\bar{\varepsilon}_{j,t}) = -\nu \ln m_{jj,t} \tag{1.A.6}$$

By substituting from (1.A.5) and (1.A.6) into (1.A.4), we get the linear regression equation of the mobility cost.

$$\begin{aligned}(\ln m_{t,jj'} - \ln m_{t,jj}) - \beta(\ln m_{jj',t+1} - \ln m_{j'j',t+1}) &= \\ - \frac{(1-\beta)}{\nu} \phi_{jj'} + \frac{\beta}{\nu} (W_{j',t+1} - W_{j,t+1}) + u_{t+1}\end{aligned} \tag{1.A.7}$$

where u_{t+1} is news revealed at $t+1$.

[33]See Artuç, Chaudhuri, and McLaren (2010) for details and derivations.

Chapter 2

The Role of Labour Mobility Friction

2.1 Introduction

While many workers desire to get a job in a sector which offers the most attractive remuneration or benefit package, it is generally not easy for workers to switch sectors during their careers for various reasons. Undoubtedly, a common reason is that they do not have enough qualifications or do not meet criteria in terms of the education or work experience required in the sector. However, while correct, this argument forms only part of the story. Even when individuals have high levels of human capital, they still have trouble switching sectors. As argued in Chapter 1, there is compelling evidence for the presence of labour market frictions or barriers to inter-sectoral labour mobility as well as an increase in their level, especially in advanced economies. Thus, it is sufficiently likely that labour tends to gather in the low-wage sector because of these frictions even though the wage gap between the high-wage sector and the low-wage sector has increased, indicating the possibility of linking inter-sectoral labour mobility with the sectoral wage gap. An example of this is that an accountant in low-paying retail trade services has difficulties in moving to a position of accountant in high-paying IT manufacturing.

Since the Lewis's 'dual economy model' (1954) and Krueger and Summers's 'efficiency wage model' (1988), many studies have explored what drives labour reallocation between sectors (or structural transformation) and the sectoral wage differentials. Acemoglu and Guerrieri (2008) argue that structural transformation occurs with technological change, showing that technology development in the capital-intensive sector causes its labour allocation to fall. They consider that labour reallocation across sectors is attributed to the change in labour demand triggered by technological progress. Likewise, Ngai and Pissarides (2007) show that structural transformation comes about in such a way that labour moves from the high TFP growth sectors to low ones. Regarding the sectoral wage gap, many studies focus on a worker's unobserved ability. According to Katz and Autor (1999) and Herrendorf and Schoellman (2015, 2018), labour is efficiently allocated in an economy on the basis of unobserved ability, by the 'self-selection' mechanism. They claim that the sectoral wage gap is explained by nothing but the differences in ability among workers, and thus only high ability persons work in the high-wage sector.

As an alternative approach, many others pay attention to frictions in inter-sectoral labour mobility leaving labour demand factors and workers' ability aside. Hayashi and Prescott (2008) find out the barrier to labour flow from the agricultural to the non-agricultural sector as a reason for stalled labour mobility during prewar Japan. Restuccia, Yang, and Zhu (2008) impose a restriction, or an exogenous barrier to labour mobility, in a two-sector framework which results in a relatively low wage in agriculture and then overuse of labour in the sector. According to Artuç, Chaudhuri, and McLaren (2010), the fact that workers hesitate to respond quickly to sectoral wage differences is closely linked to considerable pecuniary costs when switching sectors. Hsieh et al. (2013) point out labour market frictions as the possible cause of the difference in occupational distribution by gender or race group. Cardi and Restout (2015) show that an essential element to account for the change in the wage gap between traded and non-traded sectors is imperfect labour mobility across sectors. The extant literature, however, falls short of clarifying the relationship and interaction between the wage differentials and inter-sectoral labour mobility. Furthermore, we can hardly find the research that demonstrates the effects of labour mobility frictions on the wage gap and labour allocation between sectors.

In this chapter, I present a multi-sector general equilibrium model with the rigidity of labour movements between sectors to show the role of mobility frictions on labour market dynamics. While analysing the model, the relationship between the wage gap and labour allocation will be evident. The proposed model partly develops upon the existing models on the structural transformation and wage gap but frictions in inter-sectoral labour mobility are fed into the model as constraints for the household's labour supply decision. Mobility costs, for example, the costs and time spent in job search, training for skills required, and moving to a new place act as direct constraints. Mobility uncertainty such as matching frictions between workers and firms are associated with latent restrictions on switching sectors, which come from economic fluctuation, policy changes, or skill mismatch, to name a few. Hence, a household decides the allocation of members across sectors to maximise its utility, taking account of such frictions as mobility costs and uncertainty in switching sectors.

Incorporating labour mobility frictions into the model can contribute to an explanation for the reasons why many workers get stuck in the low-wage sector despite higher potential wage options available in other career paths. The mobility frictions play a central role in distorting labour market by worsening the sectoral wage differentials via labour misallocation. By contrast, factors of the labour demand side, which have been a focus of much existing research, are not able to simultaneously explain both the increasing wage gap and labour clustering in the low-wage sector. Rather, the variations in labour demand side factors, e.g. technology progress, result in labour reallocation toward the sector whose wage level rises. Therefore, the mobility frictions in the model are a key parameter to account for the labour market puzzle.

Additional findings suggest that the degree of labour mobility frictions has become much higher after 2000 than in the previous decade. This higher level of frictions gives rise to a non-trivial economic loss and even exacerbating labour market distortions compared to a lower friction economy.

The rest of this chapter is organised as follows. In section 2.2, a discussion about the standard multi-sector model without frictions suggests the need to consider imperfect labour mobility. Section 2.3 presents a multi-sector general equilibrium model embedded with labour mobility frictions and discusses further insights into the frictions. Next, I calibrate the two-sector case (high- and low-wage sectors) and explain the findings such as the degree of frictions, economic loss, and dynamic responses to sector-biased shocks in section 2.4. Section 2.5 concludes. The Appendices provide further details and derivations on the proposed model and data.

2.2 A Multi-sector Model Revisited

In the standard multi-sector model (Acemoglu, 2001; Acemoglu and Guerrieri, 2008; Acemoglu and Autor, 2011), the final good firm has a CES-type aggregator of production function and each sector's firm has a Cobb-Douglas production function.

$$Y_t = \left(\sum_{j=1}^{J} \gamma_j \cdot Y_{jt}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2.2.1}$$

$$Y_{jt} = (Z_{jt} L_{jt})^{\alpha} K_{jt}^{1-\alpha} \tag{2.2.2}$$

where Y_t is the output of the final goods, Y_{jt} is sector j's output, and $\gamma_j \in (0,1)$, $\sum_j \gamma_j = 1$, is a parameter corresponding to technological distribution or the relative importance of sector j's goods in the aggregation production. $\sigma \in (0, \infty)$ is the elasticity of substitution between intermediate goods. Each sector uses labour and capital inputs, L_{jt} and K_{jt}, to produce its output. Z_{jt} is the sector-specific labouraugmenting technology, and α is the labour income share.

With these technologies, a stand-in household's utility maximisation problem can be written as follows:

$$\max_{\{C_{t+s},N_{j,t+s},K_{t+s+1}\}_{s=0}^{\infty}} \quad U = \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left(\frac{C_{t+s}^{1-\theta}}{1-\theta} - \nu \frac{\left(\sum_{j=1}^{J} N_{j,t+s}\right)^{1+\chi}}{1+\chi} \right) \tag{2.2.3}$$

$$s.t. \quad C_t + K_{t+1} - (1-\delta)K_t = \sum_{j=1}^{J} W_{jt}N_{jt} + R_t K_t + \Pi_t \tag{2.2.4}$$

where C_t is the household's aggregate consumption of goods and K_t is the total capital stock. W_{jt} is each sector's real wage and N_{jt} is labour supply for each sector. R_t is the economy-wide, real rental rate of capital,[1] and Π_t is the profit from firms. β is the discount factor, and θ is the risk aversion parameter (the inverse of intertemporal elasticity of substitution for consumption). ν controls intratemporal substitution between consumption and leisure, and χ represents the Frisch elasticity of labour supply. δ is the depreciation rate of capital.

By solving this decentralised problem where no frictions exist, we get two conditions which are (i) wage equality across sectors, namely, the law of one wage and (ii) labour allocation which is the same as the ratio of nominal outputs between sectors as[2]

$$\text{(i)} \quad \frac{W_{jt}}{W_{it}} = 1 \quad \Longleftrightarrow \quad \Delta \ln W_{jt} = \Delta \ln W_{it} \tag{2.2.5}$$

$$\text{(ii)} \quad \frac{N_{jt}}{N_{it}} = \frac{P_{jt}Y_{jt}}{P_{it}Y_{it}} \quad \Longleftrightarrow \quad \Delta \ln \frac{N_{jt}}{N_{it}} = \Delta \ln \frac{P_{jt}Y_{jt}}{P_{it}Y_{it}} \tag{2.2.6}$$

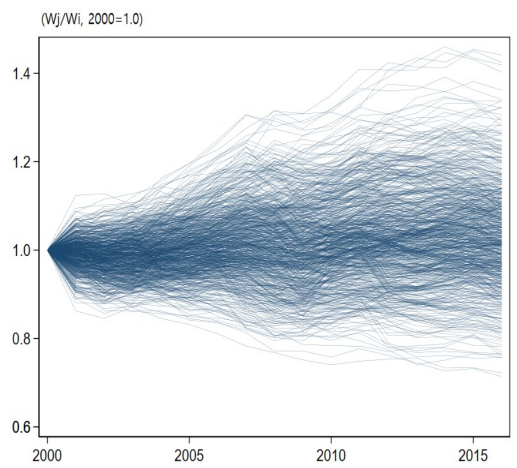
where the subscripts i, j denote any two sectors and P_{jt} is the price of sector j's goods. The explanation is straightforward. With the assumption of perfect labour mobility across sectors, the level and growth rate of each sector's wage are the same

[1] It is assumed that capital freely moves across sectors, so the capital rental rate R_t does not depend upon which sector rents capital.

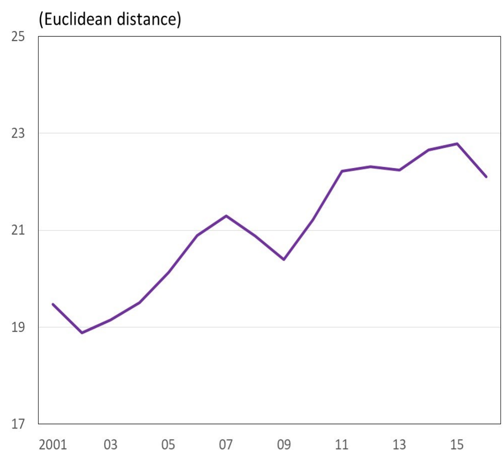
[2] See the Appendix 2.A.1 for the derivation.

as others. The relative labour allocation and its growth are equivalent to those of the relative nominal output.

To evaluate the relevance of this standard model to the real economy, we explore the wage gaps and labour allocation across all industry pairs in the US. To get the trends of wage gaps of all industry pairs, I use the data of per capita wage by industry from BEA NIPA. It consists of 38 sub-industries, so there are total 703 industry pairs ($={}_{38}C_2$). Figure 2.1(a) displays the time series of the wage gaps of all industry pairs in the US from 2000 to 2016. The time series are indexed to 1.0 in 2000 to visualise the relative change of each pair and check the convergence of wage gaps. This figure does not support the relation of equation (2.2.5). Indeed, wage gaps have spread over time. Euclidean distance of the wage gaps from wage equality (the vector of ones) has also increased over time, succinctly describing the divergence of wage gaps (Figure 2.1(b)).



(a) wage gaps across sectors[a]



(b) Euclidean distance from wage equality[b]

Figure 2.1: Trend of wage gap, W_{jt}/W_{it}, US

Source: Author's own, from BEA National Income and Product Accounts (NIPA)
Notes: [a]Every pair of 38 sub-industries (total 703 combinations $= {}_{38}C_2$) is drawn. [b]Euclidean distance describes the distance of the vector of wage gaps $(\frac{W_1}{W_1}, \frac{W_2}{W_1}, \frac{W_3}{W_1}, ..., \frac{W_{38}}{W_{37}})$ from the vector of ones $(1, 1, 1, ..., 1)$, or $\sqrt{\sum_i \sum_{j \neq i} (W_j/W_i - 1)^2}$, where industrial wages are arranged in ascending order. If $W_j/W_i = 1$, $\forall\ i, j$, Euclidean distance will be zero.

The second relation (2.2.6) is also not supported by actual data. I use the annual data of the nominal value added and the number of employees by industry in the US between 2000 and 2015 from EU KLEMS database.[3] There are 29 sub-industries and thus total 406 industry pairs ($= {}_{29}C_2$). Figure 2.2 plots the growth rates of the relative employment share *vis-à-vis* the growth rates of nominal output gap for all industry pairs during the period 2000 - 2015. According to the model without labour mobility frictions, both growth rates are the same and hence, graphically, all industry pairs must be positioned on the black 45 degree line in the figure. However, the slope of the red fitted line is even flatter than the black line, indicating that many industry pairs have a higher growth rate in nominal output gap than the growth rate in employment ratio, or vice versa. Simple panel data regressions of employment ratio on nominal output gap show that the slope of nominal output gap is significantly different from 1 in terms of both level and growth rate as in Table

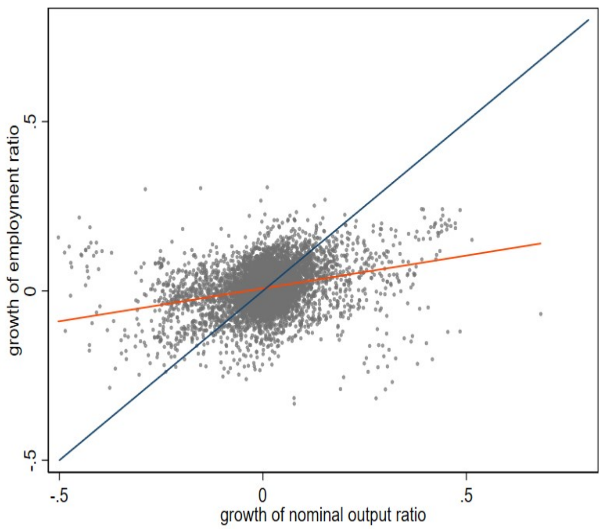


Figure 2.2: Labour allocation and nominal output gap, US

Source: Author's own, from EU KLEMS

Notes: The scatter plot depicts the growth rates of the relative labour allocation ($\Delta \ln(N_{jt}/N_{it})$) against the growth rates of the nominal output ratio ($\Delta \ln(P_{jt}Y_{jt}/P_{it}Y_{it})$). The black line is 45° line and the red line is fitted line.

[3]The result is identical with the data of hours worked of employees.

2.1. The results tell us that a one percentage point increase in the nominal output gap (the growth of the nominal output gap) is linked to the increase of 0.29 (0.13) percentage points of the employment ratio (the growth of the employment ratio).

Table 2.1: Panel GLS estimates of equation (2.2.6), US

	$\frac{N_{jt}}{N_{it}} = \alpha_t + \beta \frac{P_{jt}Y_{jt}}{P_{it}Y_{it}} + c_{ij} + u_{ij,t}$	$\Delta ln \frac{N_{jt}}{N_{it}} = \alpha_t + \beta \Delta ln \frac{P_{jt}Y_{jt}}{P_{it}Y_{it}} + c_{ij} + u_{ij,t}$
β	0.294 (0.009)***	0.127 (0.008)***
95% conf.	[0.28, 0.31]	[0.11, 0.14]
$t(\beta) = 1$	0.000	0.000
no.obs.	6,496	6,090

Source: Author's own, from EU KLEMS

Notes: Hausman tests show that the random effects model is not rejected at (1) and is rejected at (2). *** indicates statistical significance at the 1% level. Values within ( ) indicate standard errors. $t(\beta) = 1$ reports the p-value of the test $H_0 : \beta = 1$.

2.3 A Multi-sector Model with Mobility Friction

In this section, I present a multi-sector general equilibrium model with labour mobility frictions. The economic environment consists of J industries, indexed by $j = 1, 2, \cdots, J$. The economy is populated by a stand-in infinitely lived household. The household consists of a continuum of working-age members normalised at the closed interval $[0, 1]$ who are either employed in any one of J sectors, or are enjoying leisure. All members are homogeneous in ability and thus equally productive across sectors. The final good is produced as an aggregate of these J sectors' intermediate goods, and all goods and factor markets are competitive.[4] In this model, the initial

[4] If markets are imperfectly competitive, there are heterogeneous goods and workers. Galí (2015) adopts the differentiated goods and labour supply to introduce price and wage stickiness. The differentiated labour supply can also be applied when workers are heterogeneous in skills. In this thesis, however, we focus on frictions in inter-sectoral labour mobility. For example, even if a worker in sector 1 has the same skills as a worker in sector 2, it would be difficult for her in sector 1 to move to sector 2 because of various types of mobility frictions, e.g. training costs, search and moving costs, and/or matching uncertainty. In this context, introducing heterogeneous workers will be a type of mobility frictions as in Jones' (1971) specific factor model.

sectoral wage gap stems from the difference in the relative importance in producing the final goods or the relative level of technology. The allocation of members across sectors is given at the beginning and then some try to switch sectors every period. However, labour cannot move freely across sectors for two reasons. On the labour demand side, finite substitutability between intermediate goods limits labour movements. On the labour supply side, there exist barriers for members to move to another sector. The barriers are called 'labour mobility frictions' on which we focus in this chapter.

2.3.1 Model

2.3.1.1 Households

The household seeks to maximise its utility subject to the period budget constraint which takes the form of

$$C_t + K_{t+1} - (1-\delta)K_t = W_t N_t + R_t K_t + \Pi_t \tag{2.3.1}$$

where W_t is the aggregate real wage index which is an aggregator of all sectors' wages W_{jt}, and N_t is the aggregate labour supply index which is a combination of labour supplies N_{jt} for each of the sectors.

The household supplies its members to each sector as labour input, N_{jt}. If labour can freely switch sectors, all workers are willing to move to the sector which pays the highest wage. However, as discussed in Chapter 1, frictions to labour movements across sectors exist. I adopt a comprehensive labour mobility friction, which includes all types of mobility frictions, in the form of limited substitutability in labour supply according to Casas (1984), Horvath (2000), Cardi and Restout (2015), and Katayama and Kim (2018). In line with this, the aggregate labour supply index is assumed to be a CES-type form.[5]

[5]This is a parsimonious way to represent labour mobility frictions in the form of limited labour

$$N_t \equiv \left(\sum_{j=1}^{J} \varphi_j^{-\frac{1}{\phi_t}} \cdot N_{jt}^{\frac{\phi_t+1}{\phi_t}} \right)^{\frac{\phi_t}{\phi_t+1}} \tag{2.3.2}$$

It is noted that workers are identical across sectors, but they face constraints in switching sectors. The time-varying, deterministic parameter $\phi_t \in [0, \infty)$ is the elasticity of substitution in labour supply between sectors and controls the extent to which labour can switch sectors. To keep the notation clean, I omit the time subscript on ϕ. This parameter captures the degree of combined labour mobility frictions. As $\phi \to \infty$, labour supplies can be perfectly substitutable between sectors (the so-called perfect labour mobility) and thus members would move to the highest wage sector until all sectors' wages are equalised. In this case, sectoral labour allocation is determined only by the demand side of the labour market and thus (2.3.2) reduces to $N_t = \sum_j N_{jt}$. When $\phi < \infty$, labour supplies are not perfect substitutes and members cannot move freely across sectors. $\phi = 0$ is the case of total immobility. Hence, the smaller ϕ, the more difficult labour movements across sectors. A lower level of ϕ represents a higher cost of labour reallocation in utility terms so that this parameter can be thought of as a comprehensive mobility friction. This involves any explicit mobility costs (e.g. job search and application fees, training costs, moving costs) that workers pay, any opportunity costs, as well as unobserved frictions (e.g. matching uncertainty, separation probability, changes in labour market institutions) incurred when workers try to switch sectors.[6] It is noteworthy that while there are no pecuniary costs, the mobility costs can be captured in utility terms. When ϕ is finite meaning that there exist mobility frictions, labour reallocation between sectors increases the total labour supply, which leads to the decrease in the household's

substitutability between sectors. The elasticity of substitution here is not the preference of the household but exogenously given. By using this way, we simply show the role of mobility frictions on the wage gap and labour allocation. However, we do not know what drives this parameter or what the source is. In Chapter 3, we discuss the source of mobility frictions in more detail.

[6]These mobility frictions can depend on the sector or can be asymmetric, e.g. it might take more time for workers to switch from the low- to the high-wage sector. Here, we focus on the degree of economy-wide mobility frictions and its role in the labour market.

utility (2.3.7).[7] Thus, ϕ can be interpreted as labour supply adjustment cost (or time constraint) in utility terms.

The parameter $\varphi_j \in (0,1)$, $\sum_j \varphi_j = 1$, is the weight of labour supply to sector j. This parameter can be intuitively thought of as the long-term average proportion of sector j in total labour supply.[8] Thus, φ_j can be a public policy parameter because the long-term labour supply to a sector is mainly determined by long-standing labour market policies.

From this aggregate labour supply index, we can find the aggregate real wage index as[9]

$$W_t = \left(\sum_{j=1}^{J} \varphi_j \cdot W_{jt}^{1+\phi} \right)^{\frac{1}{\phi+1}} \tag{2.3.3}$$

where W_{jt} denotes the real wage in sector j. When labour is totally immobile ($\phi = 0$) because of a very high level of mobility friction, the aggregate wage index will be a linear combination of J sectors' wages, $W_t = \sum_j (\varphi_j W_{jt})$. As the level of friction is lowered (ϕ increases), the contribution of the high-wage sector to the aggregate wage increases due to labour moving to this sector.[10]

In this circumstance, the household's optimisation problem can be broken down into two parts. The household first needs to determine the optimal labour allocation across sectors with a certain degree of labour mobility friction. This problem can be solved in a way that the household minimises N_t for any given earning level $\mathcal{Q}_t \equiv \sum_j (W_{jt} N_{jt})$ by deciding labour allocation N_{jt}. This is namely the disutility minimisation problem since labour supply entails disutility to the household.

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[7] From equations (2.3.2) and (2.3.7), the following relation is derived: $\frac{\partial U_t}{\partial N_{jt}} = \underset{(-)}{\frac{\partial U_t}{\partial N_t}} \cdot \underset{(+)}{\frac{\partial N_t}{\partial N_{jt}}} < 0$

[8] If we let φ_j be the average proportion of sector j in total labour supply over the time periods, or $\bar{N}_j/\bar{N}$, equation (2.3.2) shows that the average total labour supply is equivalent to the sum of the average sectoral labour supplies, $\bar{N} = \sum_j \bar{N}_j$.

[9] See the Appendix 2.A.1 for the derivation.

[10] Sector j's contribution to the aggregate wage can be expressed as $\varphi_j (W_{jt}/W_t)^{1+\phi}$. As ϕ goes up, sector j's contribution increases relative to sector i's, if $W_{jt} > W_{it}$.

$$\min_{\{N_{jt}\}_j} \quad N_t = \left(\sum_{j=1}^{J} \varphi_j^{-\frac{1}{\phi}} \cdot N_{jt}^{\frac{\phi+1}{\phi}} \right)^{\frac{\phi}{\phi+1}} \tag{2.3.4}$$

$$s.t. \quad \mathcal{Q}_t \equiv \sum_{j=1}^{J} W_{jt} N_{jt} \tag{2.3.5}$$

The optimal labour allocation conditions yield the labour supply function for each sector.[11]

$$N_{jt} = \varphi_j \left(\frac{W_{jt}}{W_t} \right)^{\phi} N_t \tag{2.3.6}$$

The second problem is a dynamic problem where the household decides how much to consume and save for physical capital, and how large a fraction of its members to work. The household receives utility from consumption and incurs disutility from labour supply. The household maximises its lifetime utility subject to the flow budget constraint (2.3.1).

$$\max_{\{C_{t+s}, K_{t+s+1}, N_{t+s}\}_{s=0}^{\infty}} \quad \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s U(C_{t+s}, N_{t+s}) = \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left(\frac{C_{t+s}^{1-\theta}}{1-\theta} - \nu \frac{N_{t+s}^{1+\chi}}{1+\chi} \right) \tag{2.3.7}$$

I assume that the utility function is separable in consumption and labour in which the marginal utility of consumption is decreasing and the marginal disutility of working is increasing.[12] It is assumed, according to Hayashi and Prescott (2008), that there is no barrier to capital mobility between sectors so that the real rental rate of capital, R_t, is determined regardless of sector.

[11] See the Appendix 2.A.1 for the derivation.

[12] We relax this assumption and examine a non-separable utility later. Analytical results reveal that the non-separability of consumption and leisure in preferences does not affect the wage gap and labour allocation.

The first order conditions in the dynamic problem are

$$[C_t] \qquad C_t^{-\theta} = \lambda_t \tag{2.3.8}$$

$$[K_{t+1}] \qquad \lambda_t = \beta\lambda_{t+1}(1 + R_{t+1} - \delta) \tag{2.3.9}$$

$$[N_t] \qquad \lambda_t W_t = \nu N_t^{\chi} \tag{2.3.10}$$

where λ_t is the Lagrange multiplier. And the transversality condition is

$$\lim_{s\to\infty} \beta^s \lambda_{t+s} K_{t+s} = 0 \tag{2.3.11}$$

2.3.1.2 Technologies and Firms

In the spirit of Acemoglu (2001), the technology for producing the unique final output is assumed to take the following CES form between intermediate goods, meaning that the final output is produced by combining J sectors' goods.

$$Y_t = \left(\sum_{j=1}^{J} \gamma_j \cdot Y_{jt}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2.3.12}$$

where the elasticity of substitution σ captures the extent of substitutability between intermediate goods in producing the final goods.[13] As $\sigma \to \infty$, J goods are perfect substitutes and thus the final goods producers are willing to use only the cheapest intermediate goods. When $\sigma < \infty$, the combination of inputs cannot be easily adjusted. When $\sigma \to 0$, J intermediate goods become perfect complements (or Leontief production function), and when $\sigma \to 1$, it is the case of the Cobb-Douglas production function.

The final good firm's profit maximisation yields the set of demands for the J intermediate goods as[14]

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[13]The elasticity of substitution is assumed to be the same between any two sectors in order to make the multi-sector model tractable. In numerical analysis, we will discuss a two-sector case in which the issue about the assumption of the same elasticity will lessen.

[14]See the Appendix 2.A.1 for the derivation.

$$P_{jt} = \gamma_j \left(\frac{Y_{jt}}{Y_t}\right)^{-\frac{1}{\sigma}} \tag{2.3.13}$$

where P_{jt} is the price of each sector's goods. The price of the final goods, P_t, can be derived from the output aggregator (2.3.12) and is here assumed to be the numeraire.[15]

$$P_t = \left(\sum_{j=1}^{J} \gamma_j^{\sigma} \cdot P_{jt}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \equiv 1 \tag{2.3.14}$$

The intermediate goods, Y_{jt}, is produced competitively within the sector by using labour and capital inputs, L_{jt}, and K_{jt}. The production function is assumed to be the following Cobb-Douglas form.

$$Y_{jt} = (Z_{jt}L_{jt})^{\alpha} K_{jt}^{1-\alpha} \tag{2.3.15}$$

where the labour income share, α, is assumed to be the same across sectors.[16]

Now, we can derive the factor prices from intermediate sectors' cost minimisation problems using the Shepard's lemma and the equivalence between the price of goods and its marginal cost since the intermediate goods are competitively produced. The sectoral wages and capital rental rate are determined by[17]

$$W_{jt} = \alpha\gamma_j \Big(\frac{Y_t}{Y_{jt}}\Big)^{\frac{1}{\sigma}} \frac{Y_{jt}}{L_{jt}} \tag{2.3.16}$$

$$R_{jt} = (1-\alpha)\gamma_j \Big(\frac{Y_t}{Y_{jt}}\Big)^{\frac{1}{\sigma}} \frac{Y_{jt}}{K_{jt}} = R_t \tag{2.3.17}$$

[15] See the Appendix 2.A.1 for the derivation.

[16] We will discuss the case of different labour income share between sectors later. This relaxation has only level effects on the wage gap and labour allocation.

[17] See the Appendix 2.A.1 for the derivation. Alternatively, the factor prices are exactly the same as the marginal product of each factor from equation (2.3.12) or the value of marginal product of each factor from equation (2.3.15). Since all markets are competitive, factor prices are derived just by solving the finial firm's optimisation problem as in Acemoglu and Guerrieri (2008).

Equation (2.3.16) pins down sectoral labour demand. Note that capital freely moves so that the capital rental rate, R_t, is common across sectors.

2.3.1.3 Relative Labour Supply

What we are interested in is the relationship between labour allocation and the wage gap in this economy where barriers to labour movements exist. Firstly, by dividing any two sectors' (i and j) labour supply functions (2.3.6) with each other, we can derive

$$\digamma^{s}_{ij,t} = \frac{\varphi_j}{\varphi_i} \cdot \omega^{\phi}_{ij,t} \tag{2.3.18}$$

where $\omega_{ij,t} \equiv W_{jt}/W_{it}$ and $\digamma^{s}_{ij,t} \equiv N_{jt}/N_{it}$ are defined as the wage gap and the relative labour supply, respectively. This equation demonstrates the relationship between labour allocation and the wage gap on the labour supply side. An increase (decrease) in the relative labour supply ($\digamma_{ij,t}$) corresponds to an increase (decrease) in the wage gap ($\omega_{ij,t}$). Intuitively, if sector j pays higher wages than sector i and their wage gap increases, workers are willing to devote their labour to sector j. Yet there exists labour mobility friction ϕ which limits the labour allocation shift. As the degree of labour mobility friction becomes greater (or ϕ is smaller), the rise in the relative labour supply in relation to the increase in the wage gap is being smaller. Within the model, ϕ generates disutility from inter-sectoral labour movements, and this disutility will be the same size as the utility of consumption bought by the wage gain from the movement without frictions.

