Overhead Labour and Skill-Biased Technological Change: The Role of Product Diversification

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Abstract

Most of the literature on skill-biased technological change views both skilled and unskilled labour as variable inputs. In contrast, this study focuses on the role of skilled workers comprising overhead labour in the recent increase in skill demand. The first chapter focuses on the aggregate shift in skill demand, while succeeding chapters focus on the heterogeneity of this demand across firms.

In the first chapter, I argue that the transition from Ford-style mass production toward mass customization in the 1980s may be responsible for the increase in skill demand since introducing new goods requires fixed labour input, which is biased towards skilled workers. I present a dynamic general equilibrium model, which explains both the rapid growth in skill demand since the 1980s and the recent puzzling slowdown since the late 1990s. However, as the ratio of fixed to variable inputs cannot increase indefinitely, my model also predicts that the growth in skill demand will slow down in the long run.

In the second chapter, using UK manufacturing data, I show that the employment share of non-production workers is positively correlated with firm size but negatively correlated with the latter over time. I argue that this serves as evidence for the existence of (partially) fixed skilled labour, with the premise being that firms with larger fixed input are both larger in size and have a higher share of non-production workers. However, short-run output expansion only increases variable labour, and therefore it decreases the employment share of non-production workers.

In the third chapter, I present a second piece of evidence in support of the main thesis of this dissertation. I show that exiting firms as well as entering firms have a higher share of non-production workers in UK manufacturing industries. This phenomenon is rather puzzling as exiting firms have lower labour productivity, but nevertheless the finding presents itself as being consistent with the contention of this study that skilled workers constitute an overhead labour input.

Chapter 1

The role of product diversification in skill-biased technological change

1.1 Introduction

The wage gap between the white-collar and the blue-collar workers has risen significantly in the US since the 1980s. [1] The majority of the literature (e.g., Autor et al. [1998]; Katz and Murphy [1992]; Autor et al. [2008]) attributes this shift to technological change, indicating that recent technological developments such as the rise of information technology tend to favour skilled workers, a hypothesis referred to as the skill-biased technological change (SBTC) hypothesis.[2]

The question arises as to how technological changes affect the skill de-

[1]The UK also experienced a sharp rise in the wage differential during this period. Although this trend has been noted to be less strong in countries such as Germany and Sweden [Machin and van Reenen, 1998], the shift in labour demand towards white-collar workers has been identified as common in many industrialized countries.

[2]Autor et al. [1998], for example, found that the share of college-graduate workers had risen faster in more computer-intensive industries.

mand. The most common interpretation, described by Acemoglu and Autor [2010] as the canonical model of skill-biased technological change, is that a certain type of technological innovation enables white-collar workers to produce goods more efficiently than blue collar workers. As a result, the demand for white-collar workers as well as their wages increase relative to those of blue-collar workers. It focuses on process innovation by assuming single representative output good production function, but largely ignoring the role of product innovation. It assumes that the rising wage gap is the result of the rising productivity gap between workers, and that both white-collar and blue-collar workers constitute variable input.

However, the assumption that white-collar labour is entirely variable input is questionable, considering that most white-collar workers are working either in the office or in the laboratory rather than working in the factory with blue-collar workers, and that their tasks are rather loosely related with the production quantity. Literature suggests that non-production workers are more likely to be overhead labour or quasi-fixed rather than variable input (Dunne et al. [1996]; Nekarda and Ramey [2013]; Gujarati and Dars [1972]; Hamermesh [1993]). Therefore, in line with the above, this study will assume that white-collar workers are overhead labour, and that the shift in the skill demand occurs not because white-collar workers are replacing blue-collar workers in the production process, but because the non-production tasks, usually implemented in the office or in the laboratory, increases more than the production tasks implemented in the factory.

Although a significant portion of literature suggests the existence of overhead labour, the determinants of the demand for the overhead labour are not clear, yet. This study focuses on the role of product diversification, and presents a dynamic general equilibrium model where the demand for overhead labour, which is biased toward white-collar workers, increases with product variety. For example, to develop a new mobile phone, many white-collar workers including engineers, designers, marketing experts, project managers and other administrative support staff members are needed irrespective of production volume. Therefore, this study presents a general equilibrium model wherein the demand for white-collar workers increases with the product variety.

Although white-collar workers are assumed to be a fixed input, this does not mean that aggregate labour demand for them is independent of the GDP and their wage. White-collar employment is assumed to be fixed per each product, but equilibrium product variety increases with GDP in the long-run, increasing the demand for white-collar workers.[3] Similarly, if the wage for white-collar workers decreases, the equilibrium product variety in the economy increases due to the fall in the fixed labour cost of producing a new product, thereby increasing the demand for white-collar workers.[4] Therefore, this model also predicts the relative employment of white-collar workers is negatively related to the relative wage (to the blue-collar workers) even though white-collar workers do not directly replace blue-collar workers in the factory.

This model leads to a new interpretation of skill-biased change, which is distinguishable from the conventional view. During the 1980s in the US, product variety increased dramatically, which was interpreted as a

[3]This is in line with Gujarati and Dars (1972), who comment that 'it is assumed that wages paid to production workers are essentially variable costs of production, whereas those paid to non-production workers are mostly in the nature of overhead or fixed costs, at least in the short-run.' My model predicts that a short-run expansion of output, which does not involve an increase in product variety, does not increase the demand for white-collar workers, while long-term growth of output, which accompanies the increase in the product variety, increases the demand for white-collar workers.

[4]This implies that the elasticity of substitution between white-collar and blue-collar workers increases with the degree of aggregation.

transition from Ford style standardised production towards more diversified production, the so called "Flexible Manufacturing System" (Milgrom and Roberts [1990]; Mansfield [1993]). This study suggests that such a change could have increased relative demand for white-collar workers. As the main driver of the change was supposed to be the dramatic fall in the fixed capital cost of producing new products due to the IT revolution ([Milgrom and Roberts, 1990] argue that the rapid fall in the price of computer capital was the main driver of massive product diversification in the 1980s), this study also supports the view that the IT revolution played an important role in skill-biased technological change.

This thesis presents predictions, which differ from the standard skill-biased technological change models. Firstly, the employment share of white-collar workers is not necessarily positively related to the aggregate labour productivity. Therefore, it could help to explain the puzzling fact that the period with strong skill-biased technological change does not always accompany higher aggregate productivity growth. Secondly, skill-biased technological change always interacts with the market-structure. The source of the wage expenditure to the fixed labour come from gross-profit[5] of the firms. Therefore, if the market is in perfect competition, there is no room for the employment of white-collar workers. The size of the mark-up imposes upper bound of the share of fixed labour in the total labour force, and the mark-up depends on numerous non-technological factors as well. Thirdly, the rise in skill demand driven by the IT revolution is predicted to slow down in the long-run. Given the mark-up, the fall in the fixed capital cost, driven by the IT revolution, allows more of the firm's gross profit to be diverted towards the wage expenditure on fixed

[5] The profit before paying for fixed costs

labour (white-collar workers). However, such a shift is supposed to slow down as the share of the fixed capital cost (in the total fixed cost including both the labour part and the capital part) approaches zero. Unless the size of the price-cost mark-up increases endlessly, which is quite unlikely, the wage-bill share of white-collar workers cannot increase indefinitely, although the fall in the fixed capital cost continues indefinitely due to the continuing progress in IT technology. This is consistent with the empirical findings that skill-biased change has begun to slow down recently (Autor et al. [2008]; Beaudry et al. [2013]).

This study is not the first to inquire into the effect of product innovation on skill-biased change. For example, Xiang [2005], Thoenig and Verdier [2003] and Sanders [2002] have also argued that new goods increase the demand for skilled labour because their production processes are more skill-intensive. They all assume that white-collar workers constitute a variable input as in the conventional SBTC literature. In contrast, in this study, an increase in product variety increases the demand for white-collar workers irrespective of whether the production processes of the new goods are more skill-intensive or not.

The remainder of the chapter is structured in the following way: Section 1.2 illustrates recent labour market trends. Section 1.3 explains the role of product innovation in skill-biased technological change. Section 1.4 presents the model and the simulation results. Section 1.5 concludes.

1.2 The trend in the wage-inequality

The trend in the wage gap between college and non-college educated workers in the US is shown in Figure 1.1. The wage gap increased slowly until the early 1970s, and then it began to close in before increasing again dramatically in the 1980s and continuing a slower, but still positive, growth throughout the 1990-2000s. The dramatic shift in the 1980s drew much attention, and there was contention in a significant portion of the literature that the adoption of PCs in the 1980s was responsible for it.

Figure 1.1: College/High school graduates wage ratio, 1963-2008

Source: Acemoglu and Autor [2010]

Although the pattern was not identical, such a shift did not remain confined to the US. Machin and van Reenen [1998] studied the US, the UK, Germany, Japan, France, Denmark, and Sweden and found that both the employment share and the wage-bill share of non-production workers rose in all of these countries, while the wage gap remained stable, with the exception of the US and the UK. The fact that the employment share rose in all the investigated countries implies that the shift in labour demand towards white-collar workers existed for all of these countries, although the wage gap did not increase for most of them.[6]

[6]The wage differential between non-production workers and production workers in Sweden declined slightly from 1.549 in 1977 to 1.509 in 1989, but the employment share of non-production workers rose from 0.288 to 0.303.