By taking the logarithm of (2.3.18), we obtain a linear relationship as

$$\ln \digamma^{s}_{ij,t} = \ln \frac{\varphi_j}{\varphi_i} + \phi \ln \omega_{ij,t} \tag{2.3.19}$$

2.3.1.4 Relative Labour Demand

On the labour demand side, from any two sectors' marginal products of labour (2.3.16), the following relationship is derived.[18]

$$\begin{aligned} \digamma^d_{ij,t} &= \frac{\gamma_j}{\gamma_i}\left(\frac{Y_{jt}}{Y_{it}}\right)^{\frac{\sigma-1}{\sigma}} \frac{1}{\omega_{ij,t}} \\ &= \left(\frac{\gamma_j}{\gamma_i}\right)^{\sigma}\left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha(\sigma-1)}\left(\frac{1}{\omega_{ij,t}}\right)^{1+\alpha(\sigma-1)} \end{aligned} \qquad (2.3.20)$$

where $\digamma^d_{ij,t} \equiv L_{jt}/L_{it}$ denotes the relative labour demand. By taking logs, we get

$$\ln \digamma^d_{ij,t} = \sigma \ln \frac{\gamma_j}{\gamma_i} + \alpha(\sigma-1)\ln\frac{Z_{jt}}{Z_{it}} - (1+\alpha(\sigma-1))\ln \omega_{ij,t} \qquad (2.3.21)$$

There is a negative relationship between the relative labour demand and the wage gap. If sector j pays higher wages than sector i, sector j's marginal cost and its good price increase given the technology. Then, the final good producer's demand for sector j's goods decreases and accordingly firms in sector j scale down their production by reducing the comparatively high-priced labour inputs. In this case, the substitutability of intermediate goods affects the relationship between the wage gap and the relative labour demand. As the elasticity of substitution between intermediate goods (σ) becomes larger, meaning that intermediate substitutability is higher, the final good producer can more easily replace intermediate goods with cheaper ones (sector i's goods). The relative labour demand ($\digamma^d_{ij,t}$) is more sensitive to the change in the wage gap ($\omega_{ij,t}$) as σ increases, and vice versa. When $\sigma \to 1$, the wage gap elasticity of the relative labour demand converges to unity.

[18] See Appendix 2.A.1 for the derivation.

2.3.1.5 Equilibrium

All goods, labour and capital markets are clear in equilibrium.

$$Y_t = C_t + K_{t+1} - (1-\delta)K_t \tag{2.3.22}$$

$$N_{jt} = L_{jt} \quad \Rightarrow \quad \digamma^{s}_{ij,t} = \digamma^{d}_{ij,t} \tag{2.3.23}$$

$$K_t = \sum_{j=1}^{J} K_{jt} = \sum_{j=1}^{J} (\kappa_{jt} \cdot K_t) \ , \quad \sum_{j=1}^{J} \kappa_{jt} = 1 \tag{2.3.24}$$

where κ_{jt} is the capital share of sector j. Sectoral labour market clearing condition (2.3.23) is sufficient for equating the relative labour supply with the relative labour demand.

A *dynamic equilibrium* given the sequence of exogenous variables $\{\phi_t,\, Z_{jt}\}_{t=0}^{\infty}$, $j \in \{1,2\}$ and the initial capital stock K_0, is a sequence of prices, quantities, and ratios $\{C_t, N_t, K_{t+1}, P_{jt}, N_{jt}, W_{jt}, R_t, \kappa_{jt}, \omega_{ij,t}, \digamma_{ij,t}\}_{t=0}^{\infty}$, satisfying (i) the household's optimisation conditions, (ii) the firms' optimisation conditions, and (iii) the goods and factor markets clearing conditions.

The optimal conditions besides the transversality condition can be reduced to the following conditions.

(Euler equation)

$$\frac{1}{C_t^{\theta}} = \beta \frac{1}{C_{t+1}^{\theta}} (1 + R_{t+1} - \delta) \tag{2.3.25}$$

(intratemporal optimality)

$$\frac{W_t}{C_t^{\theta}} = \nu N_t^{\chi} \tag{2.3.26}$$

(sectoral labour supply)

$$N_{jt} = \varphi_j \left(\frac{W_{jt}}{W_t} \right)^{\phi} N_t \tag{2.3.27}$$

(demand for goods)

$$P_{jt} = \gamma_j \left(\frac{Y_{jt}}{Y_t}\right)^{-\frac{1}{\sigma}} \tag{2.3.28}$$

(sectoral labour demand)

$$W_{jt} = \alpha\gamma_j \left(\frac{Y_t}{Y_{jt}}\right)^{\frac{1}{\sigma}} \frac{Y_{jt}}{N_{jt}} \tag{2.3.29}$$

(marginal product of capital)

$$R_t = (1-\alpha)\gamma_j \left(\frac{Y_t}{Y_{jt}}\right)^{\frac{1}{\sigma}} \frac{Y_{jt}}{K_{jt}} \tag{2.3.30}$$

(free movement of capital)

$$\frac{\kappa_{jt}}{\kappa_{it}} = \frac{\gamma_j}{\gamma_i} \left(\frac{Y_{jt}}{Y_{it}}\right)^{\frac{\sigma-1}{\sigma}} \tag{2.3.31}$$

(relative labour supply)

$$\digamma_{ij,t} = \frac{\varphi_j}{\varphi_i} \cdot \omega_{ij,t}^{\phi} \tag{2.3.32}$$

(relative labour demand)

$$\digamma_{ij,t} = \left(\frac{\gamma_j}{\gamma_i}\right)^{\sigma} \left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha(\sigma-1)} \left(\frac{1}{\omega_{ij,t}}\right)^{1+\alpha(\sigma-1)} \tag{2.3.33}$$

(resource constraint)

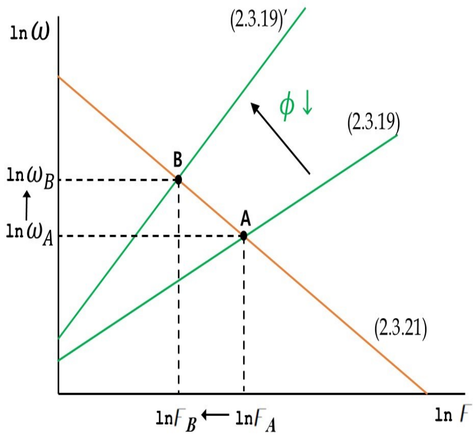
$$Y_t = C_t + K_{t+1} - (1-\delta)K_t \tag{2.3.34}$$

where auxiliary variables are $W_t = \left(\sum_{j=1}^{J} \varphi_j \cdot W_{jt}^{1+\phi}\right)^{\frac{1}{\phi+1}}$, $Y_t = \left(\sum_{j=1}^{J} \gamma_j \cdot Y_{jt}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, and $Y_{jt} = (Z_{jt}N_{jt})^{\alpha} K_{jt}^{1-\alpha}$.

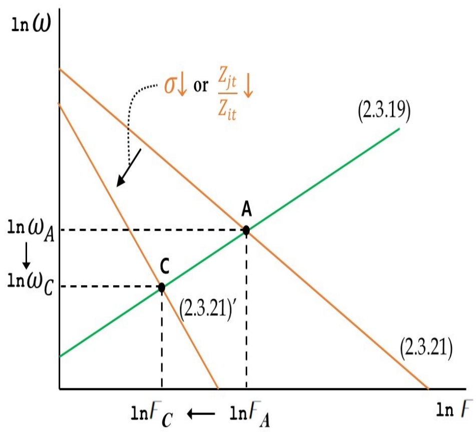
2.3.2 Sectoral Labour Allocation and Wage Gap

2.3.2.1 Equilibrium Labour Allocation and Wage Gap

Now, the equilibrium labour allocation and wage gap can be simply characterised from both log equations of the relative labour supply (2.3.19) and the relative labour demand (2.3.21). The former equation in the ($\ln \omega$, $\ln F$) plane is a right-upward sloping line with the slope of ϕ^{-1}, shown as Figure 2.3. The latter one is a right-downward sloping line with the slope of $-\{1 + \alpha(\sigma - 1)\}^{-1}$.



(a) change in ϕ



(b) change in σ or Z_{jt}/Z_{it}

Figure 2.3: Equilibrium labour allocation and wage gap

Source: Author's own

Notes: These graphs are drawn assuming $0 < \varphi_j/\varphi_i < 1$. It is also assumed $\gamma_j/\gamma_i > 1$ and $Z_j/Z_i > 1$ which imply that sector j's wage is higher than sector i's. These assumptions are correspond to the calibrations in section 2.4 or actual data.

Figure 2.3(a) demonstrates how the wage gap and labour allocation change as the extent of labour mobility friction changes. As the degree of friction is larger (or ϕ is smaller), the wage gap is bigger and the relative labour allocation shrinks. The equilibrium moves from point A to point B. The change in labour mobility friction on the labour supply side can simultaneously explain the increasing wage gap and labour clustering into the low-wage sector, namely the labour market puzzle mentioned before.

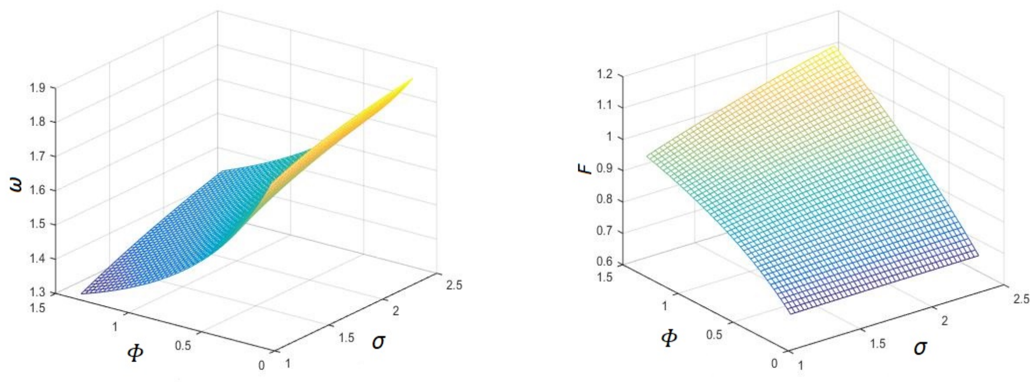
Figure 2.3(b) describes the equilibrium shift according to the changes in the labour demand side. For example, when the elasticity of substitution between goods (σ) is smaller or the ratio of productivities (Z_{jt}/Z_{it}) is lower, both the wage gap and the relative labour allocation decrease. The changes from the labour demand factors affect the wage gap and labour allocation in the same direction so that this channel cannot illustrate the labour market puzzle by itself.

Finally, by combining the two conditions, (2.3.32) and (2.3.33), the equilibrium wage gap and labour allocation can be analytically derived.

$$\omega^*_{ij,t} \equiv \frac{W_{jt}}{W_{it}} = \left[\left(\frac{\gamma_j}{\gamma_i}\right)^{\sigma} \left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha(\sigma-1)} \left(\frac{\varphi_j}{\varphi_i}\right)^{-1} \right]^{\frac{1}{1+\alpha(\sigma-1)+\phi}} \tag{2.3.35}$$

$$\digamma^*_{ij,t} \equiv \frac{N_{jt}}{N_{it}} = \left[\left(\frac{\gamma_j}{\gamma_i}\right)^{\sigma\phi} \left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha(\sigma-1)\phi} \left(\frac{\varphi_j}{\varphi_i}\right)^{1+\alpha(\sigma-1)} \right]^{\frac{1}{1+\alpha(\sigma-1)+\phi}} \tag{2.3.36}$$

Figure 2.4 depicts the equilibrium wage gap and labour allocation with varied levels of labour mobility friction and goods substitutability given that the other factors are fixed. As expected, the wages diverge from each other and the relative labour allocation of sector j (the high-wage sector) decreases as ϕ falls (or the degree of labour mobility friction rises) given a certain level of σ. The higher mobility friction, the harder labour shift, and hence the larger wage gap. By contrast, as the elasticity of substitution between goods (σ) is lowered, ω_{ij} and $\digamma_{ij}$ all decline. Intuitively, the limitation of goods substitutability devalues the relative importance of sector j's goods in producing the final goods because all goods become more indispensable. This consequently decreases both the wage gap and the employment ratio.



(a) wage gap (b) labour allocation

Figure 2.4: Wage gap and labour allocation with mobility friction

Source: Author's own

Notes: Sector j is assumed to be the high-wage sector. Accordingly, I set $\alpha = 0.66$, $\gamma_j/\gamma_i = 1.17$, $Z_j/Z_i = 2.08$ and $\varphi_j/\varphi_i = 0.47$ for this simulation. This setting is consistent with the calibration of a two-sector case in section 2.4.

2.3.2.2 Further Insights on Labour Market Distortions

Without labour mobility frictions, or $\phi \to \infty$, the equilibrium wage gap between sectors disappears in (2.3.35) as

$$\omega^*_{ij,t} \mid_{\phi\to\infty} = 1 \tag{2.3.37}$$

and the equilibrium labour allocation equation can be reduced from (2.3.36) to the following form

$$F^*_{ij,t} \mid_{\phi\to\infty} = \left(\frac{\gamma_j}{\gamma_i}\right)^{\sigma} \left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha(\sigma-1)} \tag{2.3.38}$$

In this frictionless labour market, the relative labour allocation only changes depending on the structural parameters such as technology distribution, uneven technological progress, and the elasticity of substitution between goods.

On the other hand, when labour mobility frictions exist, or $\phi < \infty$, three kinds of channels influence the wage gap and labour allocation from equations (2.3.35) and (2.3.36), as shown in Table 2.2: (i) The first channel is the change in the degree of labour mobility frictions. (ii) The second channel is the shift in labour demand across sectors whose driving force comes from the change in technologies. (iii) The third channel is policy parameters such as changes in a long-range labour supply plan or taxation system.[19]

Table 2.2: The channels which cause labour market distortions

ϕ_t (mobility friction)	(i) $\searrow$			
		$\boldsymbol{\omega}_{ij}$, F_{ij}	(ii) $\longleftarrow$	σ, Z_{jt}, γ_j, α (technologies)
φ_j, τ_j (policy parameters)	$\nearrow$ (iii)			

When it comes to the first channel, the change in the friction parameter, ϕ, affects the wage gap and the relative labour allocation in the opposite direction as previously explained. As mobility frictions increase, more workers cannot switch sectors and thus the wage gap becomes larger compared to the case of a lower level of frictions.

The second channel shows that, given the degree of labour market frictions, sector-biased structural shocks or the change in technology parameters such as the technology distribution and the elasticity of substitution between intermediate goods can affect the wage gap and labour allocation in the same direction. The explanation for this channel is straightforward. For example, sector j-biased technology shock (a shock to Z_{jt}/Z_{it}) pushes up the sector's output, and thereby its relative price goes down and the demand for the goods expands. This leads to increases in sector j's labour demand and wage relative to sector i's, with a higher than one elasticity of substitution. For yet another example, if the sector j's goods are used more in producing the final goods than before (a rise in γ_j/γ_i), the labour demand in the

[19]We shall discuss an extended model with taxation (τ) later in this section.

sector increases. As a result, both $\digamma_{ij,t}$ and $\omega_{ij,t}$ rise. However, their increments are conditional on the degree of labour mobility frictions. As the degree is higher (ϕ is smaller), the increase in the wage gap due to the changes in technology is larger and the increase in the relative labour allocation is smaller.

Policy parameters can be one of the factors responsible for the wage gap and labour allocation. With the existence of mobility frictions, the change in the ratio of long-term labour supplies (φ_j/φ_i) affects the labour market.[20] For instance, if the sector j's long-term average labour supply becomes higher than before, firms in sector j have less incentive to increase their wage level so that the wage gap would shrink.

Additionally, taxation could also distort the wage gap and labour allocation. Consider that a government levies a tax on each income. Now, the household budget constraint (2.3.1) can be rewritten as

$$C_t + K_{t+1} - (1-\delta)K_t = \sum_{j=0}^{J}(1-\tau_j)W_{jt}N_{jt} + R_tK_t - \tau_k(R_t - \delta)K_t + \Pi_t$$

where τ_j is the differential tax on the labour income and τ_k is the net capital income tax. From the equation system under this taxation scheme,[21] the equilibrium wage gap and labour allocation can be derived.

$$\omega^*_{ij,t} = \left[\left(\frac{\gamma_j}{\gamma_i}\right)^{\sigma}\left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha(\sigma-1)}\left(\frac{\varphi_j}{\varphi_i}\right)^{-1}\left(\frac{1-\tau_j}{1-\tau_i}\right)^{-\phi}\right]^{\frac{1}{1+\alpha(\sigma-1)+\phi}} \tag{2.3.39}$$

[20]As discussed in section 2.3.1.1, the parameter φ_j is the sectoral weight in the aggregate labour supply (2.3.2) and it corresponds to the steady state proportion of sector j in total labour supply. The long-term sectoral labour supply is generally determined by the government's long-standing labour market policies (e.g. government's vocational training programme for the ICT industry, manufacturing development plan, etc.) so that the parameter can be regarded as a public policy parameter.

[21]See the Appendix 2.A.2 for details.

$$F^*_{ij,t} = \left[\left(\frac{\gamma_j}{\gamma_i}\right)^{\sigma\phi} \left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha(\sigma-1)\phi} \left(\frac{\varphi_j}{\varphi_i}\right)^{1+\alpha(\sigma-1)} \left(\frac{1-\tau_j}{1-\tau_i}\right)^{(1+\alpha(\sigma-1))\phi} \right]^{\frac{1}{1+\alpha(\sigma-1)+\phi}} \tag{2.3.40}$$

Even without labour mobility frictions, the wage gap cannot dissipate, which is the so-called 'inter-sectoral labour wedge'.

$$\omega^*_{ij,t} \mid_{\phi\to\infty} = \left(\frac{1-\tau_j}{1-\tau_i}\right)^{-1} \tag{2.3.41}$$

However, this differential tax just has a level effect on the wage gap and labour allocation, and so it by itself has limits in influencing the dual labour market dynamics over time.[22]

To conclude, while various factors can influence the sectoral wages and labour allocation directly or indirectly, they work only under the premise of the existence and changes of labour mobility frictions. On top of that, the framework with mobility frictions can simultaneously explain both the widening wage disparity and the labour clustering in the low-wage sector, which cannot be captured by the standard canonical theories.

2.4 Quantitative Analyses: A Two-sector Case

In this section, quantitative analyses are conducted to see (i) how the degree of labour mobility frictions changes over time, (ii) what would have happened, had there been no labour mobility frictions, and (iii) the size of the economic loss caused by mobility frictions. To make the simulation tractable, I divide industries into two sectors, the low-wage sector (sector 1) and the high-wage sector (sector 2).

[22]The tax difference between sectors can explain the widening wage gap and labour clustering even without mobility frictions if the tax difference has increased over time. If that is the case, the tax difference can be one source of mobility frictions. However, US data show that the difference in tax brackets between the high- and the low-wage sectors has been almost constant or even slightly decreased over time. The tax bracket which matches the average wage in the high-wage sector decreased from 28% in the 1990s to 25% after 2000 while that in the low-wage sector was constant at 15% (source: US Tax Foundation).

2.4.1 Calibration

To conduct numerical simulations, it is necessary to discuss model calibration by specifying parameter values. Calibrating the model in this section is mainly intended to back out the degree of labour mobility frictions and replicate the key characteristics of the labour market dynamics, particularly the labour clustering in the low-wage sector and the increasing wage inequality between sectors, emphasising the ripple effects of labour mobility frictions.

The model is calibrated at a yearly frequency based on the main target economy, the US, since 1990. The industries are classified according to the North American Industry Classification System (NAICS) at the 38 sub-industry level and the sub-industries are divided into two sectors in terms of their ranks in the wage level as Table 2.3.[23]

From the separable consumption-leisure function as the household's utility, the preference parameters are the discount factor, the relative risk aversion coefficient, the inverse of Frisch elasticity, and the intratemporal substitution parameter $\{\beta,\ \theta,\ \chi,\ \nu\}$. I follow the standard practice in the choices of these parameters. The discount factor, β, is set to the standard annual value of 0.96 from the literature, and the risk aversion coefficient, θ, to 1.39 following the estimation for the US in Gandelman and Hernández-Murillo (2014). The inverse of Frisch elasticity, χ, is set to 1.0 which is frequently used in the literature (Shi, 2011; Garin, Pries, and Sims, 2018). I set the scale parameter of labour disutility, ν, to 2.0 which is within the range of the literature.[24]

The weight of labour supply to the high-wage sector, φ, is set to 0.32 to target the average employment share of the sector between 1990 and 2016 since this weight was defined as the long-term average proportion of a sector's labour supply. The

[23]Three industries of agriculture, forestry, fishing, and hunting; real estate and rental and leasing; government are excluded.

[24]Garin, Pries, and Sims (2018) emphasise that ν, correspondingly the steady state labour supply $\bar{N}$, should be neither too big nor too small in order to avoid making labour reallocation unnecessary and to make room for non-employment ($\bar{N} < 1$).

Table 2.3: Sector classification

sector 1 (low-wage)		sector 2 (high-wage)	
industry	wage[a]	industry	wage[a]
accommodation & food service	23.1	miscellaneous manufacturing	52.6
retail trade	30.9	electrical equipment & applications	54.9
other service (excl.government)	33.8	motor vehicles, trailers & parts	56.5
administrative & waste management	34.5	primary metals	57.6
apparel & leather & allied products	34.7	paper products	58.0
textile mills & textile product mills	37.0	machinery	58.7
wood products	37.4	wholesale trade	64.0
furniture & related products	37.8	other transportation equipment	73.9
educational services	38.3	professional & technical services	78.1
arts, entertainment & recreation	40.7	information	79.1
food & tobacco products	42.2	chemical products	79.6
printing & related activities	44.4	mining	83.9
plastics & rubber products	44.8	finance & insurance	84.7
health care & social assistance	45.6	utilities	85.5
transportation & warehousing	47.7	computer & electronic products	89.0
fabricated metal products	48.0	petroleum & coal products	91.5
nonmetallic mineral products	48.5	management of companies[c]	98.9
construction	49.4	-	-

Source: BEA NIPA

Notes: [a]Average annual wages per full-time employee between 2000-2016, in terms of thousand dollars. [b]The cutoff between the two sectors is based on the average-linkage cluster analysis using the Euclidean distance of industrial wages. See the Appendix 2.A.3 for details. [c]The industry 'management of companies' consists of firms engaged in managing companies or holding the securities and financial assets of companies. This industry is like any other industry in terms of its occupations, as it includes, for example, managers, financial specialists, IT programmers, and engineers.

labour supply weight of the low-wage sector is $(1-\varphi)$ because there are two sectors.

As far as production functions are concerned, there are three technology parameters: the labour income share, the elasticity of substitution between two sectors' goods, and the technology distribution $\{\alpha,\ \sigma,\ \gamma\}$. The labour income share, α, is set to 0.66 based on the average labour income share of the US total economy (excl. agriculture) between 1991 and 2012, the source of which is OECD. The elasticity of substitution between goods σ and the technology distribution parameter γ can be identified using the two demand functions for intermediate goods as in Acemoglu and Guerrieri (2008). By multiplying Y_{jt} to both sides of (2.3.28) and dividing the two sectors' (1 and 2) demand functions, we obtain the following log-transformed linear equation.

$$\ln\left(\frac{P_{2t}\cdot Y_{2t}}{P_{1t}\cdot Y_{1t}}\right)=\ln\left(\frac{\gamma}{1-\gamma}\right)+\frac{\sigma-1}{\sigma}\ln\left(\frac{Y_{2t}}{Y_{1t}}\right)$$

The two parameters can be estimated by regressing the ratio of output values on the ratio of volumes. The result shows that σ and γ are around 1.25 and 0.54, respectively, using the real and nominal value added between 1990 and 2015 from BEA's NIPA tables.[25]

The depreciation rate of physical capital, δ, is set to 0.04 to match the average depreciation rate since 1990 which is calculated by using the law of capital accumulation (source: IMF WEO, PWT).

The baseline labour income tax rate is set to 0.25 for sector 1 (τ_1) and 0.28 for sector 2 (τ_2) which correspond to the tax brackets of their sectoral average wages in the US (source: US Tax Foundation). The tax rate on net capital income, τ_k, is taken from the estimate in McDaniel (2011) which is 0.27 on average in the US since 1990.

Table 2.4: Baseline parameter values

Parameter	Value	Description
β	0.96	discount factor
θ	1.39	relative risk aversion
χ	1.00	inverse of the Frisch elasticity
ν	2.00	disutility weight on labour
φ	0.32	labour supply weight in sector 2
α	0.66	labour income share
σ	1.25	elasticity of substitution between goods
γ	0.54	technology distribution
δ	0.04	capital depreciation rate
τ_1	0.25	labour income tax rate in sector 1
τ_2	0.28	labour income tax rate in sector 2
τ_k	0.27	net capital income tax rate

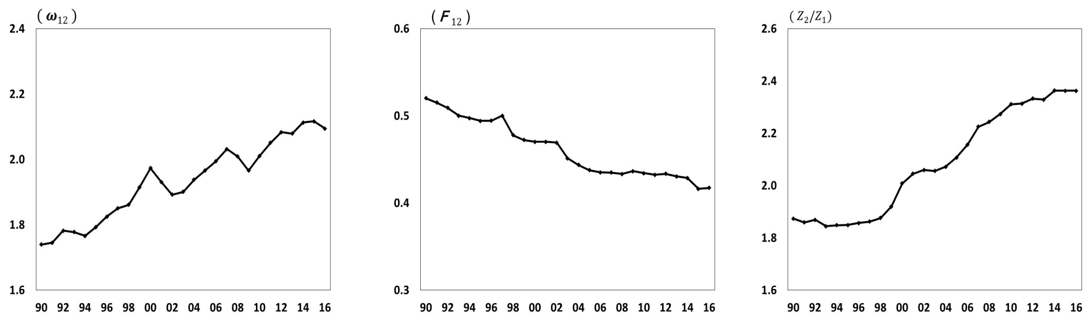
Notes: The main target economy is the US. The values are assigned to parameters in the baseline model. The motivation for each value is described in the text.

[25] $\ln\left(\frac{P_{2t}\cdot Y_{2t}}{P_{1t}\cdot Y_{1t}}\right)=0.1432+0.2015\ \ln\left(\frac{Y_{2t}}{Y_{1t}}\right),\ \overline{R}^2=0.6806$

2.4.2 The Degree of Labour Mobility Friction

We start with backing out the elasticity of substitution in labour supply between sectors, ϕ, which reflects the degree of labour mobility frictions, to see how it has changed over time. ϕ can be backed out by using other calibrated parameters and actual time series data in conjunction with the equilibrium wage gap and labour allocation equations, (2.3.39) and (2.3.40).

Three related input datasets are available from BEA NIPA and EU KLEMS: industrial wages, employment, and TFPs. Figure 2.5 shows the actual time series of inputs in the equations. As expected, the relative wage and technology[26] of the high-wage sector have increased while its labour allocation has decreased since the 1990s.



(a) wage gap (b) labour allocation (c) relative technology

Figure 2.5: Data from the US

Source: BEA NIPA, EU KLEMS

One of the ways to back out the friction parameter is to use the time series of the wage gap and labour allocation.[27] Firstly, by substituting out the relative

[26] EU KLEMS dataset provides not industrial TFP level but TFP growth. To obtain the technology ratio (Z_{2t}/Z_{1t}), I first estimate each sector's TFP in 2005 by plugging the data of gross value added, production inputs, and the calibrated α into the sectoral Cobb-Douglas production functions. Then, the time series of sectoral TFP level are extracted by applying its growth rate.

[27] Since the data of industrial TFPs is also available, we can alternatively back out ϕ from either of two equations to test the validity of the estimate. One by plugging the data of wage gap and technology ratio into (2.3.39), and the other by plugging the data of labour allocation and

technology (Z_{2t}/Z_{1t}) from (2.3.39) and (2.3.40), ϕ can be expressed as a function of the wage gap and labour allocation as[28]

$$\phi_t = F\left(\omega_{12,t},\ \digamma_{12,t}\right) = \frac{\ln \digamma_{12,t} - \ln \frac{\varphi}{1-\varphi}}{\ln \omega_{12,t} + \ln \frac{1-\tau_2}{1-\tau_1}} \tag{2.4.1}$$

By inputting two of time series into this function, ϕ can be backed out as shown in Figure 2.6. The line shows a downward move of ϕ since the 1990s. In this estimate, the average level of ϕ between 2001 and 2016 was 0.38 which is 43.3 percent lower than it was in the 1990s (0.67). In other words, the degree of mobility frictions between the high- and the low-wage sectors has increased to a great extent over the course of more than 25 years.[29]

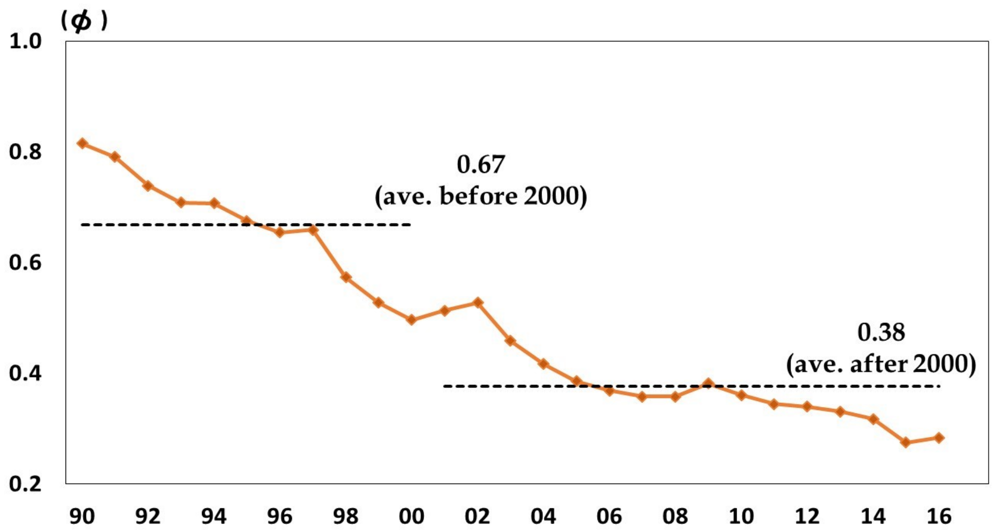


Figure 2.6: Backed-out ϕ, US

Source: Author's own, from BEA NIPA

Notes: The initial level of ϕ is adjusted from 0.33 to 0.81 in order not only to fit it with the initial levels of alternative ϕs (See Appendix 2.A.4), but also to be sure to avoid a negative value.

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technology ratio into (2.3.40). The alternatives give similar estimates to that from (2.4.1). See Appendix 2.A.4 for details.

[28]See Appendix 2.A.1 for the derivation.

[29]We discussed possible reasons for a rising degree of mobility frictions between the high- and the low-wage sectors in section 1.4.2 in Chapter 1 and will explore a major source of labour mobility

2.4.3 Distortions and Losses

Now, based on the estimated level of mobility frictions, numerical simulations are conducted to see how labour mobility frictions impinge on the process of labour allocation and the change of the sectoral wage gap.

Labour market distortions caused by mobility frictions are straightforward. Table 2.5 reports the actual data of the wage gap and labour allocation from the US labour market and the results of numerical simulations. Firstly, I set an economy with the level of mobility friction $\phi = 0.7$ as the baseline model since the wage gap obtained from the model at this level corresponds to the actual wage gap in the US during the 1990s. At $\phi = 0.7$, the equilibrium wage gap between two sectors ($\omega_{12} = W_2/W_1$) is 1.830 which are similar to the US data of 1.821 during the 1990s. As a comparison, I also report the actual data during the period between 2001 and 2016 which describes that the relative labour allocation declined from 0.496 in the 1990s to 0.435 and the wage gap rose from 1.821 to 2.011. Thus, the US labour market since the 2000s parallels the model economy with large mobility

Table 2.5: Steady state values, by level of friction, US

	data		baseline	large friction		small friction	
	1990-2000	2001-2016	$\phi = 0.7$	$\phi = 0.4$	$\phi = 0.0$	$\phi = 1.0$	$\phi = 3.0$
ω_{12}	1.821	2.011	1.830	2.038	2.566	1.692	1.341
$\digamma_{12}$	0.496	0.435	0.496	0.437	0.334	0.543	0.713
Y	-	-	-	-0.26%	-0.35%	0.27%	1.49%
W	-	-	-	-1.49%	-4.60%	1.09%	4.43%
C	-	-	-	-1.97%	-6.35%	1.39%	5.35%
V	-	-	-	-1.12%	-3.87%	0.75%	2.71%

Source: Author's own, from BEA NIPA, EU KLEMS

Notes: The data of full-time equivalent employees and wages in the US are used. Aggregate output (Y), economy-wide wage level (W), aggregate consumption (C), and welfare (V) are percentage deviations from the steady state values in the baseline. The steady state technology gap (Z_2/Z_1) is set to 2.08 which is the average value between 1990 - 2015 (EU KLEMS). The baseline labour allocation ($\digamma_{12}$) is adjusted to fit the data between 1990 - 2000 ($0.682 \rightarrow 0.496$) and the other labour allocation are adjusted with the same proportion.

frictions in Chapter 3.

friction ($\phi = 0.4$) where the relative labour allocation decreases and the wage gap increases in the similar size as the actual data. With the assumption of immobile labour, or $\phi = 0.0$, the relative employment share of sector 2 diminishes to 0.334 and the wage gap jumps to 2.566. Such labour misallocation ends up causing non-trivial economic loss compared to the baseline economy. The elevation in the level of mobility frictions first triggers output (Y) loss since workers are more inefficiently distributed across sectors. It is followed by a fall in the economy-wide wage level (W) and aggregate consumption (C). This also causes a reduction of the welfare (V) because the consumption decreases and the aggregate labour supply increases due to inefficient labour allocation. Here the welfare is defined as the present value of household utility.[30]

$$V_t = U(C_t, N_t) + \beta \mathbb{E}_t V_{t+1} \tag{2.4.2}$$

I conduct additional counter-factual simulations with lower levels of the mobility frictions which produce opposite results to the case of large frictions. As mobility frictions ease off (ϕ increases), labour allocation in the high-wage sector increases and the sectoral wage gap converges to unity, leading to extending the economy's production possibility frontier. With a low degree of mobility frictions, e.g. $\phi = 3.0$, many workers move into the high-wage sector and then two sectors' wages become close to each other. The economy-wide wage and welfare drastically increase over the baseline. Therefore, while the case with a low degree of mobility frictions fails to account for the actual data, we can explain the labour market puzzle with a higher degree of frictions.

Next, to build intuition regarding the role of labour mobility frictions in technological change, I first examine the effects of permanent technology progress in

[30] The steady state welfare level is derived as

$$V = \left(\frac{C^{1-\theta}}{1-\theta} - \nu \frac{N^{1+\chi}}{1+\chi} \right) \cdot \frac{1}{1-\beta}$$

the high-wage sector with variations of ϕ. Log-linearisation of the equilibrium wage gap (2.3.39) and labour allocation (2.3.40) equations show the relationship between sectoral technology progress and the relative wage growth, or labour reallocation as follows:

$$\hat{\omega}_{12,t} = \frac{\alpha(\sigma - 1)}{1 + \alpha(\sigma - 1) + \phi}(\hat{Z}_2 - \hat{Z}_1) \tag{2.4.3}$$

$$\hat{F}_{12,t} = \frac{\alpha(\sigma - 1)\phi}{1 + \alpha(\sigma - 1) + \phi}(\hat{Z}_2 - \hat{Z}_1) \tag{2.4.4}$$

where the percentage deviation from the initial steady state is denoted by a hat.

According to these equations, higher technology growth in sector 2 relative to sector 1 ($\hat{Z}_2 > \hat{Z}_1$) generates a rise in the relative wage of sector 2 and its relative employment with the assumption of a more than one elasticity of substitution, $\sigma > 1$. Importantly, the mobility friction parameter, ϕ, plays a major role in determining the extent to which the wage gap and labour allocation change. When the degree of mobility frictions is large enough (ϕ is very small), the wage gap greatly increases as sector 2 biased technology progress occurs. For the labour allocation, by contrast, the small ϕ offsets the relative technology growth effect. Table 2.6 displays the long-term response of the wage gap and labour allocation to a one percent permanent increase in the relative technology of the high-wage sector. It can be seen that in the economy with a higher level of mobility frictions, the wage gap is more likely to increase while workers struggle to move into the high-wage sector. This imperfect labour mobility also suppresses economic gain as seen in the last four rows of the table.

By adopting stochastic processes on sector-specific technology, we can assess the extent to which this two-sector framework with mobility frictions contributes to explaining observed fluctuations in the wage gap and labour allocation.

The sector-biased technological process, Z_{jt}, is assumed to follow an exogenous

Table 2.6: Wage gap and labour allocation responses to a permanent sector-specific technology shock, Z_2/Z_1

(%)

	baseline	large friction		small friction	
	$\phi = 0.7$	$\phi = 0.4$	$\phi = 0.0$	$\phi = 1.0$	$\phi = 3.0$
$\hat{\omega}_{12}$	0.089	0.106	0.142	0.076	0.039
$\hat{\digamma}_{12}$	0.062	0.042	0.000	0.076	0.119
$\hat{Y}$	0.475	0.474	0.472	0.476	0.481
$\hat{W}$	0.526	0.522	0.513	0.529	0.538
$\hat{C}$	0.416	0.412	0.400	0.420	0.429
$\hat{V}$	0.151	0.149	0.142	0.153	0.158

Source: Author's own

Notes: The numbers give the responses of the variables in percent to a one percent permanent increase in the relative technology ratio Z_2/Z_1.

log-normal AR(1) process as

$$\ln Z_{jt} = \rho_z \ln Z_{jt-1} + \varepsilon_{zt}, \quad \varepsilon_{zt} \sim \mathcal{N}(0, \sigma_z^2) \tag{2.4.5}$$

where ρ_z is the autoregressive coefficient and σ_z is the standard deviation of the innovation. The autoregressive coefficient is chosen as $\rho_z = 0.95$ according to Garin, Pries, and Sims (2018).[31]

Figure 2.7 describes the impulse response functions (IRFs) of the labour market related and other key variables to the relative technology shock of the high-wage sector, Z_{2t}/Z_{1t}, in the log-linearised model.

Consistent with the analytical relations (2.3.39) and (2.3.40), the relative technological progress in the high-wage sector initially generates a rise of the wage gap, ω_t, via its impact on labour demand. At the same time, its labour allocation, $\digamma_t$, also increases since the relative labour demand curve (2.3.33) shifts out when the shock occurs with a more than one elasticity of substitution between goods. Afterwards,

[31] Garin, Pries, and Sims (2018) point out that setting the autoregressive coefficient of sector-specific productivity sufficiently persistent is inevitable to generate labour reallocation across sectors in a disaggregated sector model.

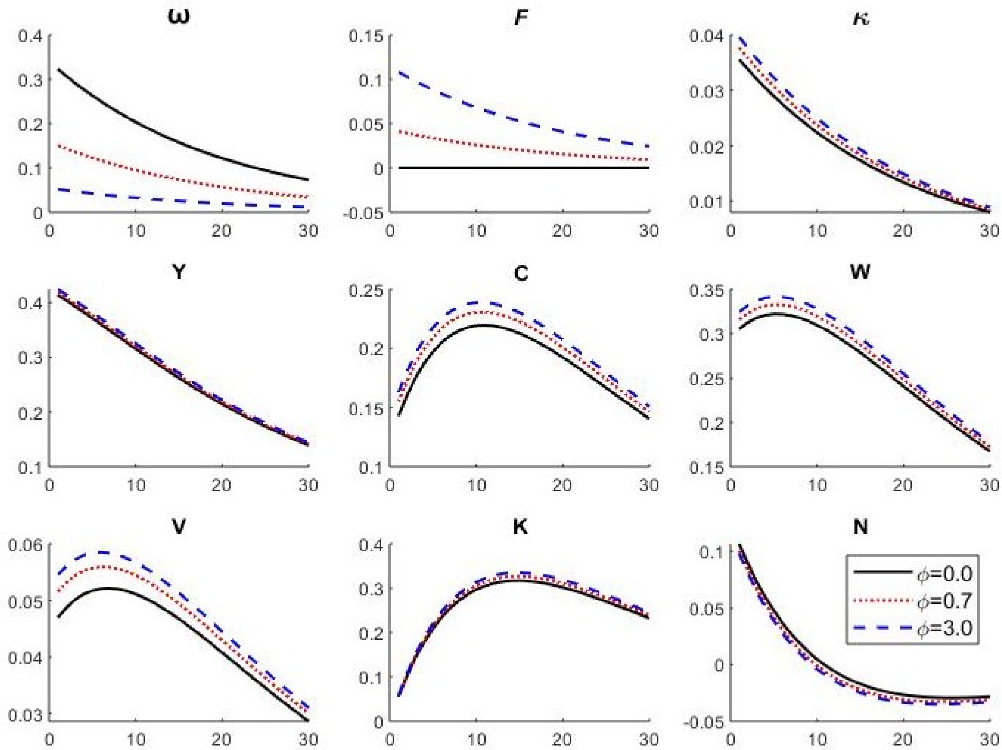

Figure 2.7: Impulse responses to a relative technology shock, Z_{2t}/Z_{1t}

Source: Author's own

Notes: A one percent relative productivity shock of sector 2, Z_{2t}/Z_{1t}, is applied. Y-axis is expressed in terms of percentage deviation. κ is the capital share of sector 2, the upper case Y, C, W, K, N represent aggregate variables, and V indicates welfare.

both revert to the steady state as the effects of the shock fade away. However, the magnitude of the impulse responses rests upon labour mobility frictions governed by the magnitude ϕ. As seen in the first two graphs, the higher degree of labour mobility frictions (or the lower ϕ), the bigger response of the wage gap and the smaller response of labour allocation. The graphs show that in the economy with $\phi = 0.0$, the case of immobile labour, the wage gap reacts substantially immediately when the shock occurs but the relative labour allocation stands still. In contrast, a counter-factual case demonstrates that in the economy with a low level of mobility friction, $\phi = 3.0$, the wage gap only slightly increases because labour can switch sectors smoothly.

We would also expect the degree of labour mobility frictions to affect the responses of other key economic variables to the relative technology shock. Particularly, the higher degree of mobility frictions (the lower ϕ) is, it is expected that aggregate output (Y_t), consumption (C_t), economy-wide wage level (W_t), and welfare (V_t) rise by less. The responses in the figure are well in line with what we would expect.

All these simulations imply that despite the relative increase of labour demand in the high-wage sector, driven by a sector-specific technology shock, it is difficult for workers to move into the high-wage sector because of barriers to inter-sectoral mobility and accordingly the wage gap between sectors expands. Such labour misallocation triggers output and welfare loss compared to those levels in the less frictional economy.

2.4.4 Modifications of the Benchmark Model

Previously, it is assumed that household preferences are separable in consumption and leisure, and the labour income share is the same across sectors. Now, we relax these assumptions and examine two modified models with alternative assumptions. The first case of modifications is to assume a non-separability of consumption and labour supply in preferences. The second case is to apply different labour income shares between sectors.

2.4.4.1 Non-separability in Preferences

The household's utility increases in its consumption and decreases in its labour supply as the benchmark model, but it has a non-separable preference as introduced by King, Plosser, and Robelo (1988).

$$U(C_t, N_t) = \frac{\left[C_{t+s}^{\xi}(1 - N_{t+s})^{1-\xi}\right]^{1-\theta} - 1}{1 - \theta} \tag{2.4.6}$$

where $\xi \in (0,1)$ determines intratemporal substitution between consumption and leisure. With this utility function, only the Euler equation and the intratemporal optimality condition are changed to[32]

(Euler equation)

$$\frac{1}{\left[C_t^{\xi}(1-N_t)^{1-\xi}\right]^{\theta} C_t^{1-\xi}} = \frac{\beta(1+R_{t+1}-\delta)}{\left[C_{t+1}^{\xi}(1-N_{t+1})^{1-\xi}\right]^{\theta} C_{t+1}^{1-\xi}} \tag{2.4.7}$$

(intratemporal optimality condition)

$$\frac{W_t}{C_t^{1-\xi}} = \frac{1-\xi}{\xi} \cdot \frac{1}{(1-N_t)^{\xi}} \tag{2.4.8}$$

Thus, non-separability of consumption and leisure in preferences does not affect on the wage gap and labour allocation across sectors. It only influences aggregate variables such as consumption, capital stock and labour supply.

2.4.4.2 Different Labour Income Shares

For the case of different labour income shares between sectors, the sectoral Cobb-Douglas production function can be rewritten as

$$Y_{jt} = (Z_{jt}L_{jt})^{\alpha_j} K_{jt}^{1-\alpha_j} \tag{2.4.9}$$

where α_j is the labour income share in sector j. The marginal product of labour and the free capital mobility condition are derived by

(marginal product of labour)

$$W_{jt} = \alpha_j \gamma_j \left(\frac{Y_t}{Y_{jt}}\right)^{\frac{1}{\sigma}} \frac{Y_{jt}}{N_{jt}} \tag{2.4.10}$$

[32] See the Appendix 2.A.5 for the derivation.

(free movement of capital)

$$\frac{\kappa_{jt}}{\kappa_{it}} = \frac{\gamma_j}{\gamma_i} \left(\frac{1-\alpha_j}{1-\alpha_i} \right) \left(\frac{Y_{jt}}{Y_{it}} \right)^{\frac{\sigma-1}{\sigma}} \tag{2.4.11}$$

These conditions are different from those in the benchmark model. Different labour income shares influence sectoral variables such as sectoral wages and employment differently.

Table 2.7 compares the results from this assumption of different labour income shares with the results from the benchmark model. Sectoral labour income shares, α_1 and α_2 are set to 0.763 and 0.625, respectively, which are simply computed as labour compensation divided by the sum of capital and labour compensation by sector in the US during 1990 to 2015 using EU KLEMS database. In this modified model, both the relative wage of the high-wage sector and its labour allocation are down from the levels in the benchmark. This is because a higher labour income share in the low-wage sector increases its marginal labour productivity followed by a rise in the wage level, relative to that in the high-wage sector. Accordingly, workers have more incentive to stay in the low-wage sector compared to in the benchmark economy. Yet this assumption of different labour income shares lowers both the wage gap and labour allocation compared to the benchmark model, so it has just level effects, which is in line with the argument in Gollin and Rogerson (2014).

Table 2.7: Modification of the benchmark model

	data	model ($\phi = 0.7$)	
	1990-2000	(1) benchmark	(2) different α
ω_{12}	1.821	1.830	1.622
$\digamma_{12}$	0.496	0.496	0.467
	data	model ($\phi = 0.4$)	
	2001-2016	(1) benchmark	(2) different α
ω_{12}	2.011	2.038	1.766
$\digamma_{12}$	0.435	0.437	0.423

Source: Author's own

Notes: α_1 and α_2 are set to 0.763 and 0.625, respectively (EU KLEMS).

To see the net effect of different labour income shares on the wage gap and labour allocation, I simulate the model with different α for a given value of ϕ. Table 2.8 shows that a fall in the labour income share in the high-wage sector (α_2) causes the decrease in both the wage gap and its labour allocation. Hence, the assumption of different labour income shares has limits in explaining the increasing wage gap. Furthermore, US data show that both sectors' labour income shares have very slightly declined since the 1990s, and thus the difference in labour income share between sectors has been almost constant (0.137 in the 1990s → 0.139 after 2000, EU KLEMS).[33]

Table 2.8: Net effect of different labour income shares

	different α, given $\phi = 0.7$	
	$\alpha_1 = 0.76$, $\alpha_2 = 0.65$	$\alpha_1 = 0.76$, $\alpha_2 = 0.60$
ω_{12}	1.655	1.590
$\digamma_{12}$	0.473	0.460

Source: Author's own

2.5 Conclusion

There is overwhelming evidence in existing studies that labour reallocation is a crucial component of economic growth and a reduction in wage inequality. In this chapter, we assessed the role of barriers to inter-sectoral labour mobility through a multi-sector general equilibrium model. In the model, labour mobility frictions are introduced in the form of limited substitutability in labour supply between sectors. It demonstrates that labour mobility frictions can play a decisive role for the increasing wage gap and labour clustering in the low-wage sector, which cannot be explained alone by changes in the labour demand side, for example, technological progress.

[33]See the Appendix 2.A.6 for details about sectoral labour income share.

The main findings from the calibrated model are that the degree of mobility frictions has increased throughout more than two decades, thus being much higher after 2000 than it was in the 1990s. Additionally, an elevation in the level of labour mobility frictions incurs a non-trivial economic loss in terms of output and welfare by worsening labour misallocation and wage inequality. When a sector-specific technology shock occurs, the largely frictional economy experiences even larger distortions in its labour market than the economy with less mobility frictions.

2.A Appendix

2.A.1 Model Derivations

2.A.1.1 Wage Gap and Labour Allocation without Frictions: Equation (2.2.5) & (2.2.6)

From the household maximisation problem, the following first order conditions are derived.

$$
\begin{aligned}
[C_t] \quad & C_t^{-\theta} = \lambda_t \\
[K_{t+1}] \quad & \lambda_t = \beta \lambda_{t+1}(1 + R_{t+1} - \delta) \\
[N_{jt}] \quad & \lambda_t W_{jt} = \nu \left(\sum_{j=1}^{J} N_{jt} \right)^{\chi}
\end{aligned}
$$

where λ_t is the Lagrange multiplier. From the last condition, the wage gap between any two sectors, i and j, becomes unity (wage equality).

$$\frac{W_{jt}}{W_{it}} = 1$$

Next, from the firms' maximisation problems, we can get each sector's demand function and marginal product of labour as

$$
\begin{aligned}
P_{jt} &= \gamma_j \left(\frac{Y_{jt}}{Y_t} \right)^{-\frac{1}{\sigma}} \\
W_{jt} &= \alpha \gamma_j \left(\frac{Y_t}{Y_{jt}} \right)^{\frac{1}{\sigma}} \frac{Y_{jt}}{N_{jt}}
\end{aligned}
$$

where the labour market clearing condition, $L_{jt} = N_{jt}$, is used. By using these conditions, we get the ratio of sectoral prices and the ratio of sectoral wages.

$$\frac{P_{jt}}{P_{it}} = \frac{\gamma_j}{\gamma_i} \left(\frac{Y_{jt}}{Y_{it}} \right)^{-\frac{1}{\sigma}}$$

$$\frac{W_{jt}}{W_{it}} = \frac{\gamma_j}{\gamma_i} \left(\frac{Y_{jt}}{Y_{it}}\right)^{1-\frac{1}{\sigma}} \left(\frac{N_{jt}}{N_{it}}\right)^{-1}$$

By combining these two equations and plugging in the wage equality condition, the labour allocation condition can be derived as

$$\frac{N_{jt}}{N_{it}} = \frac{P_{jt}Y_{jt}}{P_{it}Y_{it}}$$

2.A.1.2 Aggregate Real Wage Index: Equation (2.3.3)

The aggregate wage is conceptually the maximum earning from supplying one unit of the aggregate labour N_t. If there is a continuum of sectors $j \in [0, 1]$, the household income maximisation problem is given by

$$\max_{\{N_{jt}\}_j} \quad \int_0^1 (W_{jt}N_{jt})\, dj$$
$$s.t. \quad N_t \equiv \left[\int_0^1 \left(\varphi_j^{-\frac{1}{\phi}} \cdot N_{jt}^{\frac{\phi+1}{\phi}}\right) dj\right]^{\frac{\phi}{\phi+1}} = 1$$

The first order condition with respect to N_{jt} is

$$W_{jt} = \lambda_t \varphi_j^{-\frac{1}{\phi}} N_{jt}^{\frac{1}{\phi}} N_t^{-\frac{1}{\phi}}$$

where λ_t is the Lagrange multiplier. By dividing the first order conditions of any two sectors, i and j, we get

$$\frac{W_{jt}}{W_{it}} = \left(\frac{\varphi_j}{\varphi_i}\right)^{-\frac{1}{\phi}} \left(\frac{N_{jt}}{N_{it}}\right)^{\frac{1}{\phi}} \quad \Rightarrow \quad N_{jt} = \varphi_j \varphi_i^{-1} W_{jt}^{\phi} W_{it}^{-\phi} N_{it}$$

Putting this into the constraint yields

$$\left[\int_0^1 \varphi_j^{-\frac{1}{\phi}} \left(\varphi_j \varphi_i^{-1} W_{jt}^{\phi} W_{it}^{-\phi} N_{it}\right)^{\frac{\phi+1}{\phi}} dj\right]^{\frac{\phi}{\phi+1}} = 1 \quad \Rightarrow \quad N_{it} = \frac{\varphi_i W_{it}^{\phi}}{\left[\int_0^1 \varphi_j W_{jt}^{\phi+1} dj\right]^{\frac{\phi}{\phi+1}}}$$

By plugging this into the objective function $\int_0^1 (W_{it} N_{it}) di$, we obtain

$$\frac{\int_0^1 \varphi_i W_{it}^{\phi+1} di}{\left[\int_0^1 \varphi_j W_{jt}^{\phi+1} dj\right]^{\frac{\phi}{\phi+1}}} = \left(\int_0^1 \varphi_j \cdot W_{jt}^{1+\phi} dj\right)^{\frac{1}{\phi+1}} \equiv W_t$$

This shows that the maximum earning from supplying one unite of N_t is the same as the aggregate wage index W_t that we defined.

2.A.1.3 Labour Supply for Sector j: Equation (2.3.6)

In the general case, suppose that there is a continuum of sectors $j \in [0, 1]$. The aggregate labour supply index is

$$N_t = \left[\int_0^1 \left(\varphi_j^{-\frac{1}{\phi}} \cdot N_{jt}^{\frac{\phi+1}{\phi}}\right) dj\right]^{\frac{\phi}{\phi+1}}$$

The household minimises N_t for any given earning level $\mathcal{Q}_t \equiv \int_0^1 (W_{jt} N_{jt}) dj$ by deciding labour allocation N_{jt}. This is namely the disutility minimisation problem since labour supply entails disutility to the household.

$$\min_{\{N_{jt}\}_j} \quad N_t = \left[\int_0^1 \left(\varphi_j^{-\frac{1}{\phi}} \cdot N_{jt}^{\frac{\phi+1}{\phi}}\right) dj\right]^{\frac{\phi}{\phi+1}}$$

$$s.t. \quad \mathcal{Q}_t \equiv \int_0^1 W_{jt} N_{jt} dj$$

The first order condition with respect to N_{jt} is

$$\lambda_t W_{jt} = \varphi_j^{-\frac{1}{\phi}} N_t^{-\frac{1}{\phi}} N_{jt}^{\frac{1}{\phi}}$$

where λ_t is the Lagrange multiplier. By dividing the first order conditions of any two sectors, i and j, we get

$$N_{jt} = \frac{\varphi_j}{\varphi_i}\left(\frac{W_{jt}}{W_{it}}\right)^{\phi} N_{it}$$

Putting this into the aggregate labour supply index gives

$$N_t = \varphi_i^{-1} W_{it}^{-\phi} N_{it} \left[\int_0^1 \left(\varphi_j \cdot W_{jt}^{\phi+1}\right) dj\right]^{\frac{\phi}{\phi+1}} = \varphi_i^{-1} W_{it}^{-\phi} N_{it} W_t^{\phi}$$

By rearranging, we finally get the labour supply for sector j as

$$N_{jt} = \varphi_j \left(\frac{W_{jt}}{W_t}\right)^{\phi} N_t$$

2.A.1.4 Demands for Intermediate Goods: Equation (2.3.13)

In the general case, suppose that there is a continuum of sectors $j \in [0,1]$. The aggregate output is

$$Y_t = \left[\int_0^1 (\gamma_j \cdot Y_{jt}^{\frac{\sigma-1}{\sigma}}) dj\right]^{\frac{\sigma}{\sigma-1}}$$

The final good firm maximises its profit by optimally combining each of intermediate goods.

$$\max_{\{Y_{jt}\}_j} \; P_t Y_t - \int_0^1 (P_{jt} Y_{jt}) dj$$

where P_t is the price of final goods and P_{jt} is the price of sector j's goods. The first order condition with respect to Y_{jt} is

$$P_{jt} = \gamma_j Y_{jt}^{-\frac{1}{\sigma}} P_t Y_t^{\frac{1}{\sigma}}$$

By dividing the first order conditions of any two sectors, i and j, we obtain

$$Y_{it} = \left(\frac{\gamma_i}{\gamma_j}\right)^{\sigma} \left(\frac{P_{it}}{P_{jt}}\right)^{-\sigma} Y_{jt}$$

Putting this into the aggregate output equation yields

$$Y_t = \gamma_j^{-\sigma} P_{jt}^{\sigma} Y_{jt} \left[\int_0^1 \gamma_i^{\sigma} \cdot P_{it}^{1-\sigma} di\right]^{\frac{\sigma}{\sigma-1}} = \gamma_j^{-\sigma} P_{jt}^{\sigma} Y_{jt} \left\{ \underbrace{\left[\int_0^1 \gamma_i^{\sigma} \cdot P_{it}^{1-\sigma} di\right]^{\frac{1}{1-\sigma}}}_{= P_t \equiv 1} \right\}^{-\sigma}$$

By rearranging, we finally get the demands for good j as

$$P_{jt} = \gamma_j \left(\frac{Y_{jt}}{Y_t}\right)^{-\frac{1}{\sigma}}$$

2.A.1.5 Aggregate Price Level: Equation (2.3.14)

The aggregate price is basically the minimum cost to produce one unit of the final goods Y_t. If there is a continuum of sectors $j \in [0,1]$, the final output firm's cost minimisation problem is given by

$$\min_{\{Y_{jt}\}_j} \quad \int_0^1 (P_{jt} Y_{jt}) dj$$
$$s.t. \quad Y_t \equiv \left[\int_0^1 \gamma_j \cdot Y_{jt}^{\frac{\sigma-1}{\sigma}} dj\right]^{\frac{\sigma}{\sigma-1}} = 1$$

The first order condition with respect to Y_{jt} is

$$P_{jt} = \lambda_t \gamma_j Y_{jt}^{-\frac{1}{\sigma}} Y_t^{\frac{1}{\sigma}}$$

where λ_t is the Lagrange multiplier. By dividing the first order conditions of any two goods, i and j, we get

$$\frac{P_{jt}}{P_{it}} = \frac{\gamma_j}{\gamma_i}\left(\frac{Y_{jt}}{Y_{it}}\right)^{-\frac{1}{\sigma}} \quad \Rightarrow \quad Y_{jt} = \gamma_j^{\sigma}\gamma_i^{-\sigma}P_{jt}^{-\sigma}P_{it}^{\sigma}Y_{it}$$

Putting this into the constraint gives

$$\left[\int_0^1 \gamma_j\left(\gamma_j^{\sigma}\gamma_i^{-\sigma}P_{jt}^{-\sigma}P_{it}^{\sigma}Y_{it}\right)^{\frac{\sigma-1}{\sigma}}dj\right]^{\frac{\sigma}{\sigma-1}} = 1 \quad \Rightarrow \quad Y_{it} = \frac{\gamma_i^{\sigma}P_{it}^{-\sigma}}{\left[\int_0^1 \gamma_j^{\sigma}\cdot P_{jt}^{1-\sigma}dj\right]^{\frac{\sigma}{\sigma-1}}}$$

By plugging this into the cost function $\int_0^1(P_{it}Y_{it})di$, we obtain

$$\frac{\int_0^1 \gamma_i^{\sigma}\cdot P_{it}^{1-\sigma}di}{\left[\int_0^1 \gamma_j^{\sigma}\cdot P_{jt}^{1-\sigma}dj\right]^{\frac{\sigma}{\sigma-1}}} = \left[\int_0^1 \gamma_j^{\sigma}\cdot P_{jt}^{1-\sigma}dj\right]^{\frac{1}{1-\sigma}} \equiv P_t$$

This shows that the minimum cost to produce one unite of Y_t is the same as the aggregate price index P_t that we defined.