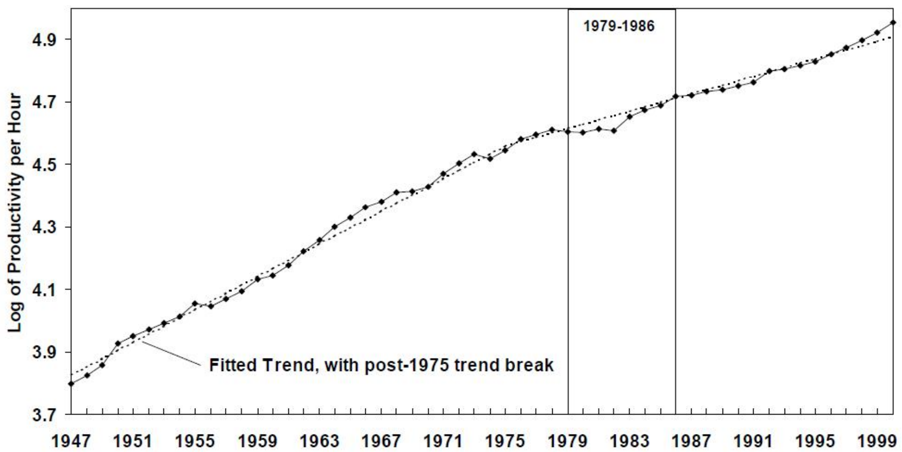
SBTC and the Productivity Puzzle

A majority of literature on SBTC has utilized the simple two factor CES function to formulate the skill biased technological change hypothesis. It is assumed that there are two types of labour input: skilled labour and unskilled labour. The functional form is as below:[7]

$$Q_t = \left[\alpha_t \left(a_t N_{s,t}\right)^{\rho} + \left(1-\alpha_t\right)\left(b_t N_{u,t}\right)^{\rho}\right]^{\frac{1}{\rho}}, \quad 0<\rho<1 \tag{1.1}$$

Here, Q_t is the output at time t, $N_{s,t}$ is the labour input of skilled workers at t, which is usually defined as the number of college graduate workers or white-collar workers. $N_{s,t}$ is the labour input of unskilled workers, defined as the number of workers with lower education or blue-collar workers. a_t is the skilled labour-augmenting technology, and b_t is the unskilled labour-augmenting technology. α_t can be interpreted as the share of production activities assigned to skilled labour. Capital is either non-existent or separable from the composite labour input.

Figure 1.2: Aggregate labour productivity



Source: Card and DiNardo [2002], Labour productivity per hour, non-farm business sector

[7] Acemoglu and Autor [2010] referred to it as the 'canonical' model

Skill-biased technological change is represented either by an increase in a_t relative to b_t or by an increase in α_t. Therefore, skill-biased technological change is supposed to increase aggregate productivity unless the decline in blue-collar labour augmenting technology is large enough to offset the rise in white-collar labour augmenting technology. However, according to Card and DiNardo (2002), the puzzling fact is that the aggregate labour productivity was stagnant during the 1980s in the US, a period when the shift in labour demand was most dramatic. This can be seen in Figure 1.2, which shows that between 1979 and 1986 the growth in labour productivity slowed down, and its level was below the long-term trend. One possible explanation is that the productivity growth of blue-collar workers slowed down during 1980s and offset the productivity growth of white-collar workers. But, it is not certain what caused the slowdown of the productivity growth of blue-collar workers.

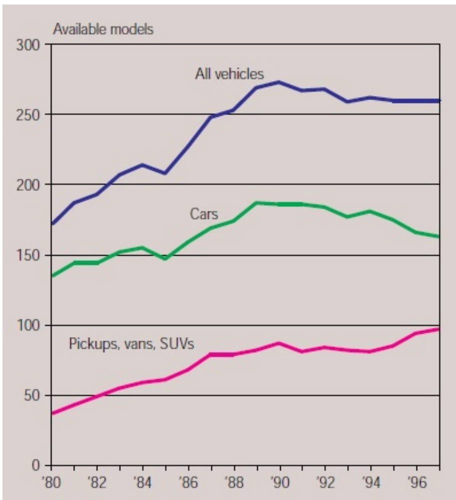
Moreover, the labour productivity growth began to accelerate in the 1990s, but the growth of wage differential by skill slowed down at the same time. Therefore, this thesis tries to focus on another channel of skill-biased technological change, which increases the wage premium of white-collar workers without necessarily increasing the aggregate labour productivity.

1.3 The role of product variety

Most existing literature on skill-biased technological change has largely focused on process innovation, while largely ignoring the role of product innovation on SBTC. They assume a single representative good and argue that technological innovations, such as the adoption of the PC, amplified the productivity of the college graduate workers relative to the productivity of the blue-collar workers. There is no place for product innovation in the theoretical framework. However, product innovation accounts for a very significant part of R&D activities. For example, according to Petrin and Warzynski [2012], 74% of the total R&D expenditure is spent on product innovation in Denmark. Similarly, Lin and Saggi [2002] also note that 'approximately three-fourths of R&D investments by firms in the United States are devoted to product R&D'.

Empirically measuring product variety is very difficult. However, there have been some attempts, and it is known that product variety has dramatically increased since the 1970s. According to Cox and Alm [1998], between the early 1970s and the late 1990s, the number of vehicle models available rose from 140 to 260, soft drinks from 20 to over 87, over-the-counter pain relievers from 17 to 141, running shoes from 5 to 285 and PCs from 0 to 400. Figure 1.3 shows how the number of vehicle models evolved over time in the US since 1980.

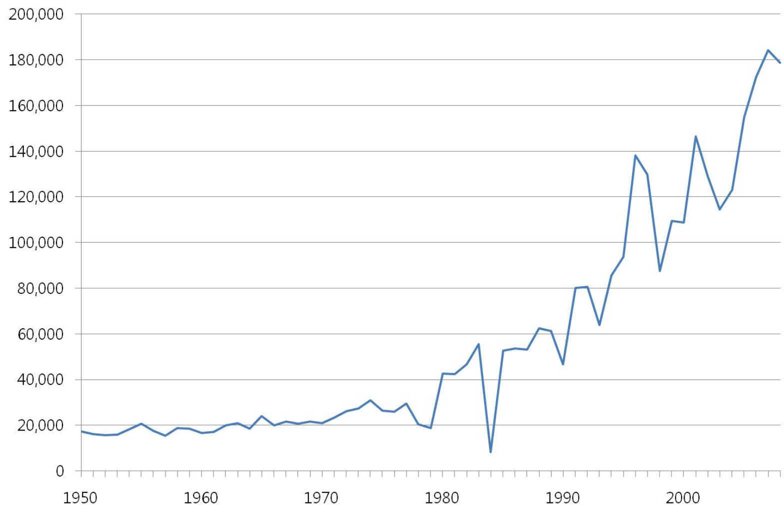
Figure 1.3: The number of vehicle models 1980-97



source: "America's Move to Mass customization", Cox and Alm [1998]

Greenwood and Uysal [2005] utilised the trademark registration statistics as a proxy for product variety. Figure 1.4 shows the trend of trademark registration in the US between 1950 and 2008. It was noted that the number of trademark registrations rose steadily since the 1980s, a trend which coincided with the rising wage inequality of the 1980s.[8] Moreover, the number of firms per capita also increased accordingly for the same period (Greenwood and Uysal [2005]) as illustrated in Figure 1.5.

Figure 1.4: The trademark registration

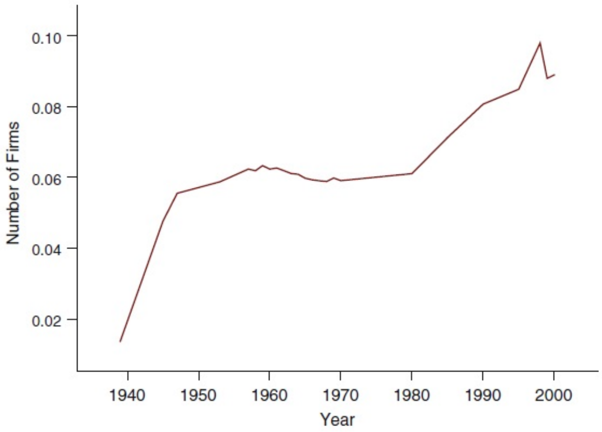


Source: WIPO, "World Intellectual Property Indicators"

There is literature, which has investigated the role of product innovation in SBTC. Xiang [2005] has argued that the introduction of new goods favours skilled labour because new goods are produced with more skill-biased technology than existing goods. This study shows that the average skill intensity of new goods was more than 40% higher than the old goods in the US manufacturing industries between the late 1970s and the 1980s. Thoenig and Verdier [2003] have argued that the competitive

[8]Xiang [2005] attributes the surge in inequality in the 1980s to the availability of new products, 'such as fiber optic cables, Windows series software, VCRs and soft contact lens.'

Figure 1.5: The number of firms per capita in the US



Source: Greenwood and Uysal [2005]

pressure from southern low-wage countries has induced northern countries to adopt skilled-labour intensive technologies because they are harder for southern countries to imitate. It is assumed that the production process of new goods is more skill intensive than that of old goods, which southern countries can also produce. Northern firms are forced to adopt the new technology to avoid competing with southern countries. Sanders [2002] has argued that the development of new goods is skill-biased because production of new goods requires more skilled labour, who can flexibly deal with uncertainty of production, which is higher in the early stage of product life cycle. However, this literature commonly assumes that introducing new products increases skill demand because the production process of new goods is more skill-intensive than old goods.[9]

Nevertheless, this is not necessarily true for every new good, especially for horizontal product differentiation. One recent example is the development of the iPhone 4 white colour version by Apple. It is identical to

[9] This contrasts with Nelson and Phelps [1966] who argue that more educated workers are needed to adopt the latest vintage of production technology more quickly.

the black colour version except for the colour, and there is no technological improvement from the black colour version.[10] This thesis will focus on the effect of horizontal product differentiation, in which case the new goods are not necessarily technologically more sophisticated, and therefore do not necessarily require more skilled workers in the production process.