2.A.1.6 Factor Prices: Equation (2.3.16) & (2.3.17)

Sector j's cost minimisation problem is

$$\min_{\{L_{jt},K_{jt}\}} \quad W_{jt}L_{jt} + R_tK_{jt}$$
$$s.t. \;\; Y_{jt} = (Z_{jt}L_{jt})^{\alpha}K_{jt}^{1-\alpha} \;,\quad L_{jt}\geq 0 \;,\; K_{jt}\geq 0$$

The first order conditions in sector j are

$$[L_{jt}] \qquad W_{jt} = \lambda_t\alpha Y_{jt}L_{jt}^{-1}$$
$$[K_{jt}] \qquad R_t = \lambda_t(1-\alpha)Y_{jt}K_{jt}^{-1}$$
$$[\lambda_t] \qquad Y_{jt} = (Z_{jt}L_{jt})^{\alpha}K_{jt}^{1-\alpha}$$

where λ_t is the Lagrange multiplier. By combining the first two conditions, we have

$$\frac{W_{jt}}{R_t} = \frac{\alpha}{1-\alpha}\frac{K_{jt}}{L_{jt}} \tag{2.A.1}$$

By substituting out K_{jt} or L_{jt} in the third condition, the conditional factor demands are derived as

$$L_{jt} = Z_{jt}^{-\alpha}\left(\frac{W_{jt}}{R_t}\frac{1-\alpha}{\alpha}\right)^{\alpha-1} Y_{jt}$$
$$K_{jt} = Z_{jt}^{-\alpha}\left(\frac{W_{jt}}{R_t}\frac{1-\alpha}{\alpha}\right)^{\alpha} Y_{jt}$$

Next, given above equations, the marginal cost in sector j can be calculated as

$$\begin{aligned} MC_{jt} &= W_{jt}\frac{\partial L_{jt}}{\partial Y_{jt}} + R_t\frac{\partial K_{jt}}{\partial Y_{jt}} = W_{jt}Z_{jt}^{-\alpha}\left(\frac{W_{jt}}{R_t}\frac{1-\alpha}{\alpha}\right)^{\alpha-1} + R_t Z_{jt}^{-\alpha}\left(\frac{W_{jt}}{R_t}\frac{1-\alpha}{\alpha}\right)^{\alpha} \\ &= W_{jt}^{\alpha}R_t^{1-\alpha}Z_{jt}^{-\alpha}(1-\alpha)^{\alpha-1}\alpha^{-\alpha} = P_{jt} \end{aligned} \tag{2.A.2}$$

The last equivalence is justified by $MC_{jt} = P_{jt}$ in perfect competition. If we substitute out R_t from (2.A.1) and (2.A.2), the wage in sector j is finally derived as

$$W_{jt} = \alpha\frac{Y_{jt}}{L_{jt}}P_{jt} = \alpha\gamma_j\left(\frac{Y_t}{Y_{jt}}\right)^{\frac{1}{\sigma}}\frac{Y_{jt}}{L_{jt}}$$

Likewise, if we substitute out W_{jt}, the capital rental rate in sector j can be derived as

$$R_t = (1-\alpha)\frac{Y_{jt}}{K_{jt}}P_{jt} = (1-\alpha)\gamma_j\left(\frac{Y_t}{Y_{jt}}\right)^{\frac{1}{\sigma}}\frac{Y_{jt}}{K_{jt}}$$

2.A.1.7 Relative Labour Demand: Equation (2.3.20)

By dividing any two sectors' (i and j) marginal products of labour (2.3.16) against each other,

$$\begin{aligned}
\frac{W_{jt}}{W_{it}} &= \frac{\gamma_j}{\gamma_i}\left(\frac{Y_{jt}}{Y_{it}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{L_{jt}}{L_{it}}\right)^{-1} \\
&= \frac{\gamma_j}{\gamma_i}\left[\left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha}\left(\frac{L_{jt}}{L_{it}}\right)^{\alpha}\left(\frac{\kappa_{jt}}{\kappa_{it}}\right)^{1-\alpha}\right]^{\frac{\sigma-1}{\sigma}}\left(\frac{L_{jt}}{L_{it}}\right)^{-1} \\
&= \frac{\gamma_j}{\gamma_i}\left(\frac{Z_{jt}}{Z_{it}}\right)^{\frac{\alpha(\sigma-1)}{\sigma}}\left(\frac{L_{jt}}{L_{it}}\right)^{\frac{\alpha(\sigma-1)-\sigma}{\sigma}}\left(\frac{\kappa_{jt}}{\kappa_{it}}\right)^{\frac{(1-\alpha)(\sigma-1)}{\sigma}}
\end{aligned}$$

From the condition of the free movement of capital (2.3.31), the ratio of capital stocks between sectors is derived as

$$\frac{\kappa_{jt}}{\kappa_{it}} = \left(\frac{\gamma_j}{\gamma_i}\right)^{\frac{\sigma}{1+\alpha(\sigma-1)}}\left(\frac{Z_{jt}}{Z_{it}}\right)^{\frac{\alpha(\sigma-1)}{1+\alpha(\sigma-1)}}\left(\frac{L_{jt}}{L_{it}}\right)^{\frac{\alpha(\sigma-1)}{1+\alpha(\sigma-1)}}$$

By substituting out κ_{jt}/κ_{it}, the equation which shows the relationship between the wage gap and the relative labour demand is finally derived.

$$\mathsf{F}^{d}_{ij,t} = \left(\frac{\gamma_j}{\gamma_i}\right)^{\sigma}\left(\frac{Z_{jt}}{Z_{it}}\right)^{\alpha(\sigma-1)}\left(\frac{1}{\omega_{ij,t}}\right)^{1+\alpha(\sigma-1)}$$

where $\omega_{ij,t} = W_{jt}/W_{it}$ and $\mathsf{F}^{d}_{ij,t} = L_{jt}/L_{it}$.

2.A.1.8 ϕ_t as a function of the wage gap and labour allocation: Equation (2.4.1)

By rearranging (2.3.39) with respect to Z_{2t}/Z_{1t}, we obtain

$$\left(\frac{Z_{2t}}{Z_{1t}}\right)^{\alpha(\sigma-1)} = \frac{\left(\frac{\varphi}{1-\varphi}\right)\left(\frac{1-\tau_2}{1-\tau_1}\right)^{\phi}}{\left(\frac{\gamma}{1-\gamma}\right)^{\sigma}} \cdot (\omega_{12,t})^{1+\alpha(\sigma-1)+\phi}$$

By plugging this into (2.3.40), we get

$$
\begin{aligned}
(\mathsf{F}_{12,t})^{1+\alpha(\sigma-1)+\phi} &= \left(\frac{\gamma}{1-\gamma}\right)^{\sigma\phi}\left(\frac{\varphi}{1-\varphi}\right)^{1+\alpha(\sigma-1)}\left(\frac{1-\tau_2}{1-\tau_1}\right)^{(1+\alpha(\sigma-1))\phi} \\
&\quad\times\frac{\left(\frac{\varphi}{1-\varphi}\right)^{\phi}\left(\frac{1-\tau_2}{1-\tau_1}\right)^{\phi^2}}{\left(\frac{\gamma}{1-\gamma}\right)^{\sigma\phi}}\cdot\left(\omega_{12,t}\right)^{(1+\alpha(\sigma-1)+\phi)\phi} \\
&= \left(\frac{\varphi}{1-\varphi}\right)^{1+\alpha(\sigma-1)+\phi}\left(\frac{1-\tau_2}{1-\tau_1}\right)^{\phi(1+\alpha(\sigma-1)+\phi)}\cdot\left(\omega_{12,t}\right)^{(1+\alpha(\sigma-1)+\phi)\phi}
\end{aligned}
$$

This can be simplified to

$$
\mathsf{F}_{12,t} = \left(\frac{\varphi}{1-\varphi}\right)\left(\frac{1-\tau_2}{1-\tau_1}\right)^{\phi}\cdot\left(\omega_{12,t}\right)^{\phi}
$$

By taking the logarithm, we finally obtain

$$
\phi_t = \frac{\ln \mathsf{F}_{12,t} - \ln\frac{\varphi}{1-\varphi}}{\ln\omega_{12,t} + \ln\frac{1-\tau_2}{1-\tau_1}}
$$

2.A.2 A Multi-sector Model with Differential Taxation

With differential taxation between sectors, the household optimisation problem can be written as

$$\max_{\{C_{t+s}, K_{t+s+1}, N_{jt+s}\}_{s=0}^{\infty}} \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left(\frac{C_{t+s}^{1-\theta}}{1-\theta} - \nu \frac{N_{t+s}^{1+\chi}}{1+\chi} \right)$$

$$s.t. \quad N_t \equiv \left(\sum_{j=1}^{J} \varphi_j^{-\frac{1}{\phi}} \cdot N_{jt}^{\frac{\phi+1}{\phi}} \right)^{\frac{\phi}{\phi+1}}$$

$$C_t + K_{t+1} - (1-\delta)K_t$$
$$= \sum_{j=1}^{J} (1-\tau_j) W_{jt} N_{jt} + R_t K_t - \tau_k (R_t - \delta) K_t + \Pi_t$$

where τ_j and τ_k are the labour income tax for sector j and the net capital income tax, respectively.

The government balances its expenditure, G_t, and tax income. Hence the government budget constraint is

$$G_t = \sum_{j=1}^{J} \tau_j W_{jt} N_{jt} + \tau_k (R_t - \delta) K_t$$

Then, the goods market clearing condition can be written as

$$Y_t = C_t + K_{t+1} - (1-\delta)K_t + G_t$$

By dividing any two sectors' labour supply functions against each other, the following equation can be derived.

$$F_{ij,t}^{s} = \frac{\varphi_j}{\varphi_i} \cdot \left(\frac{1-\tau_j}{1-\tau_i} \right)^{\phi} \cdot \omega_{ij,t}^{\phi}$$

By combining this with the relative labour demand equation (2.3.20), the equilibrium wage gap and labour allocation can be derived as

$$\omega^*_{ij,t} \equiv \frac{W_{jt}}{W_{it}} = \left[\left(\frac{\gamma_j}{\gamma_i} \right)^{\sigma} \left(\frac{Z_{jt}}{Z_{it}} \right)^{\alpha(\sigma-1)} \left(\frac{\varphi_j}{\varphi_i} \right)^{-1} \left(\frac{1-\tau_j}{1-\tau_i} \right)^{-\phi} \right]^{\frac{1}{1+\alpha(\sigma-1)+\phi}}$$

$$\digamma^*_{ij,t} \equiv \frac{N_{jt}}{N_{it}} = \left[\left(\frac{\gamma_j}{\gamma_i} \right)^{\sigma\phi} \left(\frac{Z_{jt}}{Z_{it}} \right)^{\alpha(\sigma-1)\phi} \left(\frac{\varphi_j}{\varphi_i} \right)^{1+\alpha(\sigma-1)} \left(\frac{1-\tau_j}{1-\tau_i} \right)^{(1+\alpha(\sigma-1))\phi} \right]^{\frac{1}{1+\alpha(\sigma-1)+\phi}}$$

2.A.3 Sector Classification: Cluster Analysis

The cluster analysis is a method of classifying objects on the basis of a set of measured variables into some different groups (clusters) such that objects within a group are more similar (closer) to each other than to those in other groups. To classify 35 industries into high- and low-wage sectors, I choose two variables which are mean wage (x_1) and median wage (x_2) in logarithm for each industry between 2000 and 2016. Then, the Euclidean distance between any two industries i and j is given by

$$d_{ij} = \sqrt{(x_{1i} - x_{1j})^2 + (x_{2i} - x_{2j})^2}$$

The distance between groups is measured by using the average-linked method which calculates the average distance between all pairs of objects in two groups. Figure 2A.1 illustrates the average distance between groups. Based on the dendrogram, there exist five clusters in terms of dissimilarity value 0.3. Finally, I classify the top two groups as the high-wage sector and the other groups as the low-wage sector.

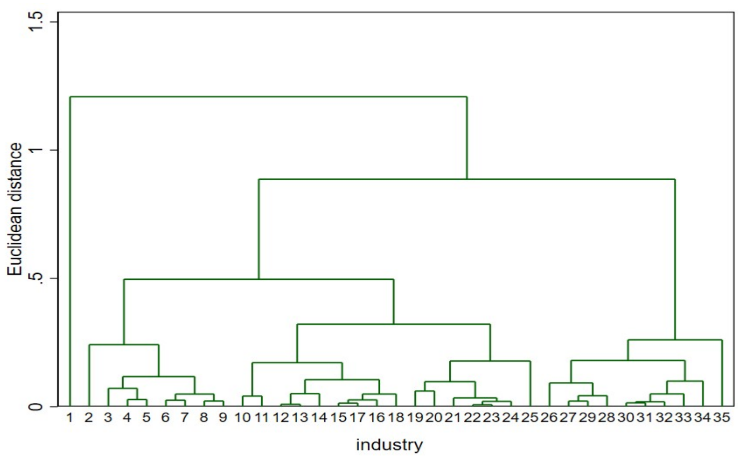

Figure 2A.1: Dendrogram, Cluster analysis of industrial wages

Source: Author's own, from BEA

Notes: Five clusters (groups): industry 1 / industries 2 - 9 / industries 10-18 / industries 19-25 / industries 26-35. Each number on the horizontal axis indicates an industry and the number is the same as the wage rank in ascending sort order as in Table 2.3.

2.A.4 Alternative Ways of Backing Out ϕ_t

By taking logs of equations (2.3.39) and (2.3.40), ϕ can be expressed as a function of the technology gap and the wage gap, or labour allocation as

$$\begin{aligned}\phi_t^A &= G\left(\frac{Z_{2t}}{Z_{1t}}, \omega_{12,t}\right)\\ &= \frac{\sigma \ln \frac{\gamma}{1-\gamma} + \alpha(\sigma-1)\ln\frac{Z_{2t}}{Z_{1t}} - \ln\frac{\varphi}{1-\varphi} - (1+\alpha(\sigma-1))\ln\omega_{12,t}}{\ln\omega_{12,t} + \ln\frac{1-\tau_2}{1-\tau_1}} \end{aligned} \tag{2.A.3}$$

$$\begin{aligned}\phi_t^B &= H\left(\frac{Z_{2t}}{Z_{1t}}, F_{12,t}\right)\\ &= \frac{(1+\alpha(\sigma-1))\left(\ln\frac{\varphi}{1-\varphi} - \ln F_{12,t}\right)}{\ln F_{12,t} - \sigma\ln\frac{\gamma}{1-\gamma} - \alpha(\sigma-1)\ln\frac{Z_{2t}}{Z_{1t}} - (1+\alpha(\sigma-1))\ln\frac{1-\tau_2}{1-\tau_1}} \end{aligned} \tag{2.A.4}$$

With other calibrated parameters and actual data, these functions allow us to estimate two alternative mobility friction parameters (ϕ_t^A and ϕ_t^B), one from (2.A.3), and the other from (2.A.4). Figure 2A.2 depicts the backed-out ϕs. Both lines similarly show downward trends.

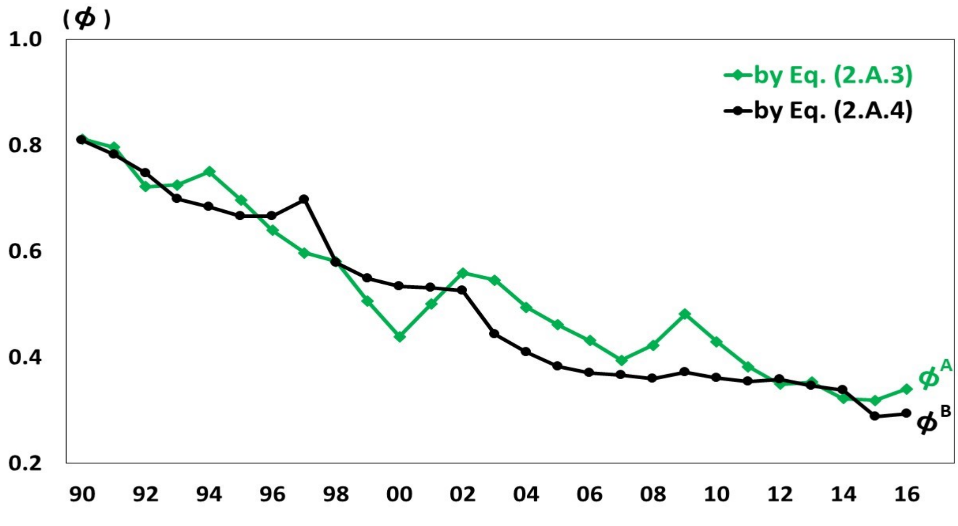

Figure 2A.2: Backed-out ϕs with alternative ways, US

Source: Author's own, from BEA NIPA, EU KLEMS

Notes: The initial level of ϕ_t^B is adjusted to fit the initial ϕ_t^A.

2.A.5 Modifications of the Benchmark Model

2.A.5.1 Non-separability in Preferences

The household maximises its lifetime utility subject to the flow budget constraint.

$$\max_{\{C_{t+s}, K_{t+s+1}, N_{t+s}\}_{s=0}^{\infty}} \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left(\frac{\left[C_{t+s}^{\xi}(1-N_{t+s})^{1-\xi}\right]^{1-\theta} - 1}{1-\theta} \right)$$

$$s.t. \;\; C_t + K_{t+1} - (1-\delta)K_t = W_t N_t + R_t K_t + \Pi_t$$

The first order conditions are

$$\begin{aligned}
[C_t] \qquad & \left[C_t^{\xi}(1-N_t)^{1-\xi}\right]^{-\theta} \cdot \xi C_t^{\xi-1} = \lambda_t \\
[K_{t+1}] \qquad & \lambda_t = \beta \lambda_{t+1}(1 + R_{t+1} - \delta) \\
[N_t] \qquad & \left[C_t^{\xi}(1-N_t)^{1-\xi}\right]^{-\theta} \cdot (1-\xi)(1-N_t)^{-\xi} = \lambda_t W_t
\end{aligned}$$

The modified optimal conditions are the Euler equation and the intratemporal optimality condition as follows:

(Euler equation)

$$\frac{1}{\left[C_t^{\xi}(1-N_t)^{1-\xi}\right]^{\theta} C_t^{1-\xi}} = \frac{\beta(1 + R_{t+1} - \delta)}{\left[C_{t+1}^{\xi}(1-N_{t+1})^{1-\xi}\right]^{\theta} C_{t+1}^{1-\xi}}$$

(intratemporal optimality condition)

$$\frac{W_t}{C_t^{1-\xi}} = \frac{1-\xi}{\xi} \cdot \frac{1}{(1-N_t)^{\xi}}$$

2.A.6 Sectoral Labour Income Share

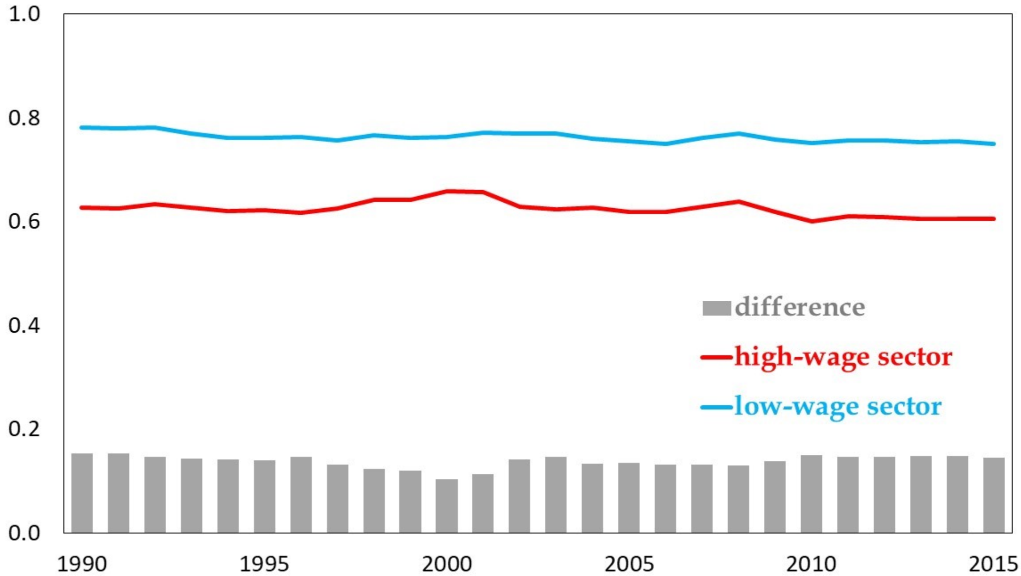

Figure 2A.3: Sectoral labour income share α_j, US

Source: Author's own, from EU KLEMS

Notes: Sectoral labour income share is computed as labour compensation divided by the sum of capital and labour compensations. It is weighted by the industrial number of persons engaged.

Chapter 3

How Differential Matching Efficiency Matters

3.1 Introduction

We have hitherto found that frictions, which exist in such forms as barriers to intersectoral labour mobility, are the key to the labour market puzzle. What still remains to be explored is to identify the principal source of labour mobility frictions.

Following the lead of the Diamond-Mortensen-Pissarides search and matching model (henceforth, DMP), the matching process of workers and jobs has been a central focus of the research on labour market dynamics. In the canonical DMP model, frictions stemming from the matching process prevent Walrasian wage determination and labour market clearing so that wages are settled upon through bargaining between firms and workers, and a portion of the labour force becomes unemployed. When production takes place in several different sectors, workers can not just move within sectors but also across sectors. It is possible that the extent of labour mobility frictions is uneven across sectors. Thus, different frictions such as differential matching efficiency will be reflected in varying labour mobility dynamics across sectors. Low matching efficiency in an industry, for example, can act as a barrier to entry and hinder labour movements to the industry.

Convincing evidence of the presence of differing matching efficiency between sectors is that the duration of the selection process in hiring employees differs across sectors. According to van Ours and Ridder (1993), a vacancy duration is composed of periods of application and selection, and the latter is much longer than the former. They define the selection period as a time span for assessing a candidate's productivity so that this duration increases with the required skill level. The duration of the selection process proxies matching efficiency since efficiency depends on the quality of the job matching process as well as its swiftness.[1]

Figure 3.1 displays the average length of the interview process by industry ordered according to their mean wage level in the US labour market. A positive relationship between the average hourly earnings and the length of the interview process is clearly observed, indicating that the higher the industry's wage, the longer the selection or screening process. This observation suggests that it is harder for firms in the high-wage sector to find the right person for their vacancies than it is for the low-wage sector, leading to more delayed hiring processes in the high-wage sector. Alternatively, it is more difficult for job seekers to obtain a job in the high-wage sector resulting in an extended job search duration. This comes down to differential matching efficiency between sectors.

The key hypothesis in this chapter is that the main source of differential matching efficiency is unbalanced sectoral productivity. This relationship can be inferred from a skill mismatch between firms and job seekers. Firms in a high productivity sector require a high level of skill set from job applicants, and therefore they are choosier in selecting workers. This results in lower matching efficiency in the high productivity sector than in the low productivity sector. This argument is consistent with Petrongolo and Pissarides (2001, pp 400) and Williamson (2013, pp

[1] In contrast, the application period is dependent on market tightness which is the ratio of vacancies to job seekers. The more job applicants relative to vacant positions, the shorter is the period of building a pool of candidates (application period).

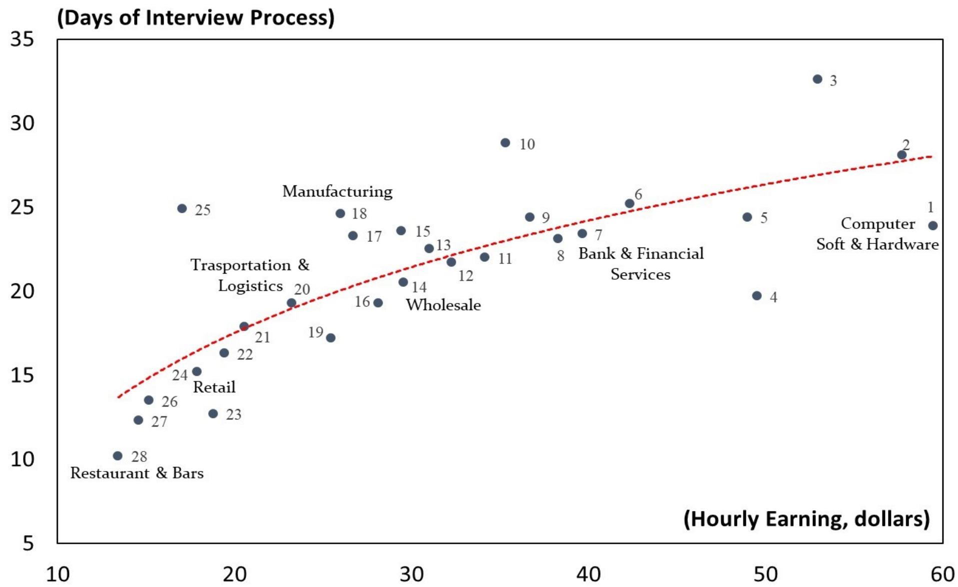

Figure 3.1: Average length of interview process by industry, US

Source: Glassdoor Economic Research, BLS Current Employment Statistics (CES)

Notes: The data of the interview process includes only the firms with at least 100 job seekers' reviews between January 2017 to June 2017. Hourly earning is the mean in the year 2016. The numbers next to the dots indicate each industry: 1-Computer Software & Hardware, 2-Biotech & Pharmaceuticals, 3-Aerospace & Defence, 4-Accounting & Legal, 5-Consulting, 6-Media & Publishing, 7-Bank & Financial Services, 8-Business Services, 9-Internet & Tech, 10-Energy & Utilities, 11-Insurance, 12-Telecommunications, 13-Health Care & Hospitals, 14-Wholesale, 15-Architecture & Civil Engineering, 16-Construction, 17-Education & Schools, 18-Manufacturing, 19-Real Estate, 20-Transportation & Logistics, 21-Arts & Entertainment, 22-Consumer Electronics, 23-Automotive, 24-Retail, 25-Farming & Agriculture, 26-Consumer Service, 27-Supermarket, 28-Restaurant & Bars

205) who point out that sectoral productivity shocks account for skill mismatch and corresponding matching inefficiency in the sector. Such a link is underpinned by a significant inverse relationship between sector-specific productivity and its matching efficiency in the US labour market, which will be validated with empirical evidence.[2]

It is common in the literature to represent a matching process as a function of the number of job seekers and vacant positions taken as inputs which are transformed into the flow of new hires as the output, in the same manner as the production function. The empirically verified standard type of DMP matching technology is

[2]We shall discuss this fact in detail later in section 3.2.

$$H_{jt} = \mu_j \cdot M(U_{jt}, V_{jt})$$

where μ_j is the residual in the matching function which is also known as 'matching efficiency', and H_{jt}, U_{jt}, and V_{jt} are the number of new matches, the unemployed and vacancy postings in sector j at time t. This function consists of two parts: The first building block, $M(U_{jt}, V_{jt})$, is determined purely by the combination of job seekers and vacancies. This part is an increasing function in both components. The second part, matching efficiency μ_j which is the central focus in this chapter, depends on unobserved factors other than inputs. This is a multiplicative shifter of the compound of both inputs. Hall and Schulhofer-Wohl (2018) define this matching efficiency as the productivity of the job matching process. Like TFP in the production function, this parameter scales the efficiency of the matching process up or down, and thus higher (lower) matching efficiency creates more (less) matches for a given number of job seekers and vacancies. This reflects the extent of frictions in matching markets.

Most previous research has focused on the former element and the relation between inputs, named the Beveridge curve. In general, less attention has been paid to matching efficiency and it is often treated as an exogenous parameter. Besides, by laying emphasis on aggregated employment and unemployment, they pay no attention to labour mobility between sectors. Even in the research about different sectors, most studies set matching efficiency to be the same across sectors (Pissarides, 1994; Dolado, Jansen, and Jimeno, 2009; Krause and Lubik, 2010).

However, some pioneering studies suggest that matching efficiency may vary in terms of sector or time and its shifts are a key source of instability of the current labour market. Petrongolo and Pissarides (2001) give several reasons for this variance. For example, the gap in skill sets possessed by job seekers and skills required by industries, the so-called skill mismatch, and the search and mobility costs can generate differential matching efficiency. Hall and Schulhofer-Wohl (2018) argue that matching efficiency depends on job seekers who are categorised by demographic characteristics and unemployment duration. Likewise, Barnichon and Figura (2015) estimate an aggregate matching function which is equipped with different matching efficiency arising from worker heterogeneity and market segmentation. Thus, it is the variations in the degree of heterogeneity that make overall matching efficiency vary over time. Davis, Faberman, and Haltiwanger (2013) and Gavazza, Mongey, and Violante (2016) construct a generalised matching function. They show that new matches depend on not only job seekers and vacancies but also recruiting intensity which differs by industry.

To analyse the relationship between matching efficiency and labour market variables and its effects on the labour market, I develop a stylised two-sector search and matching model. The key feature of the model is the salient difference in matching efficiency between sectors originating from the gap in sector-specific productivity. The main finding is that differential matching efficiency could trigger labour market distortions in such a way that the sectoral wage gap increases by preventing labour from freely flowing between sectors. This provides a clue to the puzzle of why labour has structurally been concentrated in the low-wage sector despite the widening wage gap since the 2000s. Additionally, this model economy, which effectively captures properties of the US labour market dynamics, shows that a productivity boom biased towards the high-wage sector is likely to amplify the wage gap and even decrease the relative employment share of the sector, which would not occur under a frictionless economy.

The rest of this chapter is organised as follows. Section 3.2 presents some key stylised facts about matching efficiency from the US labour market. Section 3.3 presents a two-sector search and matching model with differential matching efficiency. Section 3.4 we calibrate to the US labour market and compare it with the data. Finally, section 3.5 gives our conclusion. The Appendices provide further details and derivations on the proposed model and data.

3.2 What Determines the Matching Efficiency in the US Labour Market: Some Stylised Facts

In this section, we focus on the differences in matching efficiency across industries and investigate what creates these differences.

3.2.1 Vacancy Duration

The vacancy duration is a key concept used to assess the efficiency of the matching process or the labour market density. This duration refers to the expected average length of time taken to fill open job positions. It is calculated as the ratio of the number of vacancies V_{jt} to the number of hires H_{jt} as

$$\text{average vacancy duration} = \frac{V_{jt}}{H_{jt}}$$

where its reciprocal, H_{jt}/V_{jt}, is the probability of filling a vacancy.[3]

The vacancy duration, calculated using data from monthly Job Openings and Labour Turnover Survey (JOLTS) by the US BLS, varies across industries in the US. Notably, it is longer in most high-wage industries than in low-wage industries. Figure 3.2 displays each industry's mean vacancy duration relative to the total industry in the US ordered by wage level. The bar chart demonstrates that the duration of filling job openings in the top five industries in terms of wage level is about 1.6 times longer than in the bottom five industries. This implies that job-worker matches in the labour market of the high-wage sector are much more difficult. The vacancy duration in finance & insurance or information, which are classified into the sector with the highest wage, far exceeds the average of the whole industry (=1) while that of the low-wage sector such as accommodation & food service or retail

[3]The inverse of the probability of an event is equivalent to the expected period until the event occurs. The vacancy duration is assumed to be a random variable with a geometric or a Poisson distribution. See the Appendix 3.A.1 for the proof.

trade is far below the average.