The difference in this study is that the introduction of any new goods increases the relative demand for white-collar workers, regardless of the level of technological sophistication.

The share of fixed labour cost

Firms can pay for fixed inputs only if their gross profit (profit before paying fixed costs) is positive. This means that firms can pay for fixed inputs, which includes both a fixed labour and a fixed capital, only if the price is greater than the marginal cost. This implies that the mark-up ratio must be greater than 1. Under the assumption of free-entry, firms will earn zero net profit (profit after paying fixed costs) although their gross profit would be still positive:

$$\pi = (p \cdot q - WB_v - r \cdot k_v) - (WB_f + r \cdot k_f) = 0 \tag{1.2}$$

Here, WB_f is the total wage bill for fixed labour, and WB_v is the total wage bill for variable labour. The former is supposed to be biased towards white-collar workers while the latter is supposed to be biased towards blue-collar workers. $r \cdot k_f$ is the total expenditure on fixed capital, and $r \cdot k_v$ is the total expenditure on variable capital. The first term of the equation (1.2)

[10]However, Apple spent a significant amount on R& D because making it whiter involves some technological difficulties, such as the UV protection issue to simply to make it white.

represents the gross profit. The ratio of total fixed cost to total variable cost in the zero-profit equilibrium is :

$$\frac{WB_f + r \cdot k_f}{WB_v + r \cdot k_v} = \mu \tag{1.3}$$

Under the assumption of constant marginal cost and free entry and exit, the LHS, which is the ratio of the fixed to the variable cost, must be the same as $\mu = \frac{P-MC}{MC}$.[11] Under the assumption that white-collar labour is an entirely fixed input and blue-collar labour is an entirely variable input, the equation (1.3) is equivalent of:

$$\frac{WB_w + r \cdot \widehat{s_f} \cdot k}{WB_v + r \cdot (1 - \widehat{s_f}) \cdot k} = \widehat{\mu} \tag{1.4}$$

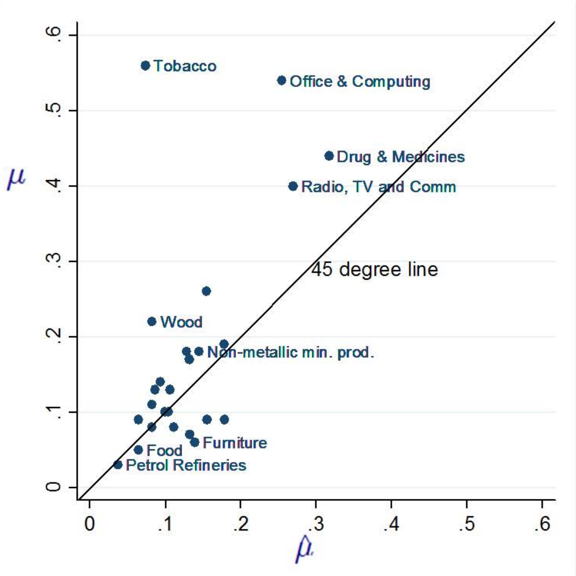
Here, WB_w is the total wage bill for white-collar labour, and WB_b is the total wage bill for blue-collar labour. $\widehat{s_f}$ is the share of fixed capital in the total capital stock, k. The values of $\widehat{\mu}$ have been constructed using US manufacturing data over 1970-1992 and compared with μ.

The data on the wage bill for both production workers and non-production workers and capital stock comes from the NBER-CES Manufacturing Industry Database, which is based on the ASM (American Survey of Manufacturers). The interest rate used here is the Baa rated corporate bond rate, which comes from the FRB (Federal Reserve Board). The inflation rate is from the U.S. Bureau of Economic Analysis.

The data on the mark-up is from Oliveira Martins et al. [1996]. In that study, the mark-up ratios for 36 manufacturing industries in the US are estimated over 1970-1992 utilizing the method of Roeger [1995], assuming that the mark-up ratio is constant over the period. However, not all indus-

[11] While mark-up is the ratio between the price and the cost, μ is the ratio between variable profit and marginal cost. $\mu =$ mark-up-1

Figure 1.6: Mark-up vs Implied Mark-up



try groups in Oliveira Martins et al. [1996] showed significant estimates for the mark-up ratio, and only the estimates for 26 industry groups amongst them are used in this study. The list of mark-up ratios for each industry and the method of estimation are shown in the Appendix. The rental rate of capital, r, is derived following Oliveira Martins et al. [1996]:

$$r = ((i - \pi) + \delta) \cdot p_k \tag{1.5}$$

Here, i is the nominal interest rate, which is given by the Baa rated corporate bond rate (by Moodies). π is the inflation rate, and δ is the depreciation rate, which is set to 5% per year. p_k is the price index of the investment good.

One problem is that the share of fixed capital in the total capital stock is unobservable. To deal with this, the share of plant and buildings in the total capital stock is used as a proxy for the share of fixed capital. The rationale is that buildings are usually adjusted more rigidly than equipment or vehicles. For example, at least one head-quarter building and one factory are needed to establish a firm. Then, it is possible to increase equipment without building another factory (upto a certain level). However, this is a crude measure as some part of equipment or vehicles might be fixed capital as well.[12]

The comparison of μ and $\widehat{\mu}$ is shown in Figure 1.6. There is a positive correlation between them. Those industries with a higher share of fixed costs, such as Office & Computing, Drug & Medicine and Radio, TV & Communications, are also shown to have a higher mark-up ratio. Those with a lower share of fixed cost, such as Food Products and Petrol Refineries, are shown to have a lower mark-up ratio.

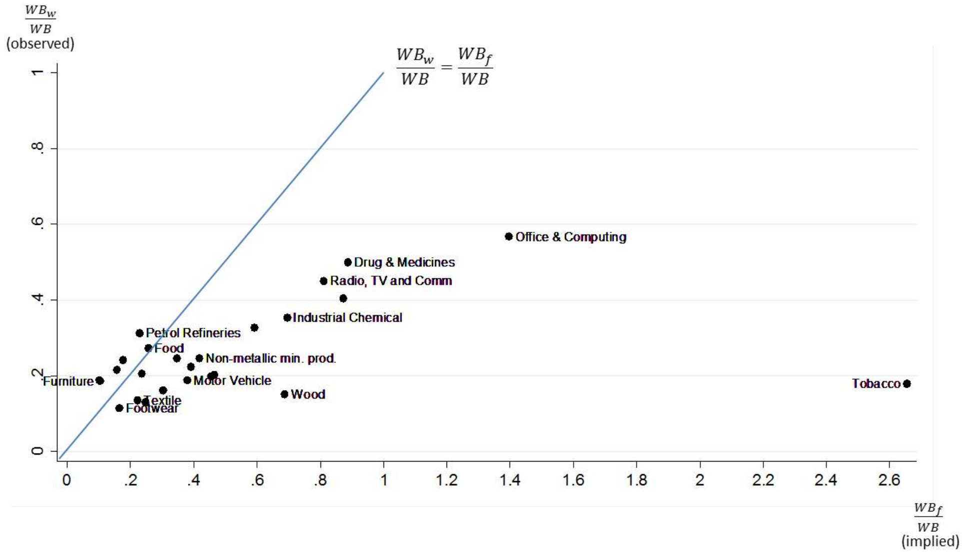
However, many industries, especially tobacco industries, show much higher mark-up ratio than is implied from the ratio of fixed cost to variable cost. This may suggest the existence of excess profit due to market power. Moreover, although it is assumed that the share of fixed capital equals the share of building and plant capital, part of equipment or vehicles may be fixed input as well, which causes downward bias in the estimated share of fixed capital, $\widehat{s_f}$ and the implied mark-up, $\widehat{\mu}$. If the assumption of constant marginal cost is violated and the actual marginal cost is decreasing in scale, it also lowers the ratio of fixed cost to variable cost relative to the mark-up ratio in the zero-profit equilibrium.

It is also possible to derive the implied wage-bill share of white-collars (relative to the total wage-bill including both white-collar and blue-collar workers) from the equation (1.3) and (1.4). Then, the actual wage-bill share of white-collar workers is compared with the implied wage-bill share

[12] As we discuss long-run equilibrium, the term "fixed capital" means the capital which does not adjust as the output level varies in the long run as well as in the short run.

of fixed labour in Figure 1.7. These two must be the same by construction if $\widehat{\mu}$ is the same as μ.

Figure 1.7: Observed wage-bill share vs implied share



For the same reasons as the implied ratios of fixed cost to variable cost (supposed to be the same as μ) are lower than μ, the observed wage-bill shares of white-collar workers are lower than the implied wage-bill share of fixed labour. The fact that the implied wage-bill share exceeds 100% for some industries, which is impossible in reality, implies that some of the implied wage-bill shares of fixed labour are clearly overestimated. However, the observed wage-bill shares of white-collar workers are shown to be positively correlated with the implied wage-bill shares of fixed labour. Although this is not a very robust result, it is consistent with the hypothesis that white-collar labour should be considered overhead labour.

1.4 Model

In this model, people value the variety of consumption as well as the quantity of consumption. People are even willing to substitute some consumption quantity for more variety of consumption. [13] To accommodate such a 'love of variety' property, this model utilizes Dixit and Stiglitz [1977] style monopolistic competition framework.

Most Dixit-Stiglitz style monopolistic competition models usually assume the existence of fixed costs, which comprise either a output good or a labour input. The modifications made in this model are : firstly, the fixed cost includes not only fixed labour cost but also fixed capital cost to incorporate the role of the decline in fixed capital cost (possibly due to IT technology), and secondly, the fixed labour input is biased toward white-collar workers (non-production workers). [14] It will be shown later in this chapter that these two seemingly minor modifications jointly generate results, which are significantly different from conventional skill-biased technological change models.

1.4.1 Utility

Consumer utility is increasing with the consumption level of composite good x:

$$U = u(x) \tag{1.6}$$

$$u' > 0, u'' < 0$$

[13]In Krugman [1979b], the motivation of technological innovation is not producing the same goods more efficiently but producing new goods to gain more monopoly power.

[14]In this study, I assume that the term 'white-collar workers' is a synonym for the 'non-production workers', and that they have a higher educational level than production workers, while the term 'blue-collar workers' is synonymous with 'production workers'.

The composite good, x, is defined by a CES function as below:

$$x = \left(\int_0^N q(i)^\rho di \right)^{\frac{1}{\rho}} \quad 0 < \rho < 1$$

Here, $i \in [0, N]$ is the index of the product variety, where N represents the maximum level of variety available in the economy ($N \in R_{++}$). The constant ρ represents the substitutability between different goods. The lower the ρ is, the lower the substitutability is. The elasticity of substitution is $\frac{1}{1-\rho}$. It is assumed that every consumer has an identical preference and the elasticity of substitution is also identical for every product i.

1.4.2 Firm's problem

Each product variety is produced with the identical technology following a Cobb-Douglas functional form, but production can begin only if the firm employs both fixed labour and fixed capital above minimum required levels ($\bar{l}$, $\bar{k}$):

$$q_i = A \cdot (l_i^b)^\alpha \cdot (k_i^v)^{1-\alpha} \qquad if \quad l_i^w \geq \bar{l} \quad \& \quad k_i^f \geq \bar{k}$$

Here, q_i is the production volume of product variety i, and l_i^b is the blue-collar labour input for producing a product i. As it is assumed that only blue-collar workers constitute variable labour input, their employment is equivalent to the variable labour input. k_i^v is the variable part of the capital input for good i. The parameter A represents the exogenous level of skill-neutral production technology, which augments all factor inputs proportionately.[15] It is assumed that the production technology, A, is

[15]TFP is defined as the change in output which is not caused by the change in input. However, A differs from typically measured TFP in that it accounts only for the change in variable input excluding fixed input, while typical TFP accounts for both fixed and

exogenous and independent from the employment of white-collar workers.

There is no economy of scope, so every firm produces only one product. Therefore, the number of product varieties is the same as the number of firms. As most firms are multi-product firms in reality, the firm in this model should be understood as one of the many divisions within a firm rather than as a firm in the form of a legal entity.[16] Moreover, even the same type of product of the same firm sold in different markets (country, region or targeting consumer's demographic group, etc.) should be interpreted as different products produced by different firms in this model.

Nekarda and Ramey [2013] suggest that the upper bound of the share of the overhead labour is the share of non-production workers, and this is because the elasticity of the employment of non-production workers with respect to the output is significantly less than that of production workers but still greater than zero.[17]

However, the fact that the employment of white-collar workers still fluctuates with the output does not contradict the assumption that the number of white-collar workers per each product variety is fixed. The employment of fixed labour comprised of white-collar workers for a multi-product firm is expected to increase with the expansion of the product range of the firm, which is very likely to be positively correlated with the output as firms need to expand to wider range of markets to sell more quantities of goods. According to Hottman et al. [2014], 'variation in firm quality and

variable input.

[16]The Dixit-Stiglitz style monopolistic competition model, which implies single product firm, is adopted for simplicity although in reality most firms are multi-product firms. Within this framework, however, multi-product firms can be understood as a group of different divisions, independently producing different goods.

[17]Nekarda and Ramey [2013] finds that 'the elasticity of the log of employment of nonproduction workers to GDP is positive and statistically significant and is about half of the elasticity of production workers with respect to GDP'

product scope explains at least four fifths of the variation in firm sales.' Therefore, overhead labour input can be still indirectly correlated with the output. To sum up, the demand for white-collar labour is fixed only per each product variety, but not fixed at more aggregated level comprising multiple products.

Although it is possible that a significant portion of white-collar labour constitutes variable labour rather than overhead labour, it is very hard to know the share of non-overhead part. Moreover, the fact that the demand for white-collar workers fluctuates with output does not necessarily reject the hypothesis that the entire white-collar labour is overhead labour. Therefore, it will be assumed in this model that the entire white-collar workforce constitutes overhead labour, which is still correlated with output at a more aggregated level.

Firm's profit maximization

Each firm is small enough not to influence the factor prices, and firms optimize the employment level of both variable and fixed factors given the factor prices to maximize the profit:

$$\begin{aligned}\pi_i =& p_i \cdot q_i - c(q_i) - fixed\ cost \\ =& (p_i - mc) \cdot q_i - fixed\ cost\end{aligned}$$

Firm i's profit, π_i, is total revenue minus the sum of the variable costs and the fixed costs. Because every firm has partial monopolistic power, firms set price higher than marginal cost. The lower the substitutability between goods, the higher is the mark-up. All firms set the same price, given the demand curve derived from the CES utility function of the equation (1.6) :

$$p_i^* = \frac{mc}{\rho}$$

$$mark\text{–}up\ (= \mu + 1) = \frac{p}{mc} = \frac{1}{\rho}$$

The total variable cost, $c(q_i)$, is the sum of total wage bill for blue-collar workers and the variable capital cost:

$$\begin{aligned} c(q_i) =& mc \cdot q_i \\ =& W_b \cdot l_i^b + r \cdot k_i^v \end{aligned}$$

Here, mc is the marginal cost, which is constant.[18] W_b is the wage for blue-collar workers, and r is the interest rate. The fixed cost, which consists of fixed labour input as well as fixed capital input is:

$$fixed\ cost = W_w \cdot \bar{l} + r \cdot \bar{k}$$

Here, W_w is the wage for white-collar workers, and $\bar{l}$ is the minimum required level of fixed labour for each product, which is assumed to be identical for all firms. The employment of white-collar labour for firm i, l_i^w, is equal to $\bar{l}$. Similarly, the employment of fixed capital equals to $\bar{k}$ for all firms. The interest rate, r, is the same for both variable capital and fixed capital.

[18] The marginal cost is constant because the Cobb-Douglas production function exhibits constant returns to scale and the factor prices do not change with the production level of individual firms.

The employment of blue-collar labour is determined so that the value of marginal revenue product of labour (MRPL) equals the wage. Here, $MRPL = MR \times MPL$. [19] Given the above CES-preferences shown in equation (1.6), $MR = p \cdot \rho$. As the price of the output, p, is normalized to 1 and $MR = \rho$. The demand for blue-collar labour for a firm i is:

$$l_{b,i} = \left\{ A \cdot \alpha \cdot k_{v,i}^{1-\alpha} \cdot \frac{\rho}{W_b} \right\}^{\frac{1}{1-\alpha}}$$

The same applies to the variable capital input:

$$k_{v,i} = \left\{ A \cdot (1-\alpha) \cdot l_{b,i}^{\alpha} \cdot \frac{\rho}{r} \right\}^{\frac{1}{\alpha}}$$

Due to the symmetry condition, every firm's optimal level of employment is identical: $l_b = l_{b,i}$ and $k_{v,i} = k_{v,i}$ for all firms i.

Zero-Profit condition

Free entry is assumed. If firms earn positive profit, new firms will enter the market, and production quantity for existing firms will decrease as a result of competition. Therefore, all firms will make zero profit in equilibrium. Hence:

$$\begin{aligned} \pi_i^* =& (p_i^* - mc) \cdot q_i^* - fixed\ cost \\ =& mc \cdot \left(\frac{1}{\rho} - 1 \right) \cdot q_i - fixed\ cost = 0 \end{aligned}$$

[19] In a monopolistic competition market, $MR < P$, unlike a perfect competitive market where $MR = P$.

$$\frac{W_w \cdot \bar{l} + r \cdot \bar{k}\,(= fixed\ cost)}{mc \cdot q\,(= total\ variable\ cost)} = \mu = \frac{1}{\rho} - 1 \tag{1.7}$$

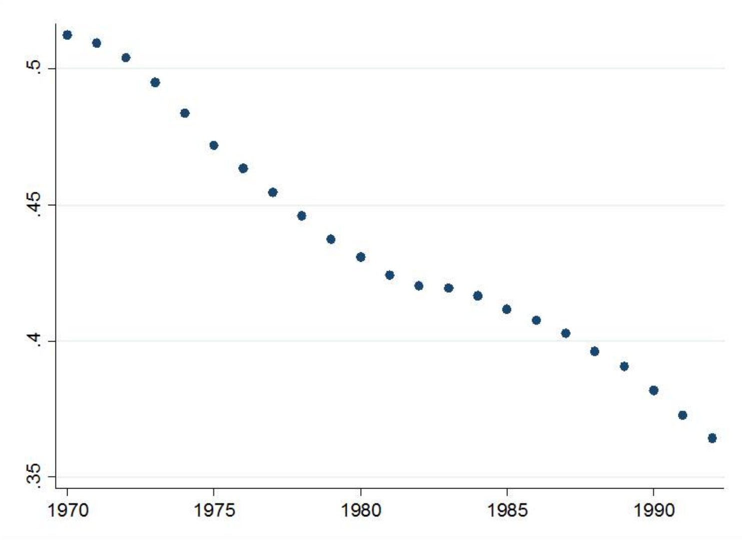
Equation (1.7) shows that ratio between the total fixed cost and the total variable cost is determined by the mark-up ratio. Under symmetry, all firms will produce the same amount of goods with the same amount of input in equilibrium. Therefore, $q_i = q$, $l_i = l$, $k_i = k$ for all i. Recall that the shift in labour demand towards white-collar workers happens for two reasons in our model:

1. mark-up$\uparrow$: Total expenditure on fixed factors increases relative to variable factors.
2. fixed capital cost$\downarrow$: Given a total expenditure for fixed factors, fixed labour cost (the employment of white-collar workers) will constitute a higher share.