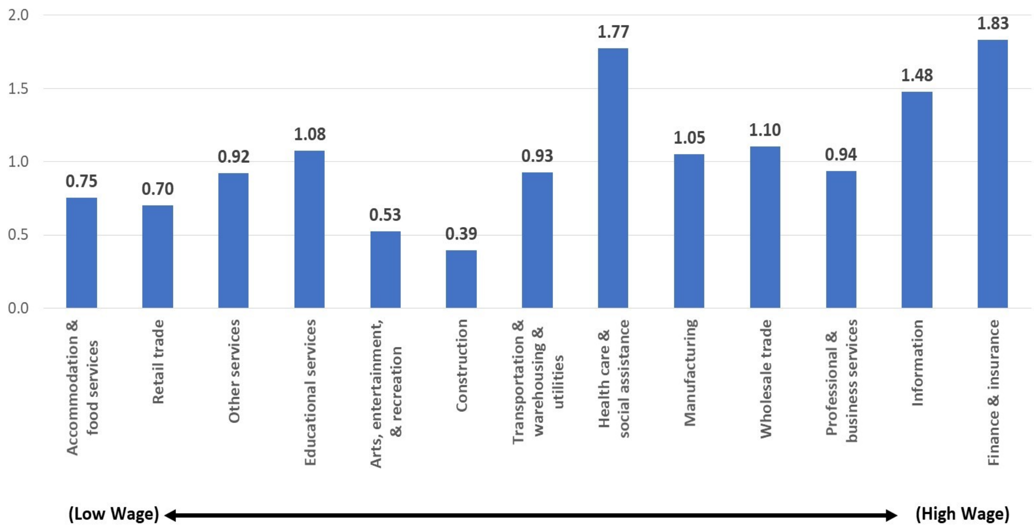

Figure 3.2: Average vacancy duration by sector, US

Source: Author's own, from US BLS Job Openings and Labor Turnover Survey (JOLTS), US BEA National Income and Product Accounts (NIPA)

Notes: Each sector's duration is averaged between Jan 2001 - Jun 2017 except for Jan 2008 - Dec 2010. The figure is the relative value with respect to the total industry (=1). Industries are ordered by average wage level during 2001 - 2016, and the wage of health care & social assistance is calculated in terms of hospital & ambulance service.

3.2.2 A Useful Decomposition of Vacancy Duration Gap

The sectoral matching function can be written as a Cobb-Douglas form with constant returns of scale which has been empirically verified in numerous previous studies (see, e.g., Petrongolo and Pissarides, 2001).

$$H_{jt} = \mu_j \cdot M(U_{jt}, V_{jt}) \quad \Leftrightarrow \quad h_{jt}L_{jt} = \mu_j \cdot M(u_{jt}L_{jt}, v_{jt}L_{jt})$$
$$\Leftrightarrow \quad h_{jt} = \mu_j \cdot M(u_{jt}, v_{jt}) = \mu_j \cdot u_{jt}^{\eta} v_{jt}^{1-\eta} \qquad (3.2.1)$$

where L_{jt} is the labour force, and h_{jt}, u_{jt}, and v_{jt} are the rate of new hires, unemployment and vacancy postings, respectively. η is the elasticity of matches with respect to the number of the unemployed.

Then, the rate of filling a vacancy is

$$q(\theta_{jt}) \equiv \frac{H_{jt}}{V_{jt}}$$
$$= \frac{\mu_j \cdot M(u_{jt}, v_{jt})}{v_{jt}} = \frac{\mu_j \cdot u_{jt}^{\eta} v_{jt}^{1-\eta}}{v_{jt}} = \mu_j \cdot \left(\frac{u_{jt}}{v_{jt}}\right)^{\eta} = \mu_j \cdot \left(\frac{1}{\theta_{jt}}\right)^{\eta} \quad (3.2.2)$$

where $\theta_{jt} \equiv v_{jt}/u_{jt}$ denotes the market tightness. By taking the logarithm,

$$\ln q(\theta_{jt}) = \ln \mu_j - \eta \cdot \ln \theta_{jt} \quad (3.2.3)$$

Since the inverse of $q(\theta_j)$ is the vacancy duration, the gap in the vacancy duration between sector 1 and sector 2 can be written as

$$\underbrace{\ln \frac{1}{q(\theta_{2t})} - \ln \frac{1}{q(\theta_{1t})}}_{\text{vacancy duration gap}} = \ln q(\theta_{1t}) - \ln q(\theta_{2t})$$
$$= \underbrace{(\ln \mu_1 - \ln \mu_2)}_{\text{(i) diff. in matching efficiency}} + \underbrace{\eta_{12} \cdot (\ln \theta_{2t} - \ln \theta_{1t})}_{\text{(ii) diff. in market tightness}}$$
$$\Rightarrow \quad \ln \frac{q(\theta_{1t})}{q(\theta_{2t})} = \ln \frac{\mu_1}{\mu_2} + \eta_{12} \ln \frac{\theta_{2t}}{\theta_{1t}} \quad (3.2.4)$$

Here the vacancy duration gap is decomposed into two parts: (i) the effect of the difference in matching efficiency, and (ii) the effect of the difference in market tightness. Table 3.1 shows the results of the decomposition of the vacancy duration gap. I regress the vacancy duration gap between one high-wage sector (sector 2) and one low-wage sector (sector 1) on the difference in market tightness using OLS over the period January 2001 through June 2017. In the first table, accommodation & food service is set as a base industry of the low-wage sector, as is retail trade in the second table.[4] Then the average contribution of each part on the vacancy

[4]Setting other low-wage industries (e.g. construction) as the base industry shows a similar result (or a large contribution of part (i) on the vacancy duration gap). See the Appendix 3.A.2 for details.

Table 3.1: Decomposition of vacancy duration gap

sector 1: Accom. & Food service	$\ln \frac{q(\overline{\theta_{1t}})}{q(\overline{\theta_{2t}})}$	(i) $\widehat{\ln \frac{\mu_1}{\mu_2}}$		(ii) $\widehat{\eta_{12}} \ln \frac{\overline{\theta_{2t}}}{\overline{\theta_{1t}}}$		
sector 2	level	level	[contrib. %]	level	[contrib. %]	$\widehat{\eta_{12}}$
finance & Insurance	0.92	0.59***	[64.1]	0.33	[35.8]	0.37***
Information	0.74	0.58***	[78.9]	0.16	[21.2]	0.50***
Professional & Business	0.25	-0.12***	[-50.1]	0.37	[150.2]	0.59***
Wholesale trade	0.40	0.31***	[76.7]	0.10	[23.9]	0.54***
Manufacturing	0.35	0.51***	[146.1]	-0.16	[-46.1]	0.45***
Health care & Social assistance	0.86	0.34***	[39.4]	0.52	[60.7]	0.52***
Transport, Warehouse & Utilities	0.22	0.22***	[99.8]	0.00	[0.4]	0.48***

sector 1: Retail trade	$\ln \frac{q(\overline{\theta_{1t}})}{q(\overline{\theta_{2t}})}$	(i) $\widehat{\ln \frac{\mu_1}{\mu_2}}$		(ii) $\widehat{\eta_{12}} \ln \frac{\overline{\theta_{2t}}}{\overline{\theta_{1t}}}$		
sector 2	level	level	[contrib. %]	level	[contrib. %]	$\widehat{\eta_{12}}$
finance & Insurance	0.96	0.65***	[67.4]	0.31	[32.7]	0.34***
Information	0.78	0.60***	[76.6]	0.19	[23.8]	0.53***
Professional & Business	0.29	-0.08*	[-26.1]	0.37	[126.7]	0.56***
Wholesale trade	0.45	0.33***	[73.4]	0.12	[27.5]	0.56***
Manufacturing	0.39	0.54***	[137.4]	-0.15	[-37.0]	0.46***
Health care & Social assistance	0.91	0.35***	[38.0]	0.57	[62.2]	0.54***
Transport, Warehouse & Utilities	0.26	0.23***	[89.2]	0.03	[11.7]	0.73***

Source: Author's own, from BLS JOLTS

Notes: Accommodation & food service and retail trade are set as the base industries of the low-wage sector (sector 1) in each table. The sample covers the period Jan 2001 - Jun 2017. The upper bar and the hat denote the mean values and the estimated values, respectively. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

duration gap is calculated using the estimated coefficients from the regressions and the sample means of the dependent and the independent variables. For example, the average contribution rate of the part (ii) to the vacancy duration gap is the fraction $\left(\widehat{\eta_{12}} \ln \frac{\overline{\theta_{2t}}}{\overline{\theta_{1t}}} / \ln \frac{q(\overline{\theta_{1t}})}{q(\overline{\theta_{2t}})}\right)$.[5] The results suggest that the vacancy duration gap is largely caused by part (i) the difference in matching efficiency, showing its relatively high contribution in most pairs of industries. The contribution of part (i) in the duration gap between the low-wage industries and the high-wage industries such as finance & insurance, information, wholesale trade, or manufacturing is over two-thirds.[6]

[5]This is similar to the growth accounting. For example, from the Solow growth accounting equation $\Delta \ln Y_t = \Delta \ln A_t + \alpha \Delta \ln L_t + (1-\alpha)\Delta \ln K_t$, we get the contribution of labour to output growth as $\alpha \Delta \ln L_t / \Delta \ln Y_t$.

[6]For the cases of professional & business or health care & social assistance, the contribution of market tightness gap is larger. Many occupations in these industries require sector-specific certificates or licences (e.g. medical licence, law licence, etc.) besides formal education. Thus, the

3.2.3 Inverse Relationship between Sector-specific Productivity and Matching Efficiency

A sector's matching efficiency turns out to be inversely related to its own productivity. This fact convincingly answers a key question about the source of differing matching efficiency across sectors, or what is a source of labour mobility frictions.

Petrongolo and Pissarides (2001) point out that low matching efficiency can be attributed to skill mismatch[7] because most firms look for industry-specific skilled persons but not all job seekers have the skills. The difference between the skills required by industries and the skills possessed by workers may also lengthen the duration spent to complete job matches for a given set of inputs. They emphasise that shocks such as technological progress increase skill mismatch and reduce matching efficiency as workers need to accommodate to new industry requirements. Behrenz (2002) estimates the effects of posted job's characteristics on its vacancy duration. His empirical results suggest that more stringent skill requirements, which might be due to technology renovation, are the primary cause of lowered matching efficiency, resulting in prolonged job vacancy. According to Williamson (2013), such a skill mismatch can come about when a sectoral shock occurs. A positive shock to productivity in a sector's production makes firms demand candidates with higher skill-sets. For example, with automation in manufacturing, the demand for routine engineering tasks (e.g. maintaining equipment and measuring its performance) is decreasing while the demand for cognitive engineering (e.g. creativity, complex in-

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job markets in such industries depend more on labour demand and supply with the certificates than on matching efficiency. As to manufacturing, the contribution of market tightness gap is negative. This implies that differential matching efficiency is a dominant factor for the vacancy duration gap although market tightness in manufacturing is less than in retail trade.

[7] To understand it intuitively, it is helpful to first look at an extreme case of zero match elasticity, or $\eta = 0$. In this case, the new matches only depends on matching efficiency and vacancies, or $h_{jt} = \mu_j \cdot v_{jt}$, and the rate of filling a vacancy is equal to the matching efficiency, or $q(\theta_{jt}) = \mu_j$. Labour supply is inelastic up to the number of vacancies, but the scale of matches is adjusted by the degree of matching efficiency μ_j. The answer to the question of what factors constrain job matches or why $\mu_j \neq 1$ will be identified by other factors apart from the number of job seekers and vacancies. Petrongolo and Pissarides (2001) regard skill mismatch as one of those causes.

formation processing) is increasing (Bughin et al., 2018). Through this process the skill mismatch between firms and job seekers in the sector increases.

Figure 3.3 describes the relationship between sector-specific productivity and its matching efficiency. Matching efficiency is implicitly derived from equation (3.2.1) using actual data of hires, vacancies and unemployed persons from the US BLS JOLTS, and is calculated on an annual basis considering its time-varying. I obtain

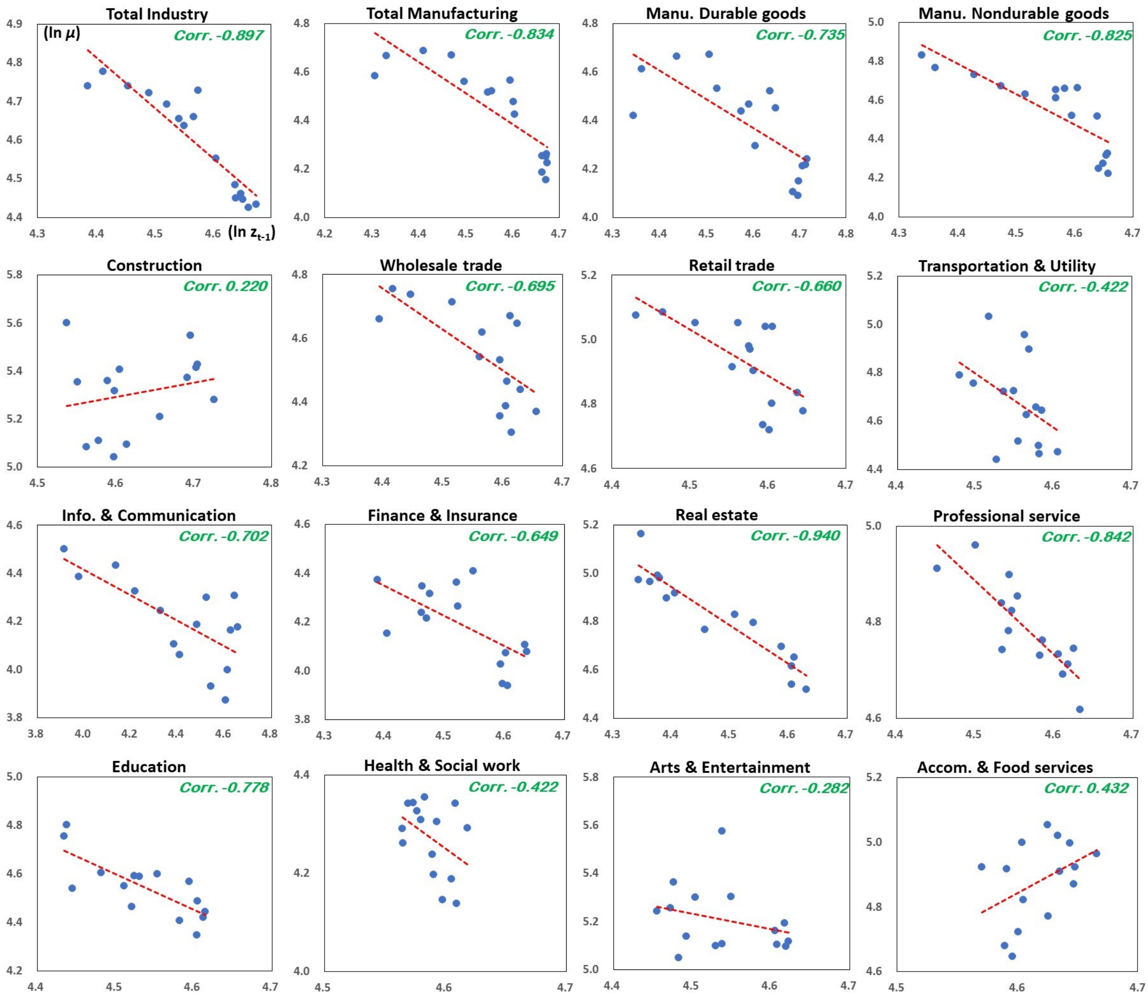

Figure 3.3: Correlation between productivity and matching efficiency by sector, US

Source: Author's own, from BLS JOLTS, EU KLEMS

Notes: X-axis is the logged productivity (1-year lagged, $\ln z_{j,t-1}$) and Y-axis is the logged implicit matching efficiency ($\ln \mu_{jt}$). Implicit matching efficiency is derived from $\mu_{jt} = h_{jt}/(u_{jt}^{\eta} v_{jt}^{1-\eta})$ using equation (3.2.1), where I use $\eta = 0.25$ as in the calibration in section 3.4. The sample covers the period from 2001 to 2015.

the data of sector-specific average labour productivity from EU KLEMS. As in the figure, matching efficiency is significantly negatively correlated with sector-specific labour productivity in the majority of industries since 2001, lending weight to the view of Petrongolo and Pissarides (2001) and Williamson (2013). For instance, in total industry and manufacturing, the correlations between matching efficiency (μ_{jt}) and lagged productivity (z_{jt-1}) are -0.897 and -0.834, respectively. Strong negative correlations are also shown in other industries such as wholesale trade, ICT industry, finance & insurance, and education.

To look in depth at the link between sectoral labour productivity and matching efficiency, I estimate panel data regressions as follows:

$$\mathrm{d}\ln\mu_{j,t} = \left(\sum_{l=1}\vartheta_l \cdot \mathrm{d}\ln\mu_{j,t-l}\right) + \zeta_0 \cdot \mathrm{d}\ln LP_{j,t} + \zeta_1 \cdot \mathrm{d}\ln LP_{j,t-1} + \nu_j + \epsilon_{j,t} \quad (3.2.5)$$

$$\epsilon_{j,t} \sim iid(0, \sigma_\epsilon^2)$$

where μ_{jt} is the time-varying matching efficiency,[8] LP_{jt} is the sector j's labour productivity at time t, ν_j is the sector-specific effect, and ϵ_{jt} is the error. The term within parenthesis is used for dynamic panel models. This panel data consists of 14 cross-sectional industries and 15-year time series between 2001 and 2015. All variables are transformed to a rate of change by taking log difference for the panel data stationarity.[9]

Table 3.2 shows the estimates of cross-industry panel data models for the relationship between sector-specific productivity and matching efficiency. The second column is the result estimated by the generalised least squares (GLS) taking account of LR test for sector-level heteroskedastic error structure and Wooldridge test for au-

[8] While we show the average contribution of the matching efficiency in the second stylised fact, here I set up the time-varying matching efficiency in order to see the relationship between productivity and matching efficiency over time and to examine their causality.

[9] According to a panel data unit root test (Im–Pesaran–Shin test), the level data of productivity and matching efficiency have unit roots. With the log-difference variables, the null hypothesis of a unit root is rejected at the 1% significance level.

tocorrelation in the panel data. Additionally, I run dynamic panel data regressions to reduce the endogeneity problem as well as considering the influence of the past matching efficiency on the current one. The last two columns are Arellano-Bond (system GMM) dynamic panel data estimations using different lags of the dependent variable as regressors.[10] All the estimations show that explanatory variables are statistically significant and the sector-specific productivity is inversely correlated with the present and future sectoral matching efficiency.[11]

Table 3.2: Estimations using panel data

dependent variable: $\text{dln}\,\mu_t$		GLS[a]	Dynamic Panel (system GMM)[b]	
$\text{dln}\,\mu_{t-1}$		-	-0.047 (0.074)	-0.053 (0.057)
$\text{dln}\,\mu_{t-2}$		-	-	-0.230 (0.058)***
$\text{dln}\,LP_t$		-0.504 (0.187)***	-1.684 (0.562)***	-1.404 (0.545)***
$\text{dln}\,LP_{t-1}$		-0.461 (0.179)***	-1.335 (0.362)***	-1.077 (0.342)***
Wald χ*-square*		16.30***	19.13***	45.94***
autocorr. test[c]	$AR(1)$	-	-2.20**	-2.51**
	$AR(2)$	-	-2.19**	-0.31
Hansen test[d]		-	11.21	7.74
No. observations		198	170	156

Source: Author's own, from BLS JOLTS, EU KLEMS

Notes: [a]Heteroskedasticity and AR(1) within panels are allowed according to LR and Wooldridge tests. [b]Arellano–Bond dynamic panel data estimations. [c]Arellano–Bond test for serial correlation in $\Delta\epsilon_{j,t}$ (H_0 : No autocorrelation). The first difference of error is necessarily autocorrelated in $AR(1)$. [d]H_0 : Overidentifying restrictions are appropriate. [e]Values within parenthesis indicate cluster-robust standard errors. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

In summary, the facts which guide the modelling in this chapter are that there exists cross-industry variation in matching efficiency. This difference influences job matching differently for each sector. Notably, different technological progress between sectors exacerbates the matching efficiency gap.

[10]In this estimation, the first difference equation is usually used to eliminate sector-specific effects, and lagged dependent variables (GMM-type instruments) and first differences of the exogenous variables (standard instruments) are used as instruments.

[11]We might consider reverse causality ($\mu \to LP$), but there is little evidence for this, empirically and theoretically. According to the variance decomposition from a VAR model based on annual data of total industry, the components of implicit matching efficiency (V, U, H) altogether account for as little as 2% - 6% of the productivity variation over a 5-year period.

3.3 A Two-sector Search and Matching Model

We have seen previously that heterogeneous matching efficiency is an essential factor in labour flow across sectors. To analyse its role in the labour market, I use a two-sector search and matching framework embedded with a differential matching efficiency mechanism.

The basic model setting follows Pissarides (1994), Acemoglu (2001), and Krause and Lubik (2006, 2010). The economic environment consists of the high-wage sector (sector 2) and the low-wage sector (sector 1), and the final goods are produced as an aggregate of these two sectors' goods. This economy is populated by a representative household. The household consists of a continuum of working-age members normalised at the closed interval $[0, 1]$ who are employed in either sector, or are unemployed.

Figure 3.4 depicts the model timeline. The initial allocation of members across sectors is given at the beginning. Once firms in each sector post job vacancies, the unemployed persons search for jobs in either sector, and workers in the low-wage sector endeavour to switch to the high-wage sector with some degree of search intensity. In these attempts, job seekers are faced with differential matching efficiency depending on in which sector they apply for a job. When a job seeker gets a job offer from a firm, the wage is determined by bilateral bargaining. Then she works at the firm until being separated from the firm. If the job seeker finds a job in the low-wage sector, she works there as well as engaging in on-the-job (OTJ) search to move to the high-wage sector. Through this labour mobility process, new matches between workers and jobs are created, a fraction of jobs are dissolved, and hence labour is reallocated across sectors at the end of the period.

The primary difference between the approach of existing research and the two-sector model put forward in this chapter is the presence of differential matching efficiency between sectors. More importantly, the process of productivity-driven matching efficiency is embedded in the model based on the empirical facts and

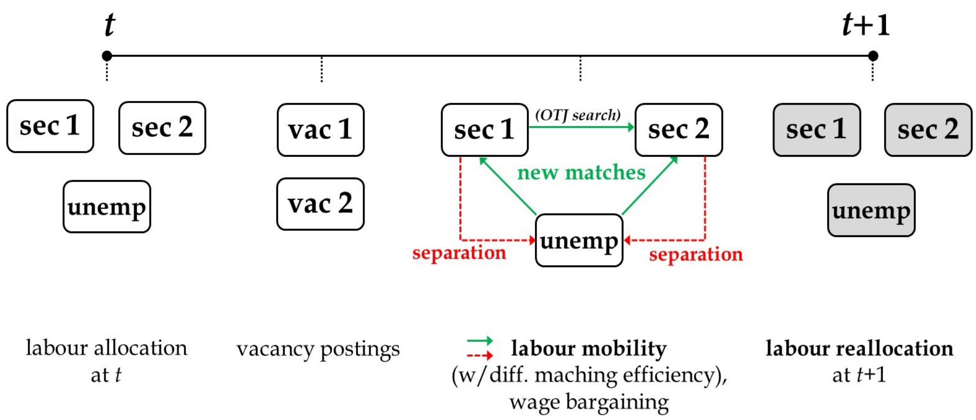

Figure 3.4: Model timeline

Notes: 'sec' represents sector, 'vac' for vacancies, and 'unemp' for unemployment.

operates as a crucial factor for labour allocation and wage distribution. Yet the explanation on the wage gap and labour misallocation is neglected by existing multi-sector search and matching models. Next, I argue that the choice of a decreasing returns to scale (DRS) technology for each sector's production is vital to track labour mobility between sectors as it shows the inverse relationship between a sector's wage and its employment share consistent with actual data. A constant returns to scale (CRS) technology as in Acemoglu (2001) and Krause and Lubik (2006, 2010) cannot explain this phenomenon. Hence, the framework proposed in this chapter can describe current labour market dynamics and show how different matching efficiency triggers labour market distortions.

3.3.1 Model

3.3.1.1 Production Technology

In the spirit of Acemoglu (2001), the technology for producing the unique final output is assumed to have a CES-type aggregator between intermediate goods, meaning that the final goods are produced by combining goods from two sectors.

$$y_t = A_t \cdot F(y_{1t}, y_{2t}) = A_t \big[(1-\gamma) y_{1t}^{\frac{\sigma-1}{\sigma}} + \gamma y_{2t}^{\frac{\sigma-1}{\sigma}}\big]^{\frac{\sigma}{\sigma-1}} \tag{3.3.1}$$

where y_t is the output of the final goods at time t, y_{jt} is the output of sector $j \in \{1, 2\}$, and A_t is the aggregate TFP. γ is the share of sector 2's goods in the aggregation production which can be interpreted alternatively as technological distribution or the relative importance of sector 2's goods. $\sigma \in (0, \infty)$ is the elasticity of substitution between two intermediate goods. When $\sigma \to \infty$, two intermediate goods are perfect substitutes, when $\sigma \to 0$, two goods are perfect complements (or Leontief production function), and when $\sigma \to 1$, it will be the Cobb-Douglas production function.

The final good firm's profit maximisation yields the set of demands for the two intermediate goods as[12]

$$p_{1t} = (1-\gamma) A_t^{\frac{\sigma-1}{\sigma}} \left(\frac{y_{1t}}{y_t}\right)^{-\frac{1}{\sigma}} \tag{3.3.2}$$

$$p_{2t} = \gamma A_t^{\frac{\sigma-1}{\sigma}} \left(\frac{y_{2t}}{y_t}\right)^{-\frac{1}{\sigma}} \tag{3.3.3}$$

where p_{jt} is the price of sector j's goods and p_t is the price of the final goods which is assumed to be the numeraire as follows:[13]

$$1 \equiv p_t = A_t^{-1} \big[(1-\gamma)^\sigma p_{1t}^{1-\sigma} + \gamma^\sigma p_{2t}^{1-\sigma}\big]^{\frac{1}{1-\sigma}} \tag{3.3.4}$$

The intermediate goods, y_{jt}, are also produced competitively within the sector using its labour input n_{jt}. Each sector has a DRS technology in labour,[14] and its output is adjusted by sector-specific productivity z_{jt}.

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[12] See the Appendix 3.A.3 for the derivation.

[13] See the Appendix 3.A.3 for the derivation.

[14] The DRS technology connects the wage level to the labour input via the marginal product of labour $\alpha y_{jt}/n_{jt}$. Whereas in the standard literature on search and matching models, it is assumed that firms have CRS technology, $y_{jt} = z_{jt} n_{jt}$. Its marginal product of labour is z_{jt} so that this technology cannot show the relationship between labour input and wage.

$$y_{jt} = z_{jt} n_{jt}^{\alpha} \ , \quad j \in \{1, 2\} \tag{3.3.5}$$

where α is the labour income share.

3.3.1.2 Matching Technology

The matching function relates job seekers and vacancies to new hires. Here each sector's job matching function is assumed to be a Cobb-Douglas form, so it is a CRS, increasing and concave function of both arguments as is standard in the literature.

$$h_{1t} = \mu(z_{1t}) \cdot M(u_{1t}, v_{1t}) = \mu(z_{1t}) \cdot u_{1t}^{\eta} v_{1t}^{1-\eta} \tag{3.3.6}$$

$$h_{2t} = \mu(z_{2t}) \cdot M(u_{2t} + s_t n_{1t}, v_{2t}) = \mu(z_{2t}) \cdot (u_{2t} + s_t n_{1t})^{\eta} v_{2t}^{1-\eta} \tag{3.3.7}$$

where s_t is the search intensity of workers in sector 1, and sector 2's matching function involves $s_t n_{1t}$ which is the measure of efficiency units of job seekers from sector 1 as in Pissarides (2000, Ch 4).[15] In the job market in sector 2, unemployed and employed job seekers coexist. I assume that the unemployed's search intensity is unity,[16] and the match elasticity η is the same for all sectors which is a common assumption in the literature.[17] Lastly, μ_{jt} is a positive time-varying matching efficiency which is a function of sector-specific productivity, or $\mu_{jt} = \mu(z_{jt})$, consistent with the third empirical fact in the previous section. The matching function satisfies the conditions of $h_{1t} \leq \min\{u_{1t}, v_{1t}\}$ and $h_{2t} \leq \min\{u_{2t} + s_t n_{1t}, v_{2t}\}$. Without labour market frictions, the number of matches is equal to the minimum of the number of

[15]Pissarides (2000) coins a new term 'efficiency unit of search' to express a worker's input or search intensity for matching.

[16]Krause and Lubik (2006, 2010) clarify that endogenous search intensity of the unemployed does not have an influence on the propagation mechanism of a two-sector search and matching model.

[17]The assumption of the constant matching elasticity across sectors is common in the disaggregated matching function literature (Barnichon and Figura, 2015). Şahin et al. (2014), by estimating match elasticity by industry, show that most of those differences between industries are statistically insignificant.

job seekers and that of vacancies.