The mark-up ratio is unlikely to have risen continuously. However, the fixed capital cost is likely to have declined relative to the fixed labour cost for two reasons. The total fixed capital cost per variety is $r \cdot \bar{k}$, where that of labour is $W_w \cdot \bar{l}$. If both the exogenous parameters, $\bar{k}$ and $\bar{l}$, remain constant, the fact that the growth rate of wage is usually higher than that of the interest rate decreases fixed capital cost relative to fixed labour cost. Moreover, the adoption of FMS (Flexible Manufacturing Systems) could have lowered the minimum fixed capital requirement to introduce new variety, $\bar{k}$.

The level of fixed capital stock is unobservable, but the capital stock of plant and buildings can be used as a rough proxy for the fixed capital as in the section 1.3. The trend in the share of the plant and buildings in the

Figure 1.8: The share of plant and building in the total capital stock in US manufacturing industries in 1970-92



source: NBER-CES manufacturing Industry databse.

total capital stock in the US manufacturing industries between the years 1970 to 1992 is shown in the Figure 1.8.

Endogenous skill supply

Both the supply and demand for the white-collar labour is endogenously determined in the model. The supply of white-collar labour is determined as a result of optimization decisions of young workers who compare the wage premium for white-collar workers and the education cost required to become white-collar workers. The demand for white-collar labour is increasing with the number of products, N. However, N is decreasing with the wage premium as lower wage premium of white-collar workers encourages further product diversification by lowering the fixed cost of introducing new products. As a result, the demand for white-collar labour is decreasing with the wage premium. The wage premium is determined so that it equalizes the supply and demand for white-collar labour:

$$L_w^S\left(\frac{W_w}{W_b}\right) = L_w^D\left(N\right) = L_w^D\left(N\left(\frac{W_w}{W_b}\right)\right)$$

In accordance with Caselli [1999], the learning cost, $\sigma_{e,i}$, is assumed to be heterogeneous between workers and only those workers whose learning cost is lower than the wage premium from the education will join education. Those with a lower learning cost will decide to go to the university and become white-collar workers, but those with a higher learning cost will be blue-collar workers. Following Caselli [1999], it is assumed, for simplicity, that each individual's subjective learning cost, $\sigma_{e,i}$, follows uniform distribution so that $\sigma_{e,i} \in [0, \bar{\sigma_e}]$.[20] $\bar{\sigma_e}$ is a exogenous parameter, which represents the learning cost of the worker with the highest learning cost.[21] However, the learning cost in monetary value is assumed to increase with the wage level of unskilled workers as the opportunity cost of education increases with the foregone wage during the period of education. Therefore, each young worker with the leaning cost, $\sigma_{e,i}$, chooses to go to university and become a white-collar worker if $W_w - W_b > \sigma_{e,i} \cdot W_b$. The average learning cost of all workers equals to $\dfrac{\bar{\sigma_e} \cdot W_b}{2}$.

As the wage premium increases, the threshold level of subjective learning cost, below which it is optimal to become a white-collar worker, increases accordingly, and the share of workers who choose to become white-collar workers increases as a result. Therefore, the labour supply of white-

[20] The learning cost is defined in broader terms, and includes not only tuition fee but also any opportunity cost of lost labour income, lost leisure, personal effort and other obstacles to education such as credit constraints.

[21] Unlike Caselli [1999], where the learning cost is independent of the wage, it is assumed that the learning cost is proportional to the wage level of blue-collar workers, as it is likely that the opportunity cost of education increases with the wage level of unskilled labour.

collar workers (relative to total labour force) increases with the wage premium (but decreases with $\bar{\sigma_e}$):

$$L_w^S = \frac{W_w - W_b}{\bar{\sigma_e} \cdot W_b} L$$

$$L_w^D = N \cdot \bar{l}$$

The wage of white-collar workers is determined so that it equates the demand, L_w^D and the supply, L_w^S, of white-collar labour:

$$\therefore W_w = W_b \cdot \left(1 + \bar{\sigma_e} \frac{L_w}{L}\right) = W_b \cdot \left(1 + \bar{\sigma_e} \frac{N \cdot \bar{l}}{L}\right)$$

An increase in N increases the wage for white-collar labour relative to blue-collar workers by increasing the demand for the white-collar labour. However, an increase in $\bar{\sigma_e}$, which represents higher average education cost, increases the wage for white-collar workers relative to blue-collar by lowering the supply of white-collar labour.

1.4.3 Market clearing conditions

Factor markets are cleared, if the sum of the demand of individual firms for each factor input equals the supply (or endowment) of the factor inputs in the whole economy. The total workforce, L, is assumed to be given exogenously but is allocated endogenously between white-collar labour and blue-collar labour:

$$L_b = N \cdot l_b = N \cdot \left\{ A \cdot \alpha \cdot k_v^{1-\alpha} \cdot \frac{\rho}{W_b} \right\}^{\frac{1}{1-\alpha}}$$

$$L_w = N \cdot l_w = N \cdot \bar{l}$$

$$L_b + L_w = L$$

L_b is the total employment of blue-collar workers in the economy, and L_w is the total employment of white-collar workers. Similarly for capital:

$$K_v = N \cdot k_v = N \cdot \left\{ A \cdot (1-\alpha) \cdot l_b^{\alpha} \cdot \frac{\rho}{r} \right\}^{\frac{1}{\alpha}}$$

$$K_f = N \cdot k_f = N \cdot \bar{k}$$

$$K_v + K_f = K$$

The total capital stock in the economy, K, is exogenously given at each point in time, but endogenously allocated between variable part, K_v and fixed part, K_f. However, I will show how capital stock accumulates endogenously over time in section 1.4.5.

1.4.4 Static equilibrium

In this model, both the number of product varieties and the relative demand for white-collar workers are endogenously determined given the total endowment of factors (labour and capital) and exogenous parameters on the technology and the consumer taste. First, the equilibrium number of product varieties, N, is determined from the zero profit condition, and then all other variables such as the relative employment share of white-collar workers and their wage premium over blue-collar workers are determined accordingly.

In this section, the level of total capital stock is supposed to be exogenously given, and firms and consumers optimize given the level of total capital stock, total labour endowment and the exogenous parameters. However, later in this chapter, it will be shown how the level of total capital stock endogenously evolves over time through dynamic optimization behaviours of agents.

Definition. 1. *A competitive equilibrium (static) is a set of consumptions and prices of each product, ($c(i)$ and $p(i)$), variable and fixed factor inputs, (L_w, L_b, K_v and K_f), the number of firms (products), N, wages, (W_w and W_b), interest rate, r, for a set of exogenous parameters, (α, A, L, ρ, $\bar{\sigma}_e$, $\bar{l}$ and $\bar{k}$), given the factor endowment, L and K, which satisfy:*

1. *Each consumer optimally chooses consumption allocation, $c(i)$, for each product i, given prices $p(i)$.*
2. *Each worker optimally chooses whether to become a white-collar worker or a blue-collar worker given the wage levels, (W_w and W_b,).*
3. *Factor allocation, (L_w, L_b, K_v and K_f), solves the firm's problem given the prices of goods and factors.*
4. *All firms run zero-profit and the number of firms (product variety), N, is consistent with the zero-profit.*
5. *All goods and factor markets clear.*

To solve the competitive equilibrium solutions, the number of products, N, will be derived given the level of endowments, L and K, from the zero-profit condition. Then, other endogenous variables will be determined accordingly.

The number of product varieties in the economy

Substituting the above market clearing conditions into the zero-profit condition of the equation (1.7) yields an equation as below:

$$\pi = \rho \cdot \frac{A \cdot L_b^{\alpha} \cdot K_v^{1-\alpha}}{N}\left(\frac{1}{\rho} - 1\right) - \left(W_w \cdot \bar{l} + r \cdot \bar{k}\right) = 0 \tag{1.8}$$

Here, α, A, ρ, $\bar{l}$ and $\bar{k}$ are exogenous parameters, while N, L_b, K_v, W_w and r are endogenous variables. Both L_t and K_t are assumed to be exogenously given at the time t, but it will be shown, later in this chapter, how the capital stock evolves endogenously over time. Substituting the above market clearing conditions into the equation (1.8 leaves only one endogenous variable, N, and it can be solved for N. As profit of a firm is monotonically decreasing in N, there must be a unique solution for N according to the intermediate value theorem. By solving the equation (1.8) for N, the equilibrium product variety is endogenously determined. Then, the equilibrium levels of other endogenous variables are derived accordingly. The examples of the competitive equilibrium solutions will be illustrated in the following sections.

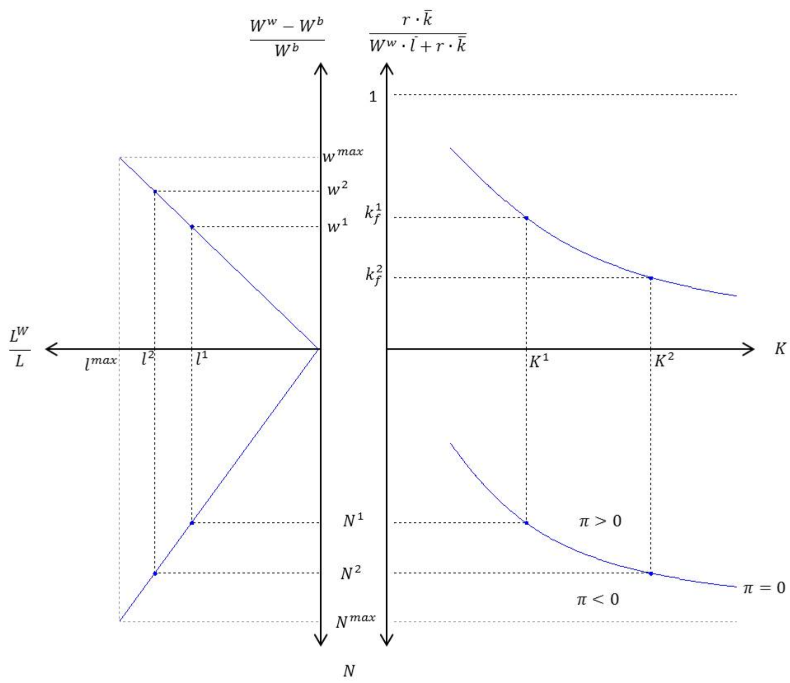
Evolution of product variety in K

Capital accumulation lowers the rental rate of capital relative to wage, ceteris paribus. The total fixed capital cost, $r \cdot \bar{k}$, falls not only relative to the fixed labour cost, $W_w \cdot \bar{l}$, but also relative to the variable labour cost, $W_b \cdot l_b$, and the variable capital cost, $r \cdot k_v$.[22] As the total fixed cost falls relative to the variable cost, total fixed cost falls below the gross profit, which is the multiplication of the mark-up and the total variable cost; hence, the net profit becomes positive. Seeking positive profit, more firms enter into the market, thereby increasing the number of product varieties. The firm entry continues until the net profit decreases to zero as the increased competition

[22] Both the output and the variable capital stock per product increase with capital accumulation while the fixed capital stock does not.

drives down the profit. Therefore, the number of products, N, is positively related with the total capital stock, K, ceteris paribus. As the product variety increases with the capital stock, the relative demand for white-collar labour, which is positively related with N, increases accordingly. The relationship is illustrated in the Figure 1.9.[23]

Figure 1.9: Evolution of product variety and skill demand in K



At the top right quadrant, it is shown how the share of fixed capital cost in the total fixed cost, $\dfrac{r \cdot \bar{k}}{W^w \cdot \bar{l} + r \cdot \bar{k}}$, declines as the capital stock increases. As the total capital stock, K, increases from K^1 to K^2, the share of the

[23]The parameters assumed to derive the competitive equilibrium solution are: L is normalized to 1, and it is assumed that there is no population growth. The CES utility function is set so that $\rho = 0.7$, which implies that the elasticity of substitution between goods eqauls to aproximately 3.33 and the mark-up ratio equals to approximately 1.43. $\bar{l}$ is 0.01, which means that the fixed labour input per product is 1% of the total labour endowment of the economy. $\bar{k} = 0.05$, which implies that the fixed capital input per product is 5% of the total capital endowment when $K = 1$. $\sigma_e = 2$, which means that the upper bound of the personal learning cost is twice the blue-collar wage, and the wage of white-collar workers must be twice the blue-collar workers to induce 50% of workers to choose university education and become white-collar workers.

fixed capital cost decreases from k_f^1 to k_f^2. As a result, the corresponding level of product variety, N, increases from N^1 to N^2. This is shown at the bottom right quadrant.

The curve at the bottom right quadrant represents the zero-profit equilibrium level of product varieties corresponding to the level of total capital stock, K. If the number of products is above the equilibrium level, the net-profit is negative, and firms begin to exit, decreasing the number of products towards the equilibrium level. If the number of products is below the equilibrium level, the net-profit is above zero, and N increases with the entrance of new firms seeking positive profit.

In the bottom left quadrant, the corresponding motion of the employment share of white-collar workers, $\dfrac{L^w}{L}$, with respect to the product variety, N, is shown. The employment of white-collar workers, L^w, linearly increases with the number of product varieties, N, and is represented as the straight line from the origin. As the number of products increases from N^1 to N^2, the corresponding employment share of white-collar workers increases from l^1 to l^2.

In the top left quadrant, the corresponding motion of the wage premium of white-collar workers with respect to the employment share of white-collar workers is shown. The wage premium of white-collar workers over blue-collar workers, $\frac{W^w}{W^b}$, is an increasing function of the employment share of white-collar workers, $\frac{L^w}{L}$. It is due to that higher wage premium is needed to induce more people to invest in education and become white-collar workers. As the employment share of white-collar workers increases from l^1 to l^2, the corresponding level of the wage premium increases from w^1 to w^2.

However, the growth rate of N decreases as K increases, and N converges towards N^{max} as K goes towards infinity. It is because capital accumulation lowers only the capital part of the fixed cost without lowering the labour part of the fixed cost. N^{max} corresponds to the equilibrium number of products when the share of fixed capital cost converges toward zero. As the product variety is upper bounded, both the employment share of white-collar workers and the wage premium are upper bounded as well. The corresponding upper bound of the employment share of white-collar workers is l^{max} and that of the wage premium of white-collar workers is w^{max}. This implies that the shift in skill-demand driven by the relative decline of the fixed capital cost is supposed to slow down in the long-run, which is consistent with the empirical findings that skill-biased change has begun to slow down recently (Autor et al. [2008]; Beaudry et al. [2013]).

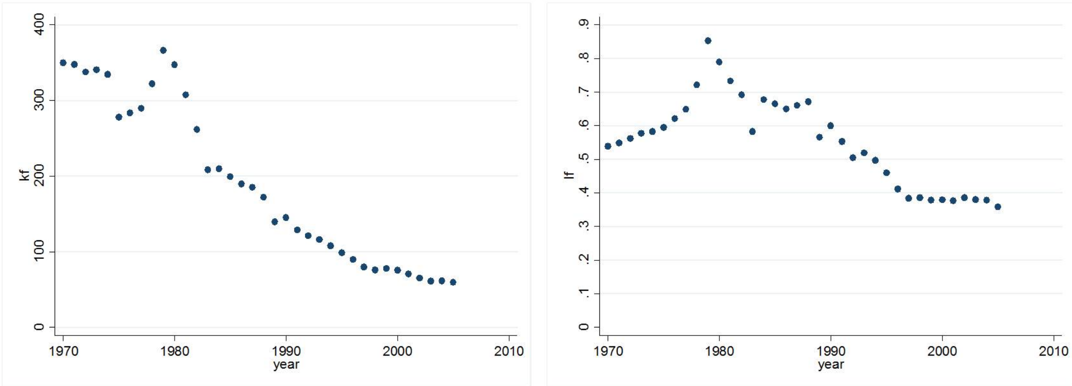
Recovering key parameters

From the data, the unobservable exogenous parameters, $\bar{k}$ and $\bar{l}$, are recovered by the model.[24] The mark-up ratio is taken from Christopoulou and Vermeulen [2008]. The ratio is for whole industries (including service industries as well as manufacturing) in the US for the period between 1981 to 2004. Data on labour and capital compensation, the number of employees and the total capital stock are drawn from the EUKLEMS dataset. In EUKLEMS, workers are categorized into three groups, which include high-skilled workers with a university education, middle-skilled workers with high school or equivalent vocational education and low-skilled workers. I identify the high-skilled workers of the data as the white-collar workers of the model. The number of products, N, is defined as the 5 year moving-

[24] $\bar{k}$ and $\bar{l}$ are calibrated to replicate the levels of employment and the wages of both white-collar and blue-collar workers given observed N, L, K, r and mark-up ratio.

average of the total trademark registration in the US.[25] The trend of the parameters, $\bar{k}$ and $\bar{l}$, is then recovered from the data, and shown in Figure 1.10.

Figure 1.10: The trend of implied fixed inputs - $\bar{k}$ & $\bar{l}$



The fixed capital input per product, $\bar{k}$, has fallen continuously since the early 1980s. This could be due to the introduction of FMS (Flexible Manufacturing System), which enabled the production of another type of good by simply changing the software settings of the machinery.[26] However, the fixed labour input per variety, $\bar{l}$, remained roughly stable until late 1980s but began to fall during 1990s. This might be due to the increasing replacement of white-collar workers in the workplace by the adoption of IT technology since the 1990s.

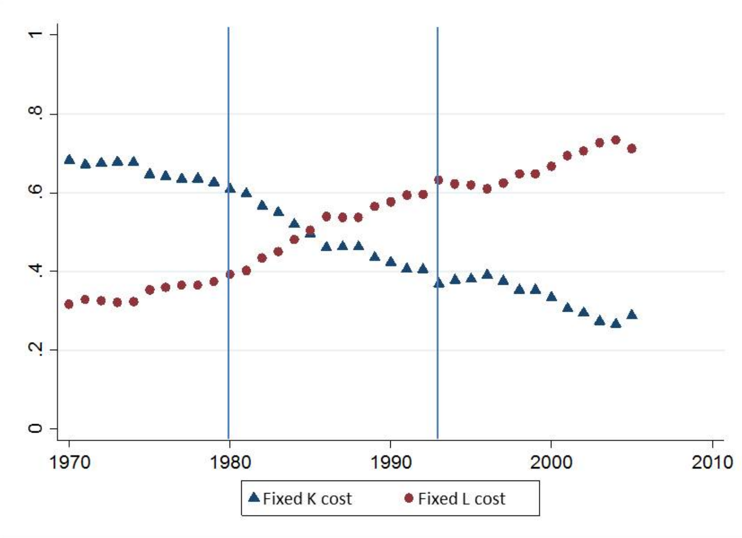
As a result, the share of fixed capital cost has fallen, while the share of fixed labour cost has risen in the total fixed cost, as is shown in Figure 1.11. The implied share of the fixed capital cost in the total fixed cost has decreased from 60.9% in 1980 to 36.9% in 1993. The decline in the share of fixed capital cost increased the implied share of the fixed labour cost from

[25] One interpretation is that a product survives for 5 years before being replaced by another.