Each sector's labour market tightness θ_{jt}, vacancy filling rate of firms $q(\theta_{jt})$, and job finding rate of job seekers $f(\theta_{jt})$ are defined as

$$\theta_{1t} \equiv \frac{v_{1t}}{u_{1t}} \tag{3.3.8}$$

$$\theta_{2t} \equiv \frac{v_{2t}}{u_{2t} + s_t n_{1t}} \tag{3.3.9}$$

$$q(\theta_{1t}) \equiv \frac{\mu(z_{1t}) \cdot M(u_{1t}, v_{1t})}{v_{1t}} = \mu(z_{1t}) \cdot \theta_{1t}^{-\eta} \tag{3.3.10}$$

$$q(\theta_{2t}) \equiv \frac{\mu(z_{2t}) \cdot M(u_{2t} + s_t n_{1t}, v_{2t})}{v_2} = \mu(z_{2t}) \cdot \theta_{2t}^{-\eta} \tag{3.3.11}$$

$$f(\theta_{1t}) \equiv \frac{\mu(z_{1t}) \cdot M(u_{1t}, v_{1t})}{u_{1t}} = \mu(z_{1t}) \cdot \theta_{1t}^{1-\eta} \tag{3.3.12}$$

$$f(\theta_{2t}) \equiv \frac{\mu(z_{2t}) \cdot M(u_{2t} + s_t n_{1t}, v_{2t})}{u_{2t} + s_t n_{1t}} = \mu(z_{2t}) \cdot \theta_{2t}^{1-\eta} \tag{3.3.13}$$

Here, the inverse of each probability, or $q(\theta_{jt})^{-1}$ and $f(\theta_{jt})^{-1}$, are the expected duration of vacancies and job seeking, respectively. Hence, the average time that it takes for a firm to find a worker, $q(\theta_{jt})^{-1}$, depends on the sector's matching efficiency $\mu(z_{jt})$, market tightness θ_{jt}, and what job seekers do before they meet firms s_t.

3.3.1.3 Firms' Value Functions

Each sector's firm maximises its expected profit by deciding the number of vacancies and labour inputs subject to the evolution of employment.[18] This maximisation problem can be cast in the 'asset value' term which is the present value of expected profit for a firm having a filled job and choosing to post a vacancy.

When a vacancy job matches with a worker, the firm's value contains the value

[18] See the Appendix 3.A.3 for directly solving the firm's profit maximisation problem.

of preserving the employment relationship and the value when the existing match dissolves. The value of a filled job (J_{jt}) can be written as

$$J_{1t} = \alpha p_{1t} z_{1t} n_{1t}^{\alpha-1} - w_{1t} \qquad (3.3.14)$$
$$+ \beta \mathbb{E}_t \left[(1-\rho)(1 - s_t f(\theta_{2t})) J_{1t+1} + (1-\rho) s_t f(\theta_{2t}) V_{1t+1} + \rho V_{1t+1} \right]$$
$$J_{2t} = \alpha p_{2t} z_{2t} n_{2t}^{\alpha-1} - w_{2t} + \beta \mathbb{E}_t \left[(1-\rho) J_{2t+1} + \rho V_{2t+1} \right] \qquad (3.3.15)$$

where β is the discount factor,[19] ρ is the separation rate, and $s_t f(\theta_{2t})$ is the probability of an employed worker in the low-wage sector being matched with a job in the high-wage sector.[20] w_{jt} is the real wage and V_{jt} is the value of a vacant position in sector j. The first term on the right-hand side, $\alpha p_{jt} z_{jt} n_{jt}^{\alpha-1}$, is the value of the marginal product of labour for each sector. Hence, in the case of a vacancy being filled, the firm earns a profit of $(\alpha p_{jt} z_{jt} n_{jt}^{\alpha-1} - w_{jt})$ and holds a continuation value. In sector 1, there are three states in the continuation period: the worker stays within the sector or she is separated from the job due to either a sector switch or a breakup. In sector 2, in the next period, the employment relationship can continue or otherwise. Thus, the firm's value is the expected present profit of filling its vacancy with a worker.

Similarly, the value from a vacant position is

$$V_{jt} = -\kappa_{jt} + \beta \mathbb{E}_t \left[q(\theta_{jt}) J_{jt+1} + (1 - q(\theta_{jt})) V_{jt+1} \right] \qquad (3.3.16)$$

where κ_{jt} is the vacancy cost in sector j. The right-hand side describes that posting a vacancy incurs costs (κ_{jt}) until the vacancy is filled.

Here, firms' free entry to the labour market is assumed. This ensures that the value of a new entry is zero; that is $V_{jt} = 0$. By plugging this into (3.3.16), we

[19]Since firms are owned by the household, they use the same discount factor to the household.

[20]The portion of workers in sector 1 who finds a job in sector 2 is $s_t n_{1t} f(\theta_{2t})$ and thus the part of $s_t f(\theta_{2t})$ is the probability of the employed workers in sector 1 finding a job in sector 2.

obtain each sector's *job creation condition* as

$$\beta \mathbb{E}_t J_{jt+1} = \frac{\kappa_{jt}}{q(\theta_{jt})} \tag{3.3.17}$$

The intuition of this condition is straightforward. Firms create jobs until the duration-weighted marginal cost from creating an additional vacancy (right-hand side) equals the expected discounted value of a filled job (left-hand side). By substituting (3.3.14) or (3.3.15) into this equation, it can be written as[21]

$$\frac{\kappa_{1t}}{q(\theta_{1t})} = \beta \mathbb{E}_t \left[\alpha p_{1t+1} z_{1t+1} n_{1t+1}^{\alpha-1} - w_{1t+1} + (1-\rho)(1 - s_{t+1} f(\theta_{2t+1})) \frac{\kappa_{1t+1}}{q(\theta_{1t+1})} \right] \tag{3.3.18}$$

$$\frac{\kappa_{2t}}{q(\theta_{2t})} = \beta \mathbb{E}_t \left[\alpha p_{2t+1} z_{2t+1} n_{2t+1}^{\alpha-1} - w_{2t+1} + (1-\rho) \frac{\kappa_{2t+1}}{q(\theta_{2t+1})} \right] \tag{3.3.19}$$

Likewise, the marginal vacancy cost weighted by the vacancy duration is equivalent to the right-hand side which can be interpreted as the expected discounted marginal benefit of having a filled job. The benefit is comprised of a period marginal profit, which is the part of the marginal product value of the employee over her wage, and a continuation value.

3.3.1.4 Workers' Value Functions

Agents consume all their income in every period and are risk neutral which means that utility is a simple linear function of consumption, $u(c_{it}) = c_{it}$, as is standard in the DMP-type search and matching model. Worker in the low-wage sector (sector 1) make a decision of how much effort to put into searching for a job in the high-wage sector (sector 2). Thus the lifetime value of the worker in sector 1 consists of two parts: (i) the surplus remaining after search costs are deducted from her wage, (ii) the continuation value which incorporates the values in three states: the value of a

[21] See the Appendix 3.A.3 for the derivation.

continued employment contract, the value of the worker moving to sector 2, and the value of when she is separated from the job. For a worker in sector 2, the lifetime value is her current wage plus the value in the continuation period in which there are two states: extension and discontinuance of the employment contract. Hence the values of an employed person in each sector, E_{jt}, can be expressed as

$$\begin{aligned} E_{1t} = \max_{s_t} \quad & w_{1t} - \phi(s_t) \\ & + \beta \mathbb{E}_t \left[(1-\rho)(1 - s_t f(\theta_{2t})) E_{1t+1} + (1-\rho) s_t f(\theta_{2t}) E_{2t+1} + \rho U_{1t+1} \right] \\ = \max_{s_t} \quad & w_{1t} - \phi(s_t) + \beta \mathbb{E}_t \left[(1-\rho) E_{1t+1} + (1-\rho) s_t f(\theta_{2t}) (E_{2t+1} - E_{1t+1}) + \rho U_{1t+1} \right] \end{aligned} \tag{3.3.20}$$

$$E_{2t} = w_{2t} + \beta \mathbb{E}_t \left[(1-\rho) E_{2t+1} + \rho U_{2t+1} \right] \tag{3.3.21}$$

In the search and matching literature, search costs represent a broad array of costs incurred to the household such as the physical cost of job search or training borne by the household. The search cost function is assumed to be $\phi(s_t) \equiv \tau s_t^{\iota}$,[22] where $\tau > 0$ is the scale parameter and $\iota > 0$ is the degree of convexity.

Similarly, the value of an unemployed individual (U_{jt}) who searches for each type of jobs is comprised of the net unemployed benefit and her continuation value, which is expressed by

$$U_{jt} = b - \tau + \beta \mathbb{E}_t \left[f(\theta_{jt}) E_{jt+1} + (1 - f(\theta_{jt})) U_{jt+1} \right] \tag{3.3.22}$$

where b is the unemployment benefit. The search intensity of an unemployed person is normalised to one ($s_t^u = 1$) as mentioned before.

Unemployed agents can apply for a job in either sector as in a standard two-sector search and matching model (Acemoglu, 2001; Krause and Lubik, 2006). Intuitively,

[22] The canonical search cost function is convex, or $\iota > 1$, considering the shoe leather cost which mounts at an increasing rate in search intensity. However, according to Gautier, Moraga-González, and Wolthoff (2016), different search cost curves coexist suggesting that if an individual spends a lot of time at an early stage of job search and gradually tapers search intensity off over time, the search cost function may be concave, or $\iota < 1$.

since the unemployed from sector 1 can apply for a job in sector 2, they can move to the pool of the unemployed in sector 2. Still, workers face different matching efficiency depending on in which sector they try to find a job. Since they can apply for any sector, the value of unemployment is the same across sectors, or $U_{1t} = U_{2t}$. Using this condition, the *unemployed free mobility condition* can be derived as

$$f(\theta_{1t})(E_{1t+1} - U_{1t+1}) = f(\theta_{2t})(E_{2t+1} - U_{2t+1}) \tag{3.3.23}$$

3.3.1.5 Bargaining

The wage is determined via Nash bargaining by maximising the weighted average of the net surpluses of firms and workers.

$$w_{jt} = \arg\max \ (E_{jt} - U_{jt})^{\psi}(J_{jt} - V_{jt})^{1-\psi} \tag{3.3.24}$$

where ψ is the worker's bargaining power.[23] This yields

$$\begin{aligned} (1-\psi)(E_{jt} - U_{jt}) &= \psi(J_{jt} - V_{jt}) \\ \Rightarrow \quad E_{jt} - U_{jt} &= \Psi J_{jt} \end{aligned} \tag{3.3.25}$$

where $\Psi \equiv \psi/(1-\psi)$. By using this condition with the job creation condition (3.3.17), the unemployed free mobility condition (3.3.23) can be rewritten as

$$\kappa_{1t}\theta_{1t} = \kappa_{2t}\theta_{2t} \tag{3.3.26}$$

[23] There is no convincing evidence for different bargaining power between sectors. Many studies on a multi-sector search and matching model, for example, Krause and Lubik (2010) and Pilossoph (2014) set the same bargaining power across sectors. Additionally, the union affiliation rate does not seem to be significantly different in two sectors: The US union affiliation rate is 5.9% in the high-wage sector and 6.9% in the low-wage sector in the year 2018 (source: US BLS).

3.3.1.6 Equilibrium Search Intensity

The investment on job search is determined by the marginal condition, derived from value maximisation of employed job seekers. From the value function of the worker in sector 1, (3.3.20), its first derivative with respect to search intensity is computed as

$$\phi'(s_t) = \tau\iota s_t^{\iota-1} = \beta\mathbb{E}_t(1-\rho)f(\theta_{2t})(E_{2t+1} - E_{1t+1}) \tag{3.3.27}$$

With the job creation condition (3.3.17) and the bargaining condition (3.3.25), we get the *equilibrium search intensity.*

$$\begin{aligned} \tau\iota s_t^{\iota-1} &= \beta\Psi\mathbb{E}_t(1-\rho)f(\theta_{2t})(J_{2t+1} - J_{1t+1}) \\ &= \Psi(1-\rho)f(\theta_{2t})\left[\frac{\kappa_{2t}}{q(\theta_{2t})} - \frac{\kappa_{1t}}{q(\theta_{1t})}\right] \end{aligned} \tag{3.3.28}$$

This demonstrates that search intensity is an increasing function of job finding rate because if the job finding rate rises, the return to search investment increases. Search intensity also increases in the difference in the marginal cost between sectors since a higher marginal cost is linked to a higher wage.

3.3.1.7 Government

The government provides unemployment benefit at a rate b per person, funded by a lump-sum tax T_t levied on households. It is assumed that the government follows a balanced budget policy as

$$T_t = b(u_{1t} + u_{2t}) = bu_t \tag{3.3.29}$$

where u_t is the total number of unemployed persons in the economy.

3.3.1.8 Household

As previously stated, the representative household consists of a continuum of working-age members who are employed in either sector, or are unemployed. The household's role is to pool members' incomes and distribute consumption goods equally to all members. There are four income sources: wage in sector 1, wage in sector 2, unemployment benefit, and profit from firms.

The household's period-by-period budget constraint is

$$c_t + \tau s_t^{\iota} n_{1t} + \tau u_t = w_{1t} n_{1t} + w_{2t} n_{2t} + b u_t + \Pi_t - T_t \tag{3.3.30}$$

where $c_t \equiv \int_0^1 c_{it}\, di$ is the aggregate consumption of goods which is the sum of individual member i's consumption. τs_t^{ι} and τ indicate the search cost of workers in sector 1 and that of the unemployed, respectively. The aggregate firm profit is denoted by $\Pi_t \equiv y_t - \sum_j (w_{jt} n_{jt} + \kappa_{jt} v_{jt})$.

3.3.1.9 Equilibrium

In equilibrium, the final goods market clears.

$$c_t + \tau s_t^{\iota} n_{1t} + \tau u_t = y_t - \kappa_{1t} v_{1t} - \kappa_{2t} v_{2t} \tag{3.3.31}$$

A *dynamic equilibrium* given the sequence of exogenous variables $\{A_t, z_{jt}\}_{t=0}^{\infty}$, $j \in \{1, 2\}$ and the initial labour allocation n_{j0}, is a sequence of quantities and prices $\{c_t, n_{jt+1}, u_{jt}, v_{jt}, s_t, T_t, p_{jt}, w_{jt}\}_{t=0}^{\infty}$ satisfying (i) each agent's optimisation condition, (ii) the bargaining condition, and (iii) the goods market clearing condition.

The following system of equations describes this equilibrium:

(demands for goods)

$$p_{1t} = (1-\gamma)A_t^{\frac{\sigma-1}{\sigma}}\left(\frac{y_{1t}}{y_t}\right)^{-\frac{1}{\sigma}} \tag{3.3.32}$$

$$p_{2t} = \gamma A_t^{\frac{\sigma-1}{\sigma}}\left(\frac{y_{2t}}{y_t}\right)^{-\frac{1}{\sigma}} \tag{3.3.33}$$

(job creation conditions)

$$\frac{\kappa_{1t}}{q(\theta_{1t})} = \beta\mathbb{E}_t\left[\alpha p_{1t+1}\frac{y_{1t+1}}{n_{1t+1}} - w_{1t+1} + (1-\rho)(1-s_{t+1}f(\theta_{2t+1}))\frac{\kappa_{1t+1}}{q(\theta_{1t+1})}\right] \tag{3.3.34}$$

$$\frac{\kappa_{2t}}{q(\theta_{2t})} = \beta\mathbb{E}_t\left[\alpha p_{2t+1}\frac{y_{2t+1}}{n_{2t+1}} - w_{2t+1} + (1-\rho)\frac{\kappa_{2t+1}}{q(\theta_{2t+1})}\right] \tag{3.3.35}$$

(equilibrium search intensity)

$$\tau\iota s_t^{\iota-1} = \Psi(1-\rho)f(\theta_{2t})\left[\frac{\kappa_{2t}}{q(\theta_{2t})} - \frac{\kappa_{1t}}{q(\theta_{1t})}\right] \tag{3.3.36}$$

(wages determination)[24]

$$w_{1t} = \psi\left(\alpha p_{1t}\frac{y_{1t}}{n_{1t}} + (1-(1-\rho)s_t)\kappa_{2t}\theta_{2t}\right) + (1-\psi)(\tau s_t^{\iota} + b - \tau) \tag{3.3.37}$$

$$w_{2t} = \psi\left(\alpha p_{2t}\frac{y_{2t}}{n_{2t}} + \kappa_{2t}\theta_{2t}\right) + (1-\psi)(b-\tau) \tag{3.3.38}$$

(evolution of employment)

$$n_{1t+1} = (1-\rho)(1-s_t f(\theta_{2t}))n_{1t} + q(\theta_{1t})v_{1t} \tag{3.3.39}$$

$$n_{2t+1} = (1-\rho)n_{2t} + q(\theta_{2t})v_{2t} \tag{3.3.40}$$

[24]See the Appendix 3.A.3 for the derivation.

(unemployment)

$$u_t = u_{1t} + u_{2t} = 1 - n_{1t} - n_{2t} \tag{3.3.41}$$

(free unemployed mobility)

$$\kappa_{1t}\theta_{1t} = \kappa_{2t}\theta_{2t} \tag{3.3.42}$$

(fiscal balance)

$$T_t = bu_t \tag{3.3.43}$$

(resource constraint)

$$c_t + \tau s_t^{\iota} n_{1t} + \tau u_t = y_t - \kappa_{1t}v_{1t} - \kappa_{2t}v_{2t} \tag{3.3.44}$$

where the output technologies $y_t = A_t\big[(1-\gamma)y_{1t}^{\frac{\sigma-1}{\sigma}} + \gamma y_{2t}^{\frac{\sigma-1}{\sigma}}\big]^{\frac{\sigma}{\sigma-1}}$, $y_{jt} = z_{jt}n_{jt}^{\alpha}$ are given, and market tightness $\theta_{1t} = v_{1t}/u_{1t}, \theta_{2t} = v_{2t}/(u_{2t} + sn_{1t})$ and vacancy filling rate $q(\theta_{jt}) = \mu(z_{jt}) \cdot \theta_{jt}^{-\eta}$ are defined as before.

3.3.2 Steady State and Comparative Statics

An important question is how a differential change in matching efficiency affects the labour market variables such as market tightness, sectoral wages, and labour allocation. Accordingly, before analysing the model quantitatively, we study the core mechanism generating labour market distortions in the model analytically. I first derive the steady state sectoral wage gap and labour allocation and then discuss the implications of differential matching efficiency.

3.3.2.1 Steady State Wage Gap

At steady state, equilibrium search intensity can be derived from (3.3.36) as

$$s^* = \left[\Psi \frac{1-\rho}{\tau\iota}\theta_2^* \left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)\right]^{\frac{1}{\iota-1}} = \bar{s} \tag{3.3.45}$$

where search intensity is assumed to be fixed as $\bar{s}$ at steady state. Start by solving for market tightness from this equation and the free unemployed mobility condition (3.3.42).

$$\theta_2^* = \frac{\tau\iota\bar{s}^{\iota-1}}{\Psi(1-\rho)\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)} \tag{3.3.46}$$

$$\theta_1^* = \frac{\kappa_2}{\kappa_1}\theta_2^* \tag{3.3.47}$$

These equations show the positive relationship between the relative matching efficiency and the market tightness. When the relative matching efficiency of sector 2 decreases, firms in the sector post fewer vacancies, which leads to less market tightness. This process, in turn, decreases sector 1's market tightness as more unemployed individuals come and apply to this sector.

Substituting out the term of firm's revenue per worker from the job creation condition (3.3.35) and the wage determination (3.3.38), sector 2's wage is solved.

$$w_2^* = \Psi\left[\left(\frac{1}{\beta} - (1-\rho)\right)\frac{\kappa_2}{\mu(z_2)}\theta_2^{*\eta} + \kappa_2\theta_2^*\right] + (b-\tau) \tag{3.3.48}$$

Likewise, sector 1's wage is derived from (3.3.34), (3.3.37), and (3.3.45).

$$w_1^* = \Psi\left[\left(\frac{1}{\beta} - (1-\rho)(1-\mu(z_2)\cdot\bar{s}\theta_2^{*1-\eta})\right)\frac{\kappa_1}{\mu(z_1)}\theta_1^{*\eta} + (1-(1-\rho)\bar{s})\kappa_2\theta_2^*\right] + b - \tau(1-\bar{s}) \tag{3.3.49}$$

Hence, the difference in steady state wage between two sectors is[25]

$$\begin{aligned} w_2^* - w_1^* &= \Psi\left[\left(\frac{1}{\beta} - (1-\rho) - \bar{s}(1-\rho)f(\theta_2^*)\right)\left(\frac{\kappa_2}{q(\theta_2^*)} - \frac{\kappa_1}{q(\theta_1^*)}\right)\right] - \bar{s}\tau \\ &= \Psi\left[\left(\frac{1}{\beta} - (1-\rho)\right)\left(\frac{\tau\iota\bar{s}^{\iota-1}}{\Psi(1-\rho)}\right)^{\eta}\frac{1}{\mu(z_2)}\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)^{1-\eta}\right] + \tau\bar{s}^{\iota}(\iota - \bar{s}^{1-\iota}) \end{aligned} \tag{3.3.50}$$

From the first line of the equation, we know that the wage gap is related to the difference in vacancy costs weighted by each sector's vacancy duration. Particularly, if both marginal vacancy costs are equal to each other, or $\kappa_2/q(\theta_2^*) = \kappa_1/q(\theta_1^*)$, with no search cost, the equilibrium becomes the Walrasian law of one wage ($w_1^* = w_2^*$). Intuitively, in the economy without frictions where there exist neither vacancy duration nor job search, all wages are equalised across sectors, even when the productivity gap remains. With frictions, however, the difference in marginal vacancy costs, which can be amplified by differential matching efficiency, prevents wage convergence between sectors. The last line of the equation elucidates the effect of differential matching efficiency on the wage gap as follows.

Proposition 1. *In the steady state, a rise in the relative productivity of sector 2 increases its relative wage via a fall in the relative matching efficiency as*

$$\underbrace{\frac{\partial(w_2^* - w_1^*)}{\partial\left(\mu(z_2)/\mu(z_1)\right)}}_{(-)} \cdot \underbrace{\frac{\partial\left(\mu(z_2)/\mu(z_1)\right)}{\partial\left(z_2/z_1\right)}}_{(-)} > 0$$

Importantly, this matching efficiency gap comes from the productivity gap z_2/z_1. Thus the productivity gap cannot induce the wage gap by itself but can do so only through the friction process, namely productivity-driven matching efficiency.

[25] Here, the wage gap is derived as the difference between sectoral wages to make it tractable. For the sake of argument, I will use the definition of the wage gap as the ratio of two wages, $\omega = w_2/w_1$, later in the numerical analysis. See the Appendix 3.A.3 for the derivation.

3.3.2.2 Steady State Sectoral Labour

The steady state total unemployment can be derived by equating the flow out of unemployment, $(f(\theta_1) + f(\theta_2))u$, with the flow into unemployment, $\rho(1-u)$.

$$u^* = \frac{\rho}{f(\theta_1^*) + f(\theta_2^*) + \rho} = \bar{u} \tag{3.3.51}$$

where we assume that the total unemployment is given as $\bar{u}$ at steady state.

The steady state equations of two sectors' employment evolution (3.3.39), (3.3.40), and unemployment (3.3.41) can be written as

$$(\rho + (1-\rho)\bar{s}f(\theta_2^*))n_1 = f(\theta_1^*)u_1 \tag{3.3.52}$$

$$\rho n_2 = f(\theta_2^*)(u_2 + \bar{s}n_1) \tag{3.3.53}$$

$$\bar{u} = u_1 + u_2 = 1 - n_1 - n_2 \tag{3.3.54}$$

By substituting (3.3.52) and (3.3.54) into (3.3.53), we have sector 2's steady state employment share as[26]

$$n_2^* = \frac{f(\theta_2^*) - \frac{f(\theta_2^*)}{f(\theta_1^*)}X^* + \frac{f(\theta_2^*)}{f(\theta_1^*)}\bar{u}X^*}{\rho + f(\theta_2^*) - \frac{f(\theta_2^*)}{f(\theta_1^*)}X^*} \tag{3.3.55}$$

where $X^* \equiv \rho + \bar{s}(1-\rho)f(\theta_2^*) + (1-\bar{s})f(\theta_1^*)$.

Likewise, the sector 1's steady state employment share is

$$n_1^* = 1 - \bar{u} - n_2^* = \frac{\rho - \rho\bar{u} - \bar{u}f(\theta_2^*)}{\rho + f(\theta_2^*) - \frac{f(\theta_2^*)}{f(\theta_1^*)}X^*} \tag{3.3.56}$$

Hence, the steady state relative labour allocation of sector 2 in terms of sector 1 is derived by dividing n_2^* by n_1^* as[27]

[26] See the Appendix 3.A.3 for the derivation.

[27] See the Appendix 3.A.3 for the derivation.

$$
\begin{aligned}
\digamma^* \equiv \frac{n_2^*}{n_1^*} &= \frac{f(\theta_2^*) - \frac{f(\theta_2^*)}{f(\theta_1^*)}X^* + \frac{f(\theta_2^*)}{f(\theta_1^*)}\bar{u}X^*}{\rho - \rho\bar{u} - \bar{u}f(\theta_2^*)} \qquad (3.3.57) \\
&= \frac{1-(1-\bar{u})\left[\begin{array}{c} \frac{\rho}{\mu(z_1)}\left(\frac{\kappa_1}{\kappa_2}\right)^{1-\eta}\left(\frac{\Psi(1-\rho)}{\tau\iota\bar{s}^{\iota-1}}\right)^{1-\eta}\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)^{1-\eta} \\ +\bar{s}(1-\rho)\frac{\mu(z_2)}{\mu(z_1)}\left(\frac{\kappa_1}{\kappa_2}\right)^{1-\eta} + (1-\bar{s}) \end{array}\right]}{\frac{\rho(1-\bar{u})}{\mu(z_2)}\left(\frac{\Psi(1-\rho)}{\tau\iota\bar{s}^{\iota-1}}\right)^{1-\eta}\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)^{1-\eta} - \bar{u}}
\end{aligned}
$$

The effect of the relative matching efficiency on the sectoral labour allocation rests upon the levels of the vacancy costs, the separation rate and other parameters. In a simple case, if the separation rate is assumed to be close to zero, $\rho \simeq 0$, then the steady state relative labour allocation[28] can be simplified as

$$
\digamma^* \simeq \frac{(1-\bar{u})\left[\bar{s}\frac{\mu(z_2)}{\mu(z_1)}\left(\frac{\kappa_1}{\kappa_2}\right)^{1-\eta} + (1-\bar{s})\right] - 1}{\bar{u}} \qquad (3.3.58)
$$

It is straightforward to show the following proposition.

Proposition 2. *In the steady state, a rise in the relative productivity of sector 2 decreases its relative labour allocation via a fall in the relative matching efficiency. In other words,*

$$
\underbrace{\frac{\partial(n_2^*/n_1^*)}{\partial\left(\mu(z_2)/\mu(z_1)\right)}}_{(+)} \cdot \underbrace{\frac{\partial\left(\mu(z_2)/\mu(z_1)\right)}{\partial\left(z_2/z_1\right)}}_{(-)} \;<\; 0
$$

As the productivity-driven matching efficiency of the high-wage sector declines, its relative labour allocation will shrink.

As summarised in Table 3.3, when the relative matching efficiency of sector 2 $(\mu(z_2)/\mu(z_1))$ decreases due to the sector-specific technological progress (z_2/z_1), the wage gap (ω) consequently rises and at the same time the relative labour allocation

[28]If either y_{1t} or y_{2t} is zero in the aggregation production, there can be a corner solution. However, with the CES-type aggregator in this model, the possibility of a corner solution is ruled out since combining some of each good in the aggregation is strictly preferred to using only one good.

of sector 2 (F) ends up falling, which cannot be explained by standard neoclassical theory.[29]

Table 3.3: Source and effect of labour mobility friction

$$\frac{z_2}{z_1}\uparrow \xrightarrow{\text{(friction process)}} \frac{\mu(z_2)}{\mu(z_1)}\downarrow \xrightarrow{\text{(market distortion)}} \omega\uparrow \quad F\downarrow$$

3.4 Quantitative Analysis

3.4.1 Calibration

To solve the model quantitatively, we first need to calibrate the model by specifying parameter values and processes for exogenous variables. Calibrating the model can show how differential matching efficiency between sectors affects the sectoral wage gap and labour allocation numerically, and allows us to compare the baseline model with counter-factual models where no frictions exist. Furthermore, we can answer the question of how shocks to sector-specific productivity influence the labour market variables by simulating the calibrated model.

The model is calibrated based on the US economy from the year 2001 with quarterly frequency. The industries are classified according to the North American Industry Classification System (NAICS) at the 38 sub-industry level and the sub-industries are divided into two sectors in terms of their ranks in the wage level as Table 3.4.[30]

[29]The standard theory was discussed in section 1.2.1 "Neoclassical Theory of the Wage Gap and Labour Mobility: What It Can and Cannot Explain" in Chapter 1.

[30]Three industries of agriculture, forestry, fishing, and hunting; real estate and rental and leasing; government are excluded.

Table 3.4: Sector classification

sector 1 (low-wage)		sector 2 (high-wage)	
industries	wage[a]	industries	wage[a]
accommodation & food service	23.1	miscellaneous manufacturing	52.6
retail trade	30.9	electrical equipment & applications	54.9
other service (excl.government)	33.8	motor vehicles, trailers & parts	56.5
administrative & waste management	34.5	primary metals	57.6
apparel & leather & allied products	34.7	paper products	58.0
textile mills & textile product mills	37.0	machinery	58.7
wood products	37.4	wholesale trade	64.0
furniture & related products	37.8	other transportation equipment	73.9
educational services	38.3	professional & technical services	78.1
arts, entertainment & recreation	40.7	information	79.1
food & tobacco products	42.2	chemical products	79.6
printing & related activities	44.4	mining	83.9
plastics & rubber products	44.8	finance & insurance	84.7
health care & social assistance	45.6	utilities	85.5
transportation & warehousing	47.7	computer & electronic products	89.0
fabricated metal products	48.0	petroleum & coal products	91.5
nonmetallic mineral products	48.5	management of companies	98.9
construction	49.4	-	-

Source: BEA NIPA

Notes: [a]Average annual wages per full-time employee between 2000-2016, in terms of thousand dollars. [b] The cutoff between the two sectors is based on the average-linkage cluster analysis using the Euclidean distance of industrial wages. See the Appendix 2.A.3 for details.

3.4.1.1 Model Parameters

I set the discount factor, β, to the standard quarterly value of 0.99 from the literature. There are three technology parameters in production: the intermediate sector's output elasticity of labour, the technology distribution, and the elasticity of substitution between two sectors' goods, $\{\alpha,\ \gamma,\ \sigma\}$. α is set to 0.66 based on the average labour income share of the US total economy (excl. agriculture) between 1991 and 2012 (source: OECD). The elasticity of substitution between goods σ and the technology distribution parameter γ can be identified using the two demand functions for intermediate goods as in Acemoglu and Guerrieri (2008). By dividing the two sectors' demand functions, (3.3.32) and (3.3.33), we obtain the following log-transformed linear equation.

$$\ln\left(\frac{p_{2t}\cdot y_{2t}}{p_{1t}\cdot y_{1t}}\right)=\ln\left(\frac{\gamma}{1-\gamma}\right)+\frac{\sigma-1}{\sigma}\ln\left(\frac{y_{2t}}{y_{1t}}\right)$$

Thus the two parameters can be estimated by regressing the ratio of output values on the ratio of volumes. I use the sum of each industry's nominal value added in sector j as sector j's output value ($p_{jt}y_{jt}$), and the sum of its real value added as sector j's volume (y_{jt}). The result shows that σ and γ are around 1.25 and 0.54,[31] respectively, using the value added data between 1990 and 2015 from BEA's NIPA tables.

Next, the economy-wide match elasticity, η can be estimated by the following regression. The logarithmic transformation of the aggregate matching function is

$$\ln H_t=\ln\mu+\eta\ln U_t+(1-\eta)\ln V_t \quad\Leftrightarrow\quad \ln\frac{H_t}{V_t}=\ln\mu+\eta\ln\frac{U_t}{V_t}$$

The OLS estimate[32] is $\eta=0.25$ which is similar to the estimate in Yashiv (2000). I use the data of the number of hires (H_t), unemployed persons (U_t), and vacancies (V_t) in total industry between 2001 and 2017 from BLS JOLTS.

The separation rate between workers and firms is chosen to be $\rho=0.10$. According to Den Haan, Ramey, and Watson (2000), this value captures overall separations which include job destruction by both workers and firms, and Shimer (2005) approximates the quarterly separation rate to be 0.10 by taking the short-term unemployment rate into account.

The cost of a vacancy is likely to be proportional to output per worker (Hagedorn and Manovskii, 2008).[33] From the data of value added per person by industry

---

[31] $\ln\left(\frac{p_{2t}\cdot y_{2t}}{p_{1t}\cdot y_{1t}}\right)=0.1432+0.2015\ \ln\left(\frac{y_{2t}}{y_{1t}}\right)$, $\overline{R}^2=0.6806$

[32] $\ln\frac{H_t}{V_t}=-0.0170+0.2526\ln\frac{U_t}{V_t}$, $\overline{R}^2=0.5158$

[33] They calibrate the vacancy cost which is a function of the combination of capital and labour costs.

$$\kappa_{jt}=\kappa^K a_{jt}+\kappa^W a_{jt}^{\xi}$$

where a_{jt} is the output per unit of labour, κ^K is the steady state capital flow cost of posting a vacancy, κ^W is its flow labour cost, and ξ is a positive parameter.

between 2001 and 2015 (source: EU KLEMS), I find that value added per person in high-wage industries is on average 3.8 times as large as that in low-wage industries. I firstly choose the high-wage sector's vacancy cost, $\kappa_2 = 0.30$ so that this value, with average values of actual data (vacancy duration, per capita value added and real wage) and calibrated parameters (α, β, ρ), satisfies the following steady state job creation condition in sector 2.

$$\frac{\kappa_2}{q(\theta_2)} = \beta \left[\alpha \frac{p_2 y_2}{n_2} - w_2 + (1-\rho) \frac{\kappa_2}{q(\theta_2)} \right]$$

Then, by dividing κ_2 by 3.8, the low-wage sector's vacancy cost is set at $\kappa_1 = 0.08$.

The standard search cost function is assumed to be strictly convex as in the literature. There are two parameters associated with the search cost function: the scale of search cost, τ, and the elasticity of search cost with respect to search intensity, ι. I first choose $\iota = 1.30$ according to Christensen et al. (2005) and Krause and Lubik (2010) who regard the search cost as sufficiently elastic to search effort.[34] Given the calibrated parameters (ρ, ψ, ι) and the US average vacancy filling rate and job finding rate ($f(\cdot)$, $q(\cdot)$), the search cost parameter τ is fixed to match the equilibrium search intensity of an employed worker with one fifth of the unemployed person's search intensity as in Mortensen (1994). This yields $\tau = 0.32$.[35]

The unemployment benefit b is set to a value such that the unemployed worker's earnings, or the outside option value ($= b - \tau$),[36] is close to that in the US labour market. Since the average income replacement rate of unemployed persons' earnings

[34]Christensen et al. (2005) estimate the search elasticity to be 1.8, and Krause and Lubik (2010) choose it as 1.1.

[35]τ is calculated by plugging other parameters and data into the following equilibrium search intensity equation.

$$\tau \iota s^{\iota - 1} = \Psi(1-\rho) f(\theta_2) \left[\frac{\kappa_2}{q(\theta_2)} - \frac{\kappa_1}{q(\theta_1)} \right]$$

where search intensity s is set to 0.2 which is one fifth of the unemployed person's search intensity ($s^u = 1$).

[36]During job search, the unemployed person earns some real outside option value ($b - \tau$). According to Pissarides (2000), this value includes unemployment insurance benefits, the income from odd and irregular jobs, and the imputed return from unpaid leisure activities.

in the US between 2001 and 2011 is 13 percent (source: OECD),[37] I choose $b = 0.38$ which makes the outside option value (= 0.06) approximately 13 percent of the mean labour income (= 0.49) in the model. Setting $b = 0.38$ is also similar to the calibrations of Shimer (2005) and Krause and Lubik (2010).[38]

I choose the worker's bargaining power $\psi = 0.5$ following the convention in the labour search and matching literature.

Table 3.5 lists parameter values and their descriptions.

Table 3.5: Baseline parameter values

Parameter	Value	Description
β	0.99	discount factor
α	0.66	sector output elasticity
σ	1.25	elasticity of substitution between goods
γ	0.54	technology distribution
η	0.25	match elasticity
ρ	0.10	separation probability
κ_1	0.08	sector 1's vacancy cost
κ_2	0.30	sector 2's vacancy cost
ι	1.30	search cost elasticity (convexity)
τ	0.32	search cost scale
b	0.38	unemployment benefit
ψ	0.50	worker's bargaining power
$\bar{\mu}_1$	1.00	sector 1's average matching efficiency (normalised)
$\bar{\mu}_2$	0.62	sector 2's average matching efficiency
ζ_0	-1.60	coefficient of productivity
ζ_1	-1.20	coefficient of lagged productivity
ρ_A	0.92	autoregressive coefficient of aggregate TFP
ρ_z	0.95	autoregressive coefficient of sector-specific productivity
σ_A	0.013	standard deviation of innovation, aggregate TFP shock
σ_z	0.003	standard deviation of innovation, sector-specific shock

Notes: The main target economy is the US. The values are assigned to parameters in the baseline model. The motivation for each value is described in the text. $\bar{\mu}_j$ can be interpreted as the average matching efficiency when z_{jt} follows a log-normal AR(1) process with mean zero.

[37]The income replacement rate is defined as unemployment benefit levels (incl. unemployment insurance and unemployment assistance benefits) as a percentage of previous earnings.

[38]Shimer (2005) sets the unemployment benefit to 0.40 and Krause and Lubik (2010) calibrate it as 0.39 in a standard-type search and matching model. These values are below sectoral wages and the economy-wide wage level.

3.4.1.2 Forcing Process

As discussed in the previous section, each sector's matching efficiency is inversely related to its sector-specific productivity. This relation can be expressed by[39]

$$\mu_{jt} = \bar{\mu}_j \cdot z_{jt}^{\zeta_0} \cdot z_{jt-1}^{\zeta_1} \simeq \bar{\mu}_j \cdot z_{j,t,t-1}^{\zeta_0+\zeta_1} \tag{3.4.1}$$

where $\bar{\mu}_j$ is the average matching efficiency, ζ_0 and ζ_1 are negative coefficients. To get the rightmost term, the mean of two consecutive periods' productivities ($z_{j,t,t-1}$) is used by taking account of a slight change in productivity quarter on quarter.

As to $\bar{\mu}_j$, I calculate average sectoral matching efficiency between 2001 and 2017 by applying the actual data and the calibrated match elasticity ($\eta = 0.25$) to the matching function. When the average matching efficiency of sector 1 is normalised to $\bar{\mu}_1 = 1$, that of sector 2 becomes $\bar{\mu}_2 = 0.62$.

Finally, I set $\zeta_0 = -1.60$ and $\zeta_1 = -1.20$ to match the average coefficient estimates of the two dynamic panel regressions of matching efficiency on labour productivity as in Table 3.2.

3.4.2 Simulations

In this section, I perform numerical simulations with the above-calibrated parameters on the proposed model, with a focus on how differing matching efficiency

[39]The regression equation (3.2.5) can be written as in terms of the deviation from the initial values as

$$\begin{array}{rlcl}
 & \ln\mu_t - \ln\mu_{t-1} &=& \zeta_0(\ln z_t - \ln z_{t-1}) + \zeta_1(\ln z_{t-1} - \ln z_{t-2}) \\
 & \ln\mu_{t-1} - \ln\mu_{t-2} &=& \zeta_0(\ln z_{t-1} - \ln z_{t-2}) + \zeta_1(\ln z_{t-2} - \ln z_{t-3}) \\
 & & \vdots & \\
+ & \ln\mu_1 - \ln\mu_0 &=& \zeta_0(\ln z_1 - \ln z_0) + \zeta_1 \ln z_0 \\
\hline
 & \ln\mu_t - \ln\mu_0 &=& \zeta_0(\ln z_t - \ln z_0) + \zeta_1 \ln z_{t-1}
\end{array}$$

The last line can be transformed to $\mu_t = (\mu_0/z_0^{\zeta_0}) \cdot z_t^{\zeta_0} z_{t-1}^{\zeta_1} = \bar{\mu} \cdot z_t^{\zeta_0} z_{t-1}^{\zeta_1}$. Here the lagged dependent variables are excluded since their coefficients are small and not significant as in Table 3.2.

influences the wage gap and labour allocation between sectors. Counter-factual simulations with no inter-sectoral frictions are also carried out.[40]

3.4.2.1 Steady State Relations

In the two-sector equilibrium model, both the sectoral wage gap and labour allocation change as the relative matching efficiency changes. Differential matching efficiency is initially the result of unequal productivity between sectors in this model. As the ratio of sector-specific productivities, z_2/z_1, rises, the relative matching efficiency, $\mu_2(z_2)/\mu_1(z_1)$, decreases, otherwise it increases. Then the change in the relative matching efficiency influences labour market dynamics by changing sectoral wages and employment which further distorts the wage gap and labour allocation between sectors.

Figure 3.5 plots the steady state labour market variables and the aggregate consumption against the relative productivity. The wage gap and relative labour allocation are defined as a ratio of $\omega \equiv w_2/w_1$ and $\digamma \equiv n_2/n_1$, respectively. As the ratio of sector 2's productivity to sector 1's productivity (z_2/z_1) rises, forcing the relative matching efficiency of sector 2 $(\mu(z_2)/\mu(z_1))$ to decline, the equilibrium wage gap (ω) goes up while the relative labour allocation of sector 2 $(\digamma)$ goes down, expectedly. In accordance with our discussion in the previous section, these results demonstrate that a lower level of matching efficiency in the labour market of the high-wage sector can cause labour concentration in the low-wage sector while simultaneously causing the sectoral wage gap to widen. The third graph displays the aggregate consumption level (c) against the relative productivity. When matching efficiency is relatively balanced between sectors (or when both sectors' productivities are similar to each other), aggregate consumption grows due to the increase in aggregate output by labour reallocation. However, the consumption level begins

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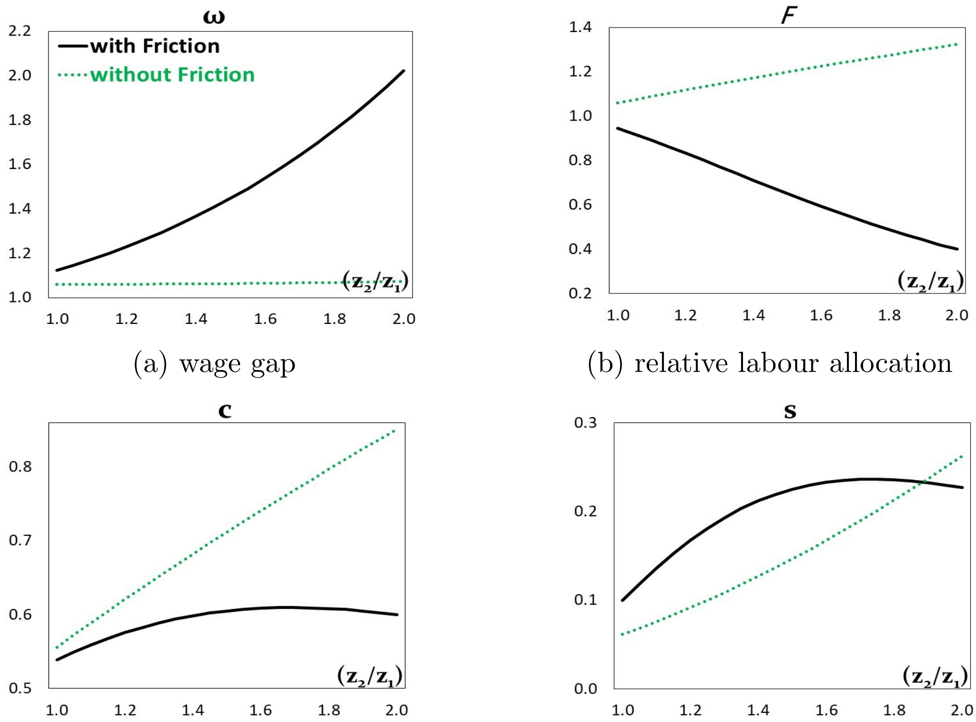
[40] In counter-factual simulations, there is no inter-sectoral mobility frictions so that the friction process (3.4.1) is turned off, $\mu_{jt} = \bar{\mu}_j$. However, there still exist search and matching type frictions from the matching function.



(a) wage gap (b) relative labour allocation

(c) aggregate consumption (d) search intensity

Figure 3.5: Steady state variables against relative productivity

Source: Author's own

Notes: In 'with Friction' simulation (baseline model, solid black line), the differential matching efficiency process driven by different sector-specific productivities is included ($\mu_{jt} = \bar{\mu}_j \cdot z_{j,t,t-1}^{\zeta_0+\zeta_1}$) while in 'without Friction' simulation (dotted green line), the process is turned off ($\mu_{jt} = \bar{\mu}_j$).

to descend when the difference in matching efficiency (or productivity) between sectors is comparatively large because labour movements from sector 1 to sector 2 will be so sluggish that the negative effect of different matching efficiency surpasses the positive effect of productivity improvement. Lastly, the differential matching efficiency matters to the extent of the equilibrium search intensity (s). The search intensity of workers in sector 1 rises in the early stage since the return to job search investment increases by enhancing the possibility of securing a higher wage job. However, as the larger difference in matching efficiency reduces its return, workers become discouraged from increasing their input on the job search.

A different result is produced from a counter-factual simulation without friction in which the process of productivity-driven matching efficiency (3.4.1) is turned off. Each sector's matching efficiency, $\mu_j = \bar{\mu}_j$, now no longer depends on its productivity. The green dotted lines in Figure 3.5 describe the changes of the four variables against the relative productivity when frictions do not exist. Without the friction process, the wage gap levels off[41] and the relative labour allocation increases with the productivity ratio, contrary to the case with frictions. This indicates that without the friction process, all wages are being equalised by inter-sectoral labour mobility even though the productivity gap increases. Put differently, the productivity gap can trigger the wage gap only via the friction process. Next, the aggregate consumption, and by extension welfare, increases monotonically because the positive effect of sector 2's productivity improvement fully contributes to the economy. The search intensity linearly increases since the lack of friction in the labour market raises a worker's chance of finding a job in the high-wage sector. This is because firms in sector 2 create more jobs as the sector's productivity goes up, and accordingly its market tightness (v_j/u_j) rises. Equilibrium search intensity of workers in sector 1 keeps increasing with the relative productivity, provided that there exist no frictions.

3.4.2.2 Deterministic Simulation

Next, I run a deterministic simulation using actual data of relative productivity, or z_2/z_1. This simulation is equivalent to the case where all agents have perfect foresight about the evolution of relative productivity. This simulation illustrates the structural transformation of employment and the transition of the wage gap over the last two decades.

To collect the time series of sectoral productivity, I take the sectoral average of labour productivity weighted by each industry's hours worked using the annual

[41] The wage gap is not equal to unity since there exist the difference in initial matching efficiency, or $\bar{\mu}_1 \neq \bar{\mu}_2$ as well as the difference in vacancy cost, or $\kappa_1 \neq \kappa_2$ in the case of no friction.

data of industrial labour productivity index between 2001 and 2016 from the US BLS Labor Productivity and Costs (LPC) database.[42] Then, quarterly data of productivity are obtained by linear interpolation between annual data. We retain the same sector classification used in Table 3.4. Figure 3.6 plots the time series of productivity ratio between sectors. According to the data, the relative labour productivity has increased at an annual rate of 0.14 percent since 2001.

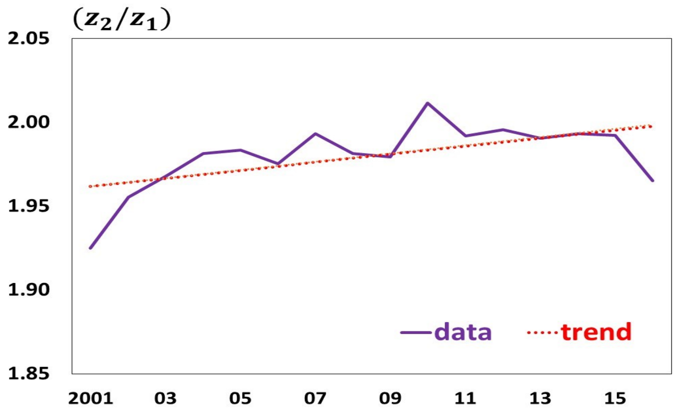


Figure 3.6: Relative productivity (z_2/z_1), US

Source: BLS Labor Productivity and Costs (LPC)

Notes: Each sector's productivity (z_j) is averaged over all industries within its sector, weighted by industrial hours worked. The trend shows an annual growth rate of 0.14 percent between 2001 - 2016. Since the data provided from BLS are indexed, the initial level is adjusted from 1.00 to 1.93 for the wage gap in the model to fit the actual wage gap in 2001.

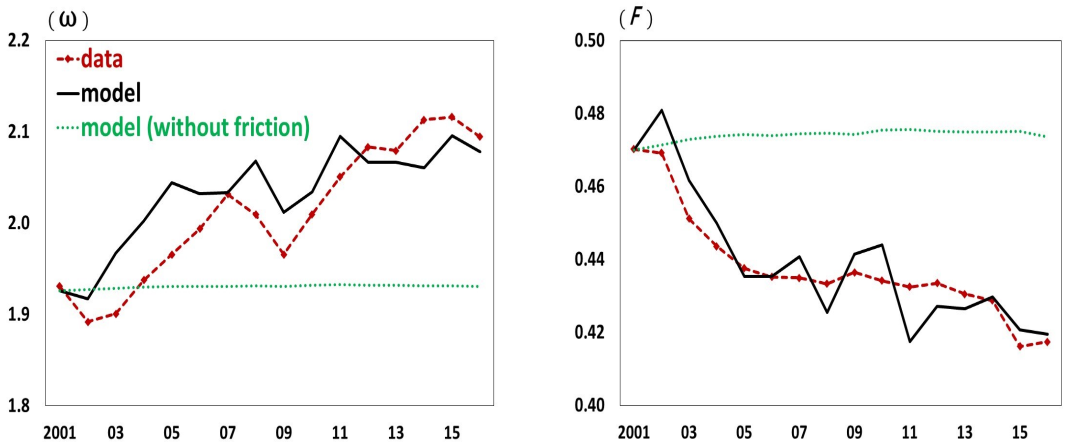
To implement this deterministic simulation, the following steps are carried out.

- step 1: Feed the actual data of relative productivity z_2/z_1 (z_1 is normalised to 1) in 2001 into the model equation system in section 3.3.
- step 2: Given the actual data of relative productivity, steady state values of $\{y_j,\, p_j,\, v_j,\, \theta_j,\, \mu_j,\, s,\, n_j,\, w_j\}$ can be solved and then the initial wage gap ω and labour allocation $\digamma$ are derived for the year 2001.

[42]This average labour productivity data can be a proxy for z_j $(= y_j/n_j^{\alpha})$ in the model.

- step 3: By feeding the time series of relative productivity by the year 2016, the transition paths of the wage gap and labour allocation between 2001 and 2016 are extracted. End at the new steady state with the relative labour productivity in 2016.

From this deterministic simulation, we can show how closely the proposed two-sector search and matching model tracks the actual data in the labour market. Figure 3.7 demonstrates that the model well accounts for the labour market dynamics since the 2000s. Through the process in which the relative labour productivity of the high-wage sector has risen (or its relative matching efficiency has been lower), the wage gap between sectors has increased and at the same time the relative labour allocation of the high-wage sector has shrunk. The simulation for the wage gap tracks the actual data closely in terms of level and direction. A pattern of the actual wage gap, in which the gap reduced during the global financial crisis, is also shown in the



(a) wage gap (b) relative labour allocation

Figure 3.7: Deterministic simulations

Source: Author's own, from BEA NIPA, BLS LPC

Notes: 'with Friction' (solid black line) is the simulation with the baseline model while in 'without Friction' simulation (dotted green line), the friction process of productivity-driven matching efficiency is turned off, or $\mu_{jt} = \bar{\mu}_j$. The initial (F) in the model is adjusted to fit the data of labour allocation in 2001 ($0.43 \rightarrow 0.47$). The correlation of ω between data and model is 0.86, and that of F is 0.93.

model economy. For the labour allocation, the simulation captures the actual data by displaying a downward curve, despite having more fluctuations than the actual data and thus having some difficulty generating the secular decline. This is because in the model each sector's labour allocation is directly affected by the period change in the matching efficiency. I also conduct counter-factual simulations without frictions which show that the wage gap levels off and the relative labour allocation of the high-wage sector slightly increases in contrast to the case with frictions. Again, the labour market puzzle cannot be explained alone by sector-specific productivity progress but can be explained with labour mobility frictions.

3.4.2.3 Stochastic Simulation

By adopting stochastic processes on the aggregate TFP, A_t, in equation (3.3.1) and the sector-specific productivity, z_{jt}, in equation (3.3.5), we can assess the extent to which this two-sector search and matching framework contributes to explaining observed fluctuations in the wage gap and labour allocation between sectors.

I assume that the aggregate shock, A_t, follows the Markov process of a mean zero AR(1) in logarithm as

$$\ln A_t = \rho_A \ln A_{t-1} + \varepsilon_{At}, \quad \varepsilon_{At} \sim \mathcal{N}(0, \sigma_A^2) \tag{3.4.2}$$

where ρ_A is the autoregressive coefficient and σ_A^2 is the variance of the innovation.

For the sector-specific shock, in the two-sector model, what matters is the relative productivity between two sectors. Thus, without loss of generality, I normalise sector 1's productivity to one, and specify sector 2's stochastic process as an exogenous log-normal AR(1) process.

$$\ln z_{2t} = \rho_z \ln z_{2t-1} + \varepsilon_{zt}, \quad \varepsilon_{zt} \sim \mathcal{N}(0, \sigma_z^2) \tag{3.4.3}$$

where ρ_z is the autoregressive coefficient and σ_z^2 is the variance of the innovation.

It is assumed that both shocks are orthogonal to each other. The parameter ρ_A is set as 0.92 as is fairly common in the literature. I choose the autoregressive coefficient of sector-specific productivity, $\rho_z = 0.95$ according to Garin, Pries, and Sims (2018).[43] For the shock magnitudes, I first estimate the standard deviation of the sector-specific shock as $\sigma_z = 0.003$ using the data[44] while I parameterise the standard deviation of the aggregate TFP shock as $\sigma_A = 0.013$ such that the model can match that of the US per capita output over the sample period.

Moments from this stochastic simulation are reported in Table 3.6. The time series of the US economy consists of the data from the first quarter of 2001 to the fourth quarter of 2016 (64 sample period).[45] All variables are measured on per capita and real value basis, and transformed by taking logarithms. The time series are detrended using the Hodrick-Prescott filter by setting the smoothing parameter to 1,600. To compare actual statistics with those of model, I simulate the model

Table 3.6: Cyclical properties: US economy and model economy

	US economy		model economies			
			(with friction)		(without friction)	
	$\sigma(y) = 1.15$		$\sigma(y) = 1.15$		$\sigma(y) = 1.14$	
variable (x)	$\sigma(x)/\sigma(y)$	$\rho(x, y)$	$\sigma(x)/\sigma(y)$	$\rho(x, y)$	$\sigma(x)/\sigma(y)$	$\rho(x, y)$
consumption	0.81	0.92	0.89	0.99	0.90	1.00
labour income share	0.32	-0.21	0.19	-0.26	0.13	-0.45
labour productivity	0.72	0.96	0.91	0.98	0.90	0.98
employment	0.57	0.78	0.37	0.63	0.35	0.69
real wage	0.84	0.37	0.52	0.98	0.50	1.00

Source: Author's own, from BEA, BLS

Notes: The period covered for the statistics of the US economy is from 2001.1Q to 2016.4Q (64 periods). $\sigma(x)$ is the percentage standard deviation of variable x. $\sigma(x)/\sigma(y)$ is the relative volatility of variable x with respect to output y. $\rho(x, y)$ is the correlation between variable x and output y. The US data of employment is constructed in terms of the number of employees.

[43] Garin, Pries, and Sims (2018) point out that setting the autoregressive coefficient of sector-specific productivity sufficiently persistent is inevitable to generate labour reallocation across sectors in a disaggregated sector model.

[44] The quarterly standard deviation, σ_z, is calculated by dividing the standard deviation of the annual relative productivity data (1990-2016) by the square root of four.

[45] See the Appendix 3.A.5 for a more detailed description of the data.

economy with the same period as the US time series and obtain the model economy's variables.

The table contains the cyclical properties of the US and model economies developed above. For each economy, the first column shows each variable's relative volatility with respect to output $\sigma(x)/\sigma(y)$ (x: variable, y: output), and the second column provides a correlation of each variable with output $\rho(x, y)$. The model economies, regardless of whether or not it includes the friction mechanism, replicate the actual data of the main labour market variables. These cyclical properties are quite similar to those in Merz (1995) and Andolfatto (1996).

Figure 3.8 displays impulse response functions of the labour market variables to one percent relative productivity shock of sector 2. In this simulation, the high-wage sector biased productivity improvement amplifies the wage gap and lowers its relative employment share, which the ideal frictionless economy cannot explain. These results satisfy both the negative relationship between employment and labour productivity, which is in line with the 'labour push' theory (Hansen and Randall, 1992; Ngai and Pissarides, 2007; etc.), and the widening wage gap. While Galí (1999) blames price stickiness for the negative relationship, the model put forward in this chapter shows the same result in the two-sector framework by adopting the

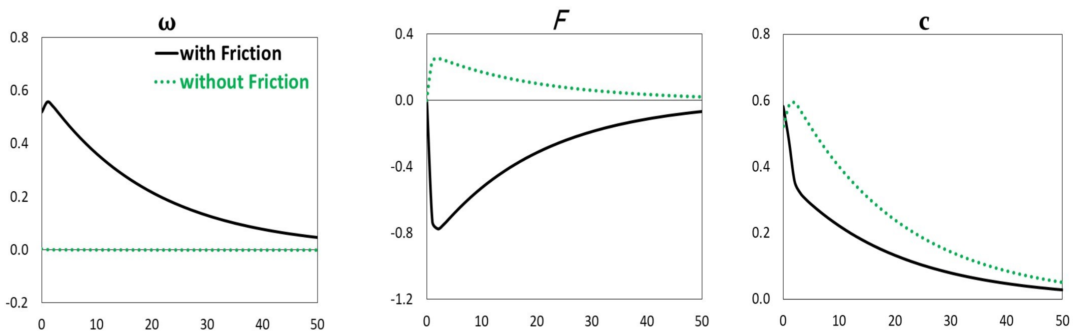


Figure 3.8: Impulse responses to relative productivity shock (z_{2t}/z_{1t})

Source: Author's own

Notes: 'with Friction' (solid black line) is the simulation with the baseline model while in 'without Friction' simulation (dotted green line), the friction process of productivity-driven matching efficiency is turned off, or $\mu_{jt} = \bar{\mu}_j$.

rigidity of labour mobility.

The dotted line depicts dynamic responses after the shock under the setting without the friction process. This counter-factual simulation shows that the response of the wage gap to the relative productivity shock is very little and the response of the relative labour allocation increases in contrast with the baseline model. Accordingly, the increase of consumption to the shock is larger and longer lasting in the frictionless economy than its increase in the frictional economy since positive productivity shocks in the high-wage sector frictionlessly contributes to the production of the economy as well as its consumption.

3.5 Conclusion

In this chapter, I have shown that job-worker matching efficiency plays a pivotal role in the labour market. Notably, the difference in matching efficiency between sectors leads to labour market distortions by standing in the way of labour mobility across sectors. That is to say, low matching efficiency in the high-wage sector acts as a barrier preventing workers from entering this sector. We have also seen that uneven sector-specific productivity progress is the primary source of differential matching efficiency.

We assessed the role of differing matching efficiency in inter-sectoral labour mobility and the wage gap dynamics through a two-sector search and matching model which is embedded with the friction process, or productivity-driven differential matching efficiency. The proposed model is quite useful in accounting for a puzzling phenomenon in the current labour market.

The model illustrates that differential matching efficiency driven by the productivity gap between sectors exacerbates the matching frictions and impedes inter-sectoral labour mobility, and therefore impacts the labour market negatively in a way that distorts labour allocation and widens the wage gap. However, the model without the friction process cannot explain the labour market puzzle, even when the productivity gap increases. We have recognised that the interaction of the productivity gap and differential matching efficiency is indispensable to demonstrate the empirically plausible wage gap and labour misallocation. All these results suggest that a reduction of the difference in matching efficiency via balanced, unbiased productivity progress across sectors might reduce labour market distortions and further improve the welfare of the economy.