[26] According to Mansfield [1993], 'the average year of first use of flexible manufacturing systems by major firms' is 1977.

39.1% to 63.1% for the same period.

Figure 1.11: The share of fixed capital and fixed labour costs



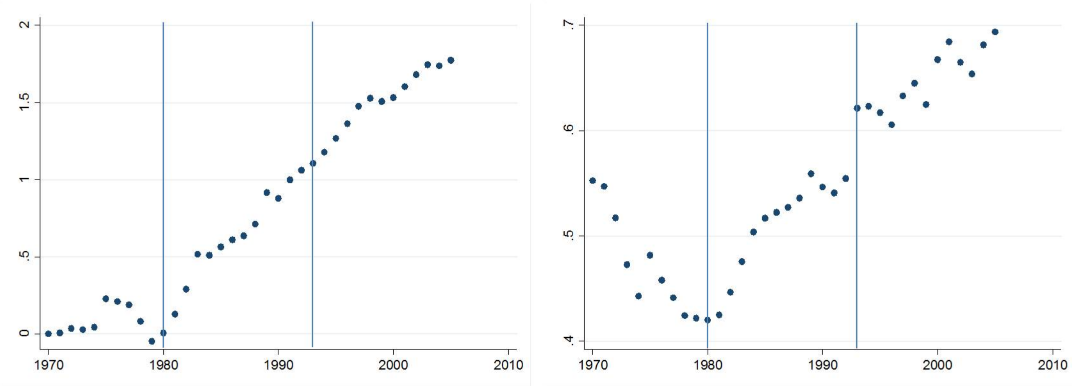
However, the increase in the implied share of fixed labour cost began to slow down since 1993, which is supposed to have slowed down the growth of wage differential between white-collar workers and blue-collar workers for the same period, as is shown in Figure 1.12. It is likely that the increase in the demand for the fixed labour input, which is biased toward white-collar workers, will continue to slow down as the share of fixed labour cost, which is the wage for white-collar workers, in the total fixed cost is approaching 100%.

Nevertheless, it does not necessarily imply that the technology growth which has caused the increase in skill demand has slowed down. Suppose the decline in $\bar{k}$ has been driven by a fixed capital saving technological change, which is represented by v_t:

$$\bar{k}_0 = v_t \cdot \bar{k}_t$$

Here, $\bar{k}_t$ is the minimum required level of fixed capital input per product at t. $\bar{k}_0$ represents the initial level of $\bar{k}$ at period 0, which is year 1970. As fixed capital saving technologies such as computerized factories and flexible manufacturing systems improve, less fixed capital is required to produce another product variety. Therefore, as the fixed capital saving technology, v_t, improves (possibly due to the IT revolution), the level of $\bar{k}_t$ declines over time relative to $\bar{k}_0$.

Figure 1.12: The trend of fixed capital saving technology $ln(v)$ & $ln(\frac{W_w}{W_b})$



The trend of the log of v_t is shown in Figure 1.12. It is shown that the implied value of the $ln(v_t)$ has kept on rising continuously even after the growth of the wage differential began to slow down from 1993 onwards. This is because the increase in v_t shifts labour demand towards fixed labour, biased toward white-collar workers, but at a decreasing rate. If the share of fixed labour in the given total fixed cost is near 100%, further increase in v_t has little effect on the demand for the fixed labour. Therefore, this is consistent with a puzzling empirical fact that the rise in wage inequality began to slow down in the 1990s, although there was no sign of the slow down in the progress of IT technology.

1.4.5 Dynamic equilibrium

In above sections, I have shown how the number of products and other endogenous variables are optimized given the level of factor endowments. However, in this section, the total capital stock is not given exogenously but evolves over time endogenously following a law of motion. As the total labour endowment (population), L_t, is assumed to be constant, K_t is the only state variable. Once K_t is determined following the law of motion, the equilibrium levels of other endogenous variables are derived accordingly given the static equilibrium solutions.

Definition. 2. *A competitive equilibrium (dynamic) is a set of sequences for consumption and price of each product, $\{c(i), p(i)\}_{t=0}^{\infty}$, variable and fixed factor inputs, $\{L_w, L_b, K_v, K_f\}_{t=0}^{\infty}$, the number of firms (products), $\{N_t\}_{t=0}^{\infty}$, wages, $\{W_w, W_b\}_{t=0}^{\infty}$, interest rate, $\{r\}_{t=0}^{\infty}$, for a set of exogenous parameters, (α, A, L, ρ, $\bar{\sigma}_e$, $\bar{l}$ and $\bar{k}$), given the constant population, L and the initial endowment of the total capital stock, K_0, which satisfy:*

1. *Each consumer optimally choose consumption allocation, $c(i)$, both across each type of product i, and over time, given prices, $p(i)$, and discount factor, β.*

2. *Each worker optimally choose whether to become a white-collar worker or a blue-collar worker given the wage levels, (W_w and W_b), which are functions of the total capital stock, K_t.*

3. *Factor allocation, (L_w, L_b, K_v and K_f), solves firm's problem given the prices of goods and factor endowment at each time period, t.*

4. *All firms run zero-profit and the number of firms (product variety), N_t, is consistent with the zero-profit, at each time period, t.*

5. *All goods and factor markets clear, at each time period, t.*

Following two-period Overlapping Generations Model framework, it is assumed that the agents live across two periods. In the first period, they are young and earn labour income, W_t. They divide it into consumption,C_t, and saving, S_t. In the second period, they retire and live on the capital income from the savings accumulated in the previous period.

$$young: \ C_t + S_t = W_t$$

$$old: \ C_{t+1} = (1 + r_{t+1}) \cdot S_t$$

They maximize the inter-temporal utility of the two periods by selecting the optimal level of consumption and saving at time t:

$$\max_{\{C_t\}} . \ U(C_t) + \beta \cdot U(C_{t+1})$$

$$U^{'}(C_t) = \beta \cdot (1 + r_{t+1}) \cdot U^{'}(C_{t+1}) \tag{1.9}$$

There are two points of departure from the standard OLG model. Firstly, there are two types of agents, white-collar and blue-collar workers, instead of homogeneous representative agents. However, they are different only in wage income, and the same type of agents has the same level of wage. Both types of agents have the same utility function and discount rate. Secondly, the goods are heterogeneous, and the utility of consumption increases with product variety given the total consumption expenditure.

It is assumed that the utility function with respect to the CES consumption bundle, x, takes a log form, so that $U = u(x) = ln(x)$. A consumer of j type (j = white-collar or blue-collar workers) optimizes the consumption of each product, $c(i)$, given the total expenditure, $C^j = \int_0^N p(i) \cdot c(i)di$. Under symmetry condition, $p(i) = 1$ for all i, and $c(i)$ is constant for all i. The maximized utility given the total consumption expenditure is:

$$
\begin{aligned}
U(x) =& ln\left(\left\{\int_0^{N_t} c(i)^{\rho} di\right\}^{\frac{1}{\rho}}\right) \\
=& ln\left(\left\{N_t \cdot \left(\frac{C^j}{N_t}\right)^{\rho}\right\}^{\frac{1}{\rho}}\right) \\
=& ln\left(N_t^{(\frac{1}{\rho}-1)} \cdot C^j\right) \\
=& ln\left(N_t^{(\frac{1}{\rho}-1)}\right) + ln\left(C^j\right)
\end{aligned}
$$

$$\therefore U'(C_t^j) = \frac{1}{C_t^j} \tag{1.10}$$

By applying (1.10) into the Euler equation of (1.9), the optimal consumption levels of young workers (of type j) at t are:

$$C_t^{j*} = \frac{1}{1+\beta} \cdot W_t^j$$

The saving rate, $\dfrac{S_t^j}{W_t^j} = \dfrac{\beta}{1+\beta}$, is the same for every agent, and independent from the interest rate as is common in two-period models with log utility. One noteworthy feature is that the number of products, N_t, does not influence the optimal saving decision if the log utility is assumed. It is because the increase in product variety only increases the level of utility without raising the marginal utility, under the assumption of log utility.

The law of the motion of capital

For a heterogeneous good model, it is possible that the real investment is not the same as the foregone real consumption as the prices of the investment goods and the consumption goods can differ. However, I will show that this is not the case within this model. It is assumed that the capital stock fully depreciates each period. Therefore, the total (real) capital stock in the economy at $t+1$, K_{t+1} equals to the total (real) investment at t, I_t:

$$K_{t+1} = I_t = \int_0^{N_t} I_t(i)di$$

For simplicity, it is assumed the same type of goods are used for both consumption and investment.[27] However, the total capital stock is the simple sum of each type of investment goods rather than a CES composite. Due to their consumption smoothing behaviour, agents will divert the same portion of every type of goods into investment goods[28], and the price of investment goods is identical to the price of consumption goods, $p(i) = 1$. Therefore, $S_t^j = \int_0^{N_t} I_t(i)di = I_t$, and the total real investment, I_t equals the nominal saving S_t.[29] Then, the total real capital stock equals the total saving in the previous period:

$$\begin{aligned} K_{t+1} =& S_t \\ =& \frac{\beta}{1+\beta} \cdot \left(W_t^b \cdot L_{b,t} + W_t^w \cdot L_{w,t}\right) \end{aligned}$$

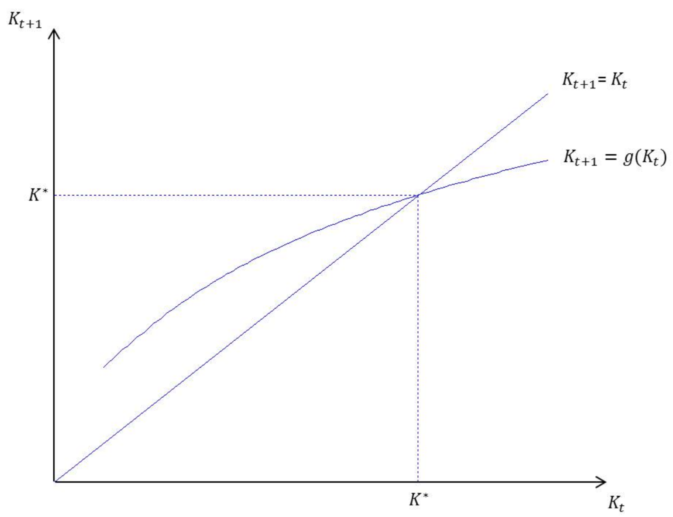
[27] In this model, investment goods are not inherently different from consumption goods, and there is no separate investment good sector

[28] Because $c(i)$ is the same for all i, the ratio of investment goods to consumption goods, $\frac{I(i)}{c(i)}$ is the same for all i.