3.A Appendix

3.A.1 Expected Vacancy Duration

Let φ denote the probability of filling a vacancy and m denote the discrete length of time until a vacancy is successfully filled. The probability by time length can be

$$\begin{aligned}
Prob(m = 1) &= \varphi \\
Prob(m = 2) &= (1 - \varphi) \cdot \varphi \\
Prob(m = 3) &= (1 - \varphi)^2 \cdot \varphi \\
&\vdots \\
Prob(m = t) &= (1 - \varphi)^{t-1} \cdot \varphi \\
&\vdots
\end{aligned}$$

Then, the expected vacancy duration is

$$\begin{aligned}
\mathbb{E}(m) &= \sum_{t=1}^{\infty} \left[t \cdot (1 - \varphi)^{t-1} \cdot \varphi \right] \\
&= \varphi + 2(1 - \varphi)\varphi + 3(1 - \varphi)^2\varphi + 4(1 - \varphi)^3\varphi + \cdots \\
&= \varphi + \ (1 - \varphi)\varphi + \ (1 - \varphi)^2\varphi + \ (1 - \varphi)^3\varphi + \cdots \quad \Rightarrow \quad 1 \\
&\quad\ + \ (1 - \varphi)\varphi + \ (1 - \varphi)^2\varphi + \ (1 - \varphi)^3\varphi + \cdots \quad \Rightarrow \quad 1 - \varphi \\
&\quad\ + \ (1 - \varphi)^2\varphi + \ (1 - \varphi)^3\varphi + \cdots \quad \Rightarrow \quad (1 - \varphi)^2 \\
&\quad\ \vdots \\
&= \frac{1}{1 - (1 - \varphi)} = \frac{1}{\varphi}
\end{aligned}$$

Hence, the expected vacancy duration is equal to the reciprocal of the probability of filling a vacancy.

3.A.2 Decomposition of Vacancy Duration Gap

Table 3A.1: Decomposition of vacancy duration gap

sector 1: Arts, Ent. & Rec.[a]	$\ln \frac{q(\overline{\theta_{1t}})}{q(\overline{\theta_{2t}})}$	(i) $\widehat{\ln \frac{\mu_1}{\mu_2}}$		(ii) $\widehat{\eta_{12}} \ln \frac{\overline{\theta_{2t}}}{\overline{\theta_{1t}}}$		
sector 2	level	level	[contrib. %]	level	[contrib. %]	$\widehat{\eta_{12}}$
finance & Insurance	1.25	0.80***	[64.2]	0.45	[35.8]	0.42***
Information	1.07	0.85***	[79.2]	0.23	[21.1]	0.44***
Professional & Business	0.58	0.11*	[18.6]	0.47	[81.7]	0.58***
Wholesale trade	0.74	0.54***	[73.0]	0.20	[27.5]	0.54***
Manufacturing	0.68	0.76***	[111.3]	-0.08	[-11.1]	0.48***
Health care & Social assistance	1.20	0.60***	[50.4]	0.60	[49.7]	0.49***
Transport, Warehouse & Utilities	0.55	0.46***	[83.4]	0.09	[17.0]	0.47***

sector 1: Construction	$\ln \frac{q(\overline{\theta_{1t}})}{q(\overline{\theta_{2t}})}$	(i) $\widehat{\ln \frac{\mu_1}{\mu_2}}$		(ii) $\widehat{\eta_{12}} \ln \frac{\overline{\theta_{2t}}}{\overline{\theta_{1t}}}$		
sector 2	level	level	[contrib. %]	level	[contrib. %]	$\widehat{\eta_{12}}$
finance & Insurance	1.57	0.60***	[38.0]	0.97	[61.7]	0.51***
Information	1.39	0.70***	[50.4]	0.69	[49.6]	0.51***
Professional & Business	0.90	0.03*	[2.9]	0.87	[96.9]	0.53***
Wholesale trade	1.05	0.49***	[46.5]	0.56	[53.5]	0.47***
Manufacturing	1.00	0.66***	[65.9]	0.34	[33.8]	0.50***
Health care & Social assistance	1.52	0.57***	[37.3]	0.95	[62.6]	0.46***
Transport, Warehouse & Utilities	0.87	0.37***	[43.1]	0.49	[56.7]	0.48***

Source: Author's own, from BLS JOLTS

Notes: [a]Arts, entertainment, and recreation. [b]The sample covers the period Jan 2001 - Jun 2017. The upper bar and the hat denote the mean values and the estimated values, respectively. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

3.A.3 Model Derivations

3.A.3.1 Demands for Goods: Equation (3.3.2) & (3.3.3)

In the general case, suppose that there is a continuum sectors $j \in [0,1]$. The aggregate output is

$$y_t = A_t \left[\int_0^1 (\gamma_j y_{jt}^{\frac{\sigma-1}{\sigma}}) dj \right]^{\frac{\sigma}{\sigma-1}}$$

where γ_j is the technology distribution parameter. The final good firm maximises its profit by optimally combining each of intermediate goods.

$$\max_{\{y_{jt}\}_j} \quad p_t y_t - \int_0^1 (p_{jt} y_{jt}) dj$$

The first order condition with respect to y_{jt} is

$$p_{jt} = p_t A_t \left[\int_0^1 (\gamma_j y_{jt}^{\frac{\sigma-1}{\sigma}}) dj \right]^{\frac{1}{\sigma-1}} \gamma_j y_{jt}^{-\frac{1}{\sigma}}$$

where p_t is the price of final goods and p_{jt} is the price of sector j's goods. By dividing the first order conditions of any two goods, i and j, we obtain

$$y_{it} = \left(\frac{\gamma_i}{\gamma_j} \right)^{\sigma} \left(\frac{p_{it}}{p_{jt}} \right)^{-\sigma} y_{jt}$$

Plugging this into the aggregate output equation yields

$$y_t = A_t \gamma_j^{-\sigma} p_{jt}^{\sigma} y_{jt} \left[\int_0^1 \gamma_i^{\sigma} p_{it}^{1-\sigma} di \right]^{\frac{\sigma}{\sigma-1}} = A_t^{1-\sigma} \gamma_j^{-\sigma} p_{jt}^{\sigma} y_{jt} \Bigg\{ \underbrace{A_t^{-1} \left[\int_0^1 \gamma_i^{\sigma} p_{it}^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}}_{= \, p_t \, \equiv \, 1} \Bigg\}^{-\sigma}$$

By rearranging, we finally get the demands for good j as

$$p_{jt} = \gamma_j A_t^{\frac{\sigma-1}{\sigma}} \left(\frac{y_{jt}}{y_t} \right)^{-\frac{1}{\sigma}}$$

3.A.3.2 Aggregate Price Level: Equation (3.3.4)

The aggregate price is the minimum cost to produce one unit of the final goods y_t. If there is a continuum of sectors $j \in [0,1]$, the final output firm's cost minimisation problem is given by

$$\min_{\{y_{jt}\}_j} \quad \int_0^1 (p_{jt} y_{jt}) dj$$
$$s.t. \quad y_t \equiv A_t \left[\int_0^1 \gamma_j y_{jt}^{\frac{\sigma-1}{\sigma}} dj \right]^{\frac{\sigma}{\sigma-1}} = 1$$

The first order condition with respect to y_{jt} is

$$p_{jt} = \lambda_t \gamma_j A_t y_{jt}^{-\frac{1}{\sigma}} y_t^{\frac{1}{\sigma}}$$

where λ_t is the Lagrange multiplier. By dividing the first order conditions of any two goods, i and j, we get

$$\frac{p_{jt}}{p_{it}} = \frac{\gamma_j}{\gamma_i} \left(\frac{y_{jt}}{y_{it}} \right)^{-\frac{1}{\sigma}} \quad \Rightarrow \quad y_{jt} = \gamma_j^{\sigma} \gamma_i^{-\sigma} p_{jt}^{-\sigma} p_{it}^{\sigma} y_{it}$$

Putting this into the constraint gives

$$A_t \left[\int_0^1 \gamma_j \left(\gamma_j^{\sigma} \gamma_i^{-\sigma} p_{jt}^{-\sigma} p_{it}^{\sigma} y_{it} \right)^{\frac{\sigma-1}{\sigma}} dj \right]^{\frac{\sigma}{\sigma-1}} = 1 \quad \Rightarrow \quad y_{it} = \frac{\gamma_i^{\sigma} p_{it}^{-\sigma}}{A_t \left[\int_0^1 \gamma_j^{\sigma} p_{jt}^{1-\sigma} dj \right]^{\frac{\sigma}{\sigma-1}}}$$

By plugging this into the cost function $\int_0^1 p_{it} y_{it} di$, we obtain

$$\frac{\int_0^1 \gamma_i^{\sigma} p_{it}^{1-\sigma} di}{A_t \left[\int_0^1 \gamma_j^{\sigma} p_{jt}^{1-\sigma} dj \right]^{\frac{\sigma}{\sigma-1}}} = A_t^{-1} \left[\int_0^1 \gamma_j^{\sigma} p_{jt}^{1-\sigma} dj \right]^{\frac{1}{1-\sigma}} \equiv p_t$$

This shows that the minimum cost to produce one unite of y_t is the same as the aggregate price index p_t that we defined.

3.A.3.3 Firm's Profit Maximisation

Each sector's firm maximises its expected present value of profit by deciding the number of vacancies and labour inputs subject to the evolution of employment.

$$\max_{\{v_{j,t+l},\ n_{j,t+l+1}\}_{l=0}^{\infty}} \quad \mathbb{E}_t \sum_{l=0}^{\infty} \beta^l \left[p_{jt+l}y_{jt+l} - w_{jt+l}n_{jt+l} - \kappa_{jt+l}v_{jt+l}\right]$$

$$\begin{aligned} s.t.\ \ n_{1t+1} &= (1-\rho)(1-s_t f(\theta_{2t}))n_{1t} + q(\theta_{1t})v_{1t} && \text{for firms in sector 1} \\ n_{2t+1} &= (1-\rho)n_{2t} + q(\theta_{2t})v_{2t} && \text{for firms in sector 2} \end{aligned}$$

The first order conditions are

$$\begin{aligned} [v_{jt}] \quad & \kappa_{jt} = \lambda_{jt} q(\theta_{jt}) \\ [n_{1t+1}] \quad & \lambda_{1t} = \beta \mathbb{E}_t \left[\alpha p_{1t+1} z_{1t+1} n_{1t+1}^{\alpha-1} - w_{1t+1} + (1-\rho)(1-s_{t+1}f(\theta_{2t+1}))\lambda_{1t+1}\right] \\ [n_{2t+1}] \quad & \lambda_{2t} = \beta \mathbb{E}_t \left[\alpha p_{2t+1} z_{2t+1} n_{2t+1}^{\alpha-1} - w_{2t+1} + (1-\rho)\lambda_{2t+1}\right] \end{aligned}$$

where λ_j is the Lagrange multiplier. By substituting λ_j out, each sector's job creation condition is derived as

$$\begin{aligned} \frac{\kappa_{1t}}{q(\theta_{1t})} &= \beta \mathbb{E}_t \left[\alpha p_{1t+1} z_{1t+1} n_{1t+1}^{\alpha-1} - w_{1t+1} + (1-\rho)(1-s_{t+1}f(\theta_{2t+1}))\frac{\kappa_{1t+1}}{q(\theta_{1t+1})}\right] \\ \frac{\kappa_{2t}}{q(\theta_{2t})} &= \beta \mathbb{E}_t \left[\alpha p_{2t+1} z_{2t+1} n_{2t+1}^{\alpha-1} - w_{2t+1} + (1-\rho)\frac{\kappa_{2t+1}}{q(\theta_{2t+1})}\right] \end{aligned}$$

These equations are the same as equations (3.3.18) and (3.3.19).

3.A.3.4 Job Creation Conditions: Equation (3.3.18) & (3.3.19)

By substituting (3.3.14) and the free entry condition ($V_{jt} = 0$) into (3.3.17), sector 1's job creation condition is derived as

$$\begin{aligned}\frac{\kappa_{1t}}{q(\theta_{1t})} &= \beta \mathbb{E}_t J_{1t+1} \\ &= \beta \mathbb{E}_t \left[\alpha p_{1t+1} z_{1t+1} n_{1t+1}^{\alpha-1} - w_{1t+1} + \beta(1-\rho)(1 - s_{t+1} f(\theta_{2t+1})) J_{1t+2}\right] \\ &= \beta \mathbb{E}_t \left[\alpha p_{1t+1} z_{1t+1} n_{1t+1}^{\alpha-1} - w_{1t+1} + (1-\rho)(1 - s_{t+1} f(\theta_{2t+1})) \frac{\kappa_{1t+1}}{q(\theta_{1t+1})}\right]\end{aligned}$$

Likewise, by substituting (3.3.15) and the free entry condition into (3.3.17), sector 2's job creation condition is derived as

$$\begin{aligned}\frac{\kappa_{2t}}{q(\theta_{2t})} &= \beta \mathbb{E}_t J_{2t+1} \\ &= \beta \mathbb{E}_t \left[\alpha p_{2t+1} z_{2t+1} n_{2t+1}^{\alpha-1} - w_{2t+1} + \beta(1-\rho) J_{2t+2}\right] \\ &= \beta \mathbb{E}_t \left[\alpha p_{2t+1} z_{2t+1} n_{2t+1}^{\alpha-1} - w_{2t+1} + (1-\rho) \frac{\kappa_{2t+1}}{q(\theta_{2t+1})}\right]\end{aligned}$$

3.A.3.5 Wage Determinations: Equation (3.3.37) & (3.3.38)

Substituting (3.3.14), (3.3.20), and (3.3.22) into the bargaining condition (3.3.25) yields

$$\begin{aligned}& w_{1t} - \phi(s_t) + \beta \mathbb{E}_t \left[(1-\rho) E_{1t+1} + \rho U_{1t+1} + (1-\rho) s_t f(\theta_{2t})(E_{2t+1} - E_{1t+1})\right] = \\ & \quad \Psi \left(\alpha p_{1t} z_{1t} n_{1t}^{\alpha-1} - w_{1t} + \beta \mathbb{E}_t \left[(1-\rho)(1 - s_t f(\theta_{2t})) J_{1t+1} + (\rho + (1-\rho) s_t f(\theta_{2t})) V_{1t+1}\right]\right) \\ & \quad + b - \tau + \beta \mathbb{E}_t \left[f(\theta_{1t}) E_{1t+1} + (1 - f(\theta_{1t})) U_{1t+1}\right]\end{aligned}$$

By imposing the free entry condition $V_{1t} = 0$ and then rearranging, we get

$$\begin{aligned}(1+\Psi)w_{1t} &= \Psi\alpha p_{1t}z_{1t}n_{1t}^{\alpha-1} + \phi(s_t) + b - \tau \\ &\quad + \beta\mathbb{E}_t[\Psi(1-\rho)(1-s_t f(\theta_{2t}))J_{1t+1} - (1-\rho)E_{1t+1} - \rho U_{1t+1} \\ &\quad - (1-\rho)s_t f(\theta_{2t})(E_{2t+1} - E_{1t+1}) + f(\theta_{1t})E_{1t+1} + (1-f(\theta_{1t}))U_{1t+1}] \\ &= \Psi\alpha p_{1t}z_{1t}n_{1t}^{\alpha-1} + \phi(s_t) + b - \tau + \beta\mathbb{E}_t\left[\Psi f(\theta_{1t})J_{1t+1} - \Psi(1-\rho)s_t f(\theta_{2t})J_{2t+1}\right]\end{aligned}$$

With (3.3.17) and (3.3.26), sector 1's wage determination equation is derived as

$$w_{1t} = \psi\left(\alpha p_{1t}\frac{y_{1t}}{n_{1t}} + (1-(1-\rho)s_t)\kappa_{2t}\theta_{2t}\right) + (1-\psi)(\tau s_t^{\iota} + b - \tau)$$

Likewise, by substituting (3.3.15), (3.3.21), and (3.3.22) into (3.3.25) and imposing the free entry condition $V_{2t} = 0$, we obtain

$$\begin{aligned}w_{2t} + \beta\mathbb{E}_t\left[(1-\rho)E_{2t+1} + \rho U_{2t+1}\right] &= \Psi\left(\alpha p_{2t}z_{2t}n_{2t}^{\alpha-1} - w_{2t} + \beta\mathbb{E}_t\left[(1-\rho)J_{2t+1}\right]\right) \\ &\quad + b - \tau + \beta\mathbb{E}_t\left[f(\theta_{2t})E_{2t+1} + (1-f(\theta_{2t}))U_{2t+1}\right]\end{aligned}$$

By rearranging, this can be written as

$$\begin{aligned}(1+\Psi)w_{2t} &= \Psi\alpha p_{2t}z_{2t}n_{2t}^{\alpha-1} + b - \tau \\ &\quad + \beta\mathbb{E}_t\left[\Psi(1-\rho)J_{2t+1} - (1-\rho)E_{2t+1} - \rho U_{2t+1} + f(\theta_{2t})E_{2t+1} + (1-f(\theta_{2t}))U_{2t+1}\right] \\ &= \Psi\alpha p_{2t}z_{2t}n_{2t}^{\alpha-1} + b - \tau + \beta\mathbb{E}_t\left[\Psi(1-\rho)J_{2t+1} + \Psi\rho J_{2t+1} + \Psi f(\theta_{2t})J_{2t+1} - \Psi J_{2t+1}\right] \\ &= \Psi\alpha p_{2t}z_{2t}n_{2t}^{\alpha-1} + b - \tau + \beta\mathbb{E}_t\Psi f(\theta_{2t})J_{2t+1}\end{aligned}$$

With (3.3.17), sector 2's wage determination equation is derived as

$$w_{2t} = \psi\left(\alpha p_{2t}\frac{y_{2t}}{n_{2t}} + \kappa_{2t}\theta_{2t}\right) + (1-\psi)(b-\tau)$$

3.A.3.6 Steady State Wage Gap: Equation (3.3.50)

From (3.3.48) and (3.3.49), the difference in sectoral wages can be derived as

$$\begin{aligned}
w_2^* - w_1^* &= \Psi\left[\left(\frac{1}{\beta} - (1-\rho)\right)\left(\frac{\kappa_2}{\mu(z_2)}\theta_2^{*\eta} - \frac{\kappa_1}{\mu(z_1)}\theta_1^{*\eta}\right)\right] \\
&\qquad + \Psi\left[\bar{s}(1-\rho)\kappa_2\theta_2^* - \bar{s}(1-\rho)\frac{\mu(z_2)}{\mu(z_1)}\kappa_1\theta_1^{*\eta}\theta_2^{*1-\eta}\right] - \bar{s}\tau \\
&= \Psi\left[\left(\frac{1}{\beta} - (1-\rho)\right)\frac{\theta_2^{*\eta}}{\mu(z_2)}\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)\right] \\
&\qquad + \underbrace{\Psi\bar{s}(1-\rho)\theta_2^*\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)}_{=\ \tau\iota\bar{s}^{\iota}\ \text{from (3.3.45)}} - \bar{s}\tau \\
&= \Psi\left[\left(\frac{1}{\beta} - (1-\rho)\right)\left(\frac{\tau\iota\bar{s}^{\iota-1}}{\Psi(1-\rho)}\right)^{\eta}\frac{1}{\mu(z_2)}\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)^{1-\eta}\right] + \tau\bar{s}^{\iota}(\iota - \bar{s}^{1-\iota})
\end{aligned}$$

where (3.3.46) is used in the last line.

3.A.3.7 Steady State Labour Allocation: Equation (3.3.57)

The steady state total unemployment can be derived by equating the flow out of unemployment $(f(\theta_1) + f(\theta_2))u$, with the flow into unemployment $\rho(1-u)$.

$$u^* = \frac{\rho}{f(\theta_1^*) + f(\theta_2^*) + \rho} = \bar{u}$$

By substituting (3.3.52) and (3.3.54) into (3.3.53), we obtain

$$\begin{aligned}
\rho n_2 &= f(\theta_2^*)(1 - n_1 - n_2 - u_1 + \bar{s}n_1) \\
&= f(\theta_2^*)\left(1 - n_1 - n_2 - \frac{\rho + \bar{s}(1-\rho)f(\theta_2^*)}{f(\theta_1^*)}n_1 + \bar{s}n_1\right) \\
&= f(\theta_2^*)\left(1 - n_2 - \frac{\rho + \bar{s}(1-\rho)f(\theta_2^*) + (1-\bar{s})f(\theta_1^*)}{f(\theta_1^*)}(1 - n_2 - \bar{u})\right)
\end{aligned}$$

By rearranging, we obtain the sector 2's employment share as

$$n_2^* = \frac{f(\theta_2^*) - \frac{f(\theta_2^*)}{f(\theta_1^*)}X^* + \frac{f(\theta_2^*)}{f(\theta_1^*)}\bar{u}X^*}{\rho + f(\theta_2^*) - \frac{f(\theta_2^*)}{f(\theta_1^*)}X^*}$$

where $X^* \equiv \rho + \bar{s}(1-\rho)f(\theta_2^*) + (1-\bar{s})f(\theta_1^*)$.

Then, the sector 1's employment share can be

$$n_1^* = 1 - \bar{u} - n_2^* = \frac{\rho - \rho\bar{u} - \bar{u}f(\theta_2^*)}{\rho + f(\theta_2^*) - \frac{f(\theta_2^*)}{f(\theta_1^*)}X^*}$$

By dividing these sectoral employment shares from each other, the steady state relative labour allocation of sector 2 can be derived as

$$\begin{aligned}
\frac{n_2^*}{n_1^*} &= \frac{f(\theta_2^*)\left[1 - \frac{1}{f(\theta_1^*)}X^* + \frac{1}{f(\theta_1^*)}\bar{u}X^*\right]}{\rho - \rho\bar{u} - \bar{u}f(\theta_2^*)} \\
&= \frac{1 - (1-\bar{u})\left[\frac{\rho}{f(\theta_1^*)} + \bar{s}(1-\rho)\frac{f(\theta_2^*)}{f(\theta_1^*)} + (1-\bar{s})\right]}{\frac{\rho(1-\bar{u})}{f(\theta_2^*)} - \bar{u}} \\
&= \frac{1 - (1-\bar{u})\left[\frac{\rho}{\mu(z_1)\theta_1^{*1-\eta}} + \bar{s}(1-\rho)\frac{\mu(z_2)}{\mu(z_1)}\frac{\theta_2^{*1-\eta}}{\theta_1^{*1-\eta}} + (1-\bar{s})\right]}{\frac{\rho(1-\bar{u})}{\mu(z_2)\theta_2^{*1-\eta}} - \bar{u}} \\
&= \frac{1 - (1-\bar{u})\left[\frac{\rho}{\mu(z_1)\left(\frac{\kappa_2}{\kappa_1}\right)^{1-\eta}\theta_2^{*1-\eta}} + \bar{s}(1-\rho)\frac{\mu(z_2)}{\mu(z_1)}\left(\frac{\kappa_1}{\kappa_2}\right)^{1-\eta} + (1-\bar{s})\right]}{\frac{\rho(1-\bar{u})}{\mu(z_2)\theta_2^{*1-\eta}} - \bar{u}} \\
&= \frac{1 - (1-\bar{u})\left[\begin{array}{c}\frac{\rho}{\mu(z_1)}\left(\frac{\kappa_1}{\kappa_2}\right)^{1-\eta}\left(\frac{\Psi(1-\rho)}{\tau\iota\bar{s}^{\iota-1}}\right)^{1-\eta}\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)^{1-\eta} \\ +\bar{s}(1-\rho)\frac{\mu(z_2)}{\mu(z_1)}\left(\frac{\kappa_1}{\kappa_2}\right)^{1-\eta} + (1-\bar{s})\end{array}\right]}{\frac{\rho(1-\bar{u})}{\mu(z_2)}\left(\frac{\Psi(1-\rho)}{\tau\iota\bar{s}^{\iota-1}}\right)^{1-\eta}\left(\kappa_2 - \frac{\mu(z_2)}{\mu(z_1)}\kappa_1^{1-\eta}\kappa_2^{\eta}\right)^{1-\eta} - \bar{u}}
\end{aligned}$$

3.A.4 Steady State Model Equations

(demand for goods)

$$p_1 = (1-\gamma)\left(\frac{y_1}{y}\right)^{-\frac{1}{\sigma}}$$
$$p_2 = \gamma\left(\frac{y_2}{y}\right)^{-\frac{1}{\sigma}}$$

(job creation condition)

$$\frac{\kappa_1}{q(\theta_1)} = \beta\left[\alpha p_1 \frac{y_1}{n_1} - w_1 + (1-\rho)(1-sf(\theta_2))\frac{\kappa_1}{q(\theta_1)}\right]$$
$$\frac{\kappa_2}{q(\theta_2)} = \beta\left[\alpha p_2 \frac{y_2}{n_2} - w_2 + (1-\rho)\frac{\kappa_2}{q(\theta_2)}\right]$$

(equilibrium search intensity)

$$\tau\iota s^{\iota-1} = \Psi(1-\rho)f(\theta_2)\left[\frac{\kappa_2}{q(\theta_2)} - \frac{\kappa_1}{q(\theta_1)}\right]$$

(wage determination)

$$w_1 = \psi\left(\alpha p_1 \frac{y_1}{n_1} + (1-(1-\rho)s)\kappa_2\theta_2\right) + (1-\psi)(\tau s^\iota + b - \tau)$$
$$w_2 = \psi\left(\alpha p_2 \frac{y_2}{n_2} + \kappa_2\theta_2\right) + (1-\psi)(b-\tau)$$

(evolution of employment)

$$(\rho + (1-\rho)sf(\theta_2))n_1 = q(\theta_1)v_1$$
$$\rho n_2 = q(\theta_2)v_2$$

(unemployment)

$$u_1 + u_2 = 1 - n_1 - n_2$$

(free unemployed mobility)

$$\kappa_1\theta_1 = \kappa_2\theta_2$$

(fiscal balance)

$$T = b(u_1 + u_2)$$

(resource constraint)

$$c + \tau s^{\iota} n_1 + \tau u = y - \kappa_1 v_1 - \kappa_2 v_2$$

where the output technologies $y = \left[(1-\gamma)y_1^{\frac{\sigma-1}{\sigma}} + \gamma y_2^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, $y_j = z_j n_j^{\alpha}$ are given, and market tightness $\theta_1 = v_1/u_1, \theta_2 = v_2/u_2$, the vacancy filling rate $q(\theta_j) = \mu(z_j)\theta_j^{-\eta}$ are defined as before.

3.A.5 Data Series of the US Economy

The US data used in the stochastic simulations are real values for the period 2001.Q1 - 2016.Q4. This data is available from the US Bureau of Economic Analysis (BEA) and the US Bureau of Labor Statistics (BLS).

1. real gross domestic product per capita (chained 2009 dollars)
2. real personal consumption expenditures per capita (chained 2009 dollars)
3. all employees, total nonfarm payrolls
4. civilian noninstitutional population
5. weekly hours of production & nonsupervisory employees, total private
6. real compensation per hour, nonfarm business sector (index 2009=100)
7. gross domestic income
8. gross domestic income: compensation of employees
9. quarterly census of employment and wages by industry (seasonal adjusted by Census X-12 method) $\Rightarrow \mathbf{w_1},\ \mathbf{w_2},\ \mathbf{n_1},\ \mathbf{n_2}$ constructed

The constructed series using the above raw data are as follows:

- output per capita, $\mathbf{y}$ = (1)
- consumption per capita, $\mathbf{c}$ = (2)
- employment, $\mathbf{n}$ = (3) $\div$ (4)
- real wage, $\mathbf{w}$ = (5) $\times$ (6) $\times$ 12
- labour income share = (8) $\div$ (7)
- labour productivity = (1) $\div$ ((5) $\times$ 12)

Concluding Remarks

The puzzling phenomenon of labour clustering into the low-wage sector despite the widening wage gap, makes the fundamental assumptions behind the theory of competitive markets highly questionable. This thesis has explored a series of questions to seek the underlying factors for this phenomenon: (i) Are there any frictions or barriers to labour mobility across sectors? (ii) If so, can labour mobility frictions account for labour market distortions? (iii) Lastly, what is the main source of labour mobility frictions?

First, we have found empirical evidence for labour mobility frictions from the US labour market. Wage gaps between sectors have been large and increasing during the last two decades, driven by a rise in unexplained factors. Labour transition from the high- to the low-wage sectors has increased but has declined in the reverse direction, leading to labour concentration in less productive sectors. Even when controlling for a worker's characteristics, occupation, and work experience, her wage can significantly increase by an upward movement. The pecuniary costs for workers to switch sectors have increased. All this evidence supports the existence and even the increase of labour mobility frictions.

As a next step, we verified that labour mobility frictions cause labour market distortions. A multi-sector model shows that limited substitutability in labour supply between sectors triggers the widening wage gap and labour clustering in the low-wage sector while changes in the labour demand side alone cannot explain these distortions. From the calibrated model, we estimated that the degree of mobility frictions has risen and its elevation incurs a non-trivial economic loss in terms of output and utility by worsening labour misallocation and wage inequality.

In answering the last question, we identified differential matching efficiency as one important source of labour mobility frictions. More importantly, this difference stems from the productivity gap between sectors. A two-sector search and matching framework embedded with this productivity-driven friction process can simultaneously track the actual data of the wage gap and labour allocation in the US. Without the friction process, the labour market puzzle cannot be explained even when the productivity gap increases.

This study leaves some possible directions for future research. First, more empirical work on the source of labour mobility frictions is required. Such an attempt will be a stepping stone to stable growth for the labour market because finding various sources of frictions is directly connected to correctly diagnosing the root causes of frictional labour mobility and the unbalanced labour market. Additionally, it is necessary to investigate inter-sectoral labour mobility taking heterogeneous occupations or skills into account. We have treated job seekers as homogeneous, but in principle, they must be treated according to their heterogeneous skills. This disaggregated approach might help analyse current labour market distortions in more detail as well as shedding light on the driving factors for inter-sectoral labour mobility with regard to, for example, occupational structure changes. Related economic policies should also be discussed with an aim to improve economic disparity and promote growth.

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