[29] Therefore, there is no concern about the change in relative price between investment goods and consumption goods in this model.

K_{t+1} is determined by the product of the saving rate and the sum of all agents' labour income in the previous period. In the RHS of the equation, N_t, W_t^w, W_t^b, L_t^w and L_t^b are all increasing functions of K_t. Therefore, K_{t+1} can be expressed as a function of K_t, so that $K_{t+1} = g(K_t)$, where g is a difference equation which represents the motion of capital. In the steady state, $K_{t+1} = K_t$. In other words, $K^* = g(K^*)$ at steady state, and K^* is the steady state level of capital. The steady state level of N, W^w, W^b, L^w and L^b are all determined accordingly as functions of K^*.

Figure 1.13: The motion of capital



The motion of capital is depicted in the Figure 1.13 as a solid curve. The steady state, K^*, is the point where the curve of the motion of capital intersects with the 45 degree line.[30]

1.4.6 Steady state dynamics

Suppose the economy is initially in a steady state at t_1 with population and technology unchanged. If there is a shock in one of the exogenous

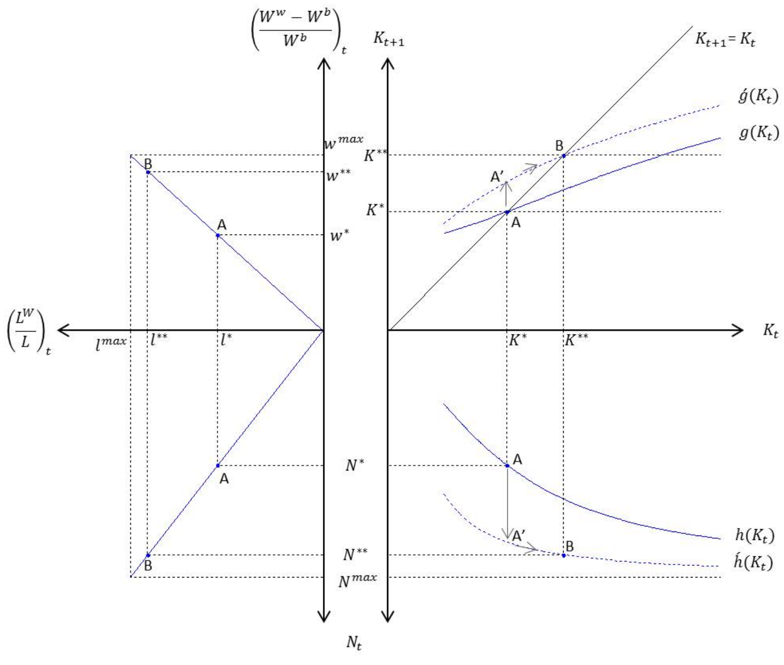
[30]The interval of one generation is assumed to be 30 years, and discount rate is assumed to be 5% per year.

parameters of the model, the economy reacts to the shock and then begins to converge towards the new steady state.

Investment specific technology shock

The decrease in the parameter value of the minimum required level of fixed capital, $\bar{k}$, can be interpreted as a specific sort of investment specific technology shock. For example, the adoption of the FMS (Flexible Manufacturing System) was mainly aimed at decreasing the fixed capital cost of producing new product varieties. Figure 1.14 shows the result of the shock which decreases $\bar{k}$. The initial equilibrium is at point A, and the new equilibrium is at point B. First, the shock on $\bar{k}$ affects the capital accumulation process, and it affects the number of product varieties. Then, both the employment share and the relative wage of white-collar workers respond to the change in the product variety.

Figure 1.14: steady states with a shock in $\bar{k}$



In the top right quadrant, the motion of total capital stock, K_t, is shown. Before the shock in $\bar{k}$ occurs, the policy function, which describes the motion of capital, is the solid curve, $K_{t+1} = g(K_t)$. It intersects the 45 degree line at the initial steady state point, A. The decrease in the minimum required level of fixed capital input per product variety, $\bar{k}$, enables more capital to be diverted to variable capital, which increases output. As saving is a function of output, it increases the saving and the future capital stock, K_{t+1}, given the current capital stock, K_t. Therefore, the curve of the motion of capital shifts upward to $K_{t+1} = g'(K_t)$, and intersects with the 45 degree line at the new steady state point B. After the shock in $\bar{k}$, capital stock jumps to the point A', and then gradually converges toward the new steady state point B. The steady state capital stock increases from K^* to K^{**}.

In the bottom right quadrant, the motion of the number of product varieties, N_t, is shown. N_t increases with the capital stock but at decreasing rate, and converges towards the virtual maximum level, N^{max}, as the level of capital stock goes to infinity. At initial steady state, the number of product varieties is N^*. After the shock, the number of product varieties jumps given the capital stock, to the point A' as the cost of introducing a new product variety decreases. After the initial jump, the product variety gradually converges to the point B as the capital stock grows towards the new steady state level, K^{**}. Therefore, the decrease in $\bar{k}$ not only increases N directly but also indirectly increases it through its effect on the capital stock.

In the bottom left quadrant, the motion of the employment share of white-collar workers, $\frac{L^w}{L}$, is shown. The employment of white-collar workers, L^w, increases with the number of product varieties, N. At the initial steady state, the number of product varieties is N^*, and the corresponding employment share of white-collar workers is l^*. After the shock in $\bar{k}$, N increases from N^* to N^{**} over time, and the steady state level of the employment share of white-collar workers increases to l^{**}.

Finally, in the top left quadrant, the motion of the wage premium of white-collar workers is shown. The wage premium of white-collar workers over blue-collar workers, $\frac{W^w}{W^b}$, is an increasing function of the employment share of white-collar workers, $\frac{L^w}{L}$. At the initial steady state, the employment share of white-collar workers is l^*, and the corresponding level of the wage premium is w^*. After the shock, the steady state level of the employment share increases to l^{**}, and the steady state level of the wage premium increases to w^{**} accordingly.

However, the decrease in $\bar{k}$ alone cannot increase the employment share of white-collar workers and the wage premium beyond l^{max} and w^{max}, which correspond to the maximum level of the product variety, N^{max}. It does not mean that the relative demand for white-collar workers can never go beyond that level at any case, but that other sort of exogenous shocks, such as taste shock, are required to shift the maximum levels. These maximum levels do not change with $\bar{k}$.[31]

TFP shock

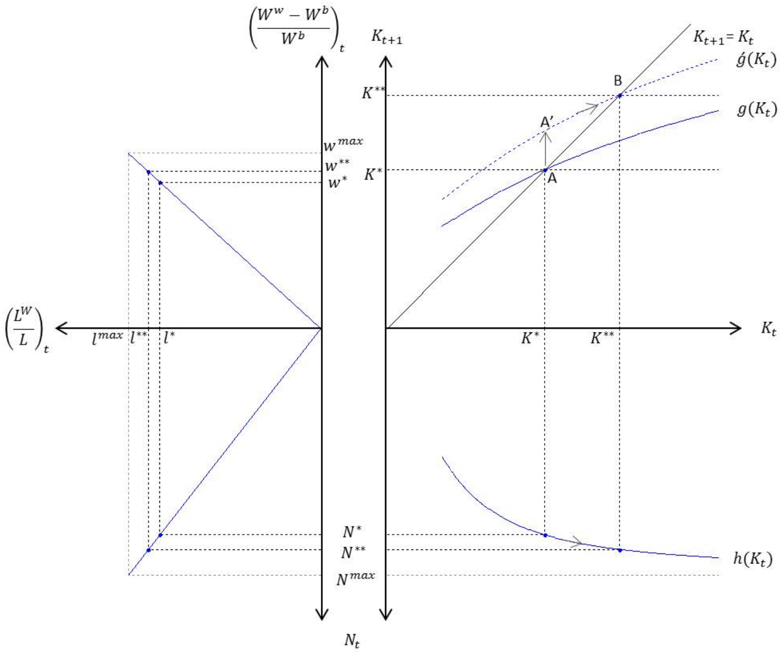
In this model, the production follows a Cobb-Douglas form, $Y = A \cdot L_b^{\alpha} \cdot K_v^{(1-\alpha)}$. The true TFP is represented by the parameter A, but it differs from measured TFP due to the existence of fixed input. A TFP shock which increases the level of A, is supposed to be skill-neutral in a sense that it in-

[31] Decreased $\bar{k}$ increases the equilibrium number of product varieties by reducing the fixed capital cost of introducing new product varieties, but the total fixed capital cost is assumed to be zero at N^{max}.

creases the marginal productivity of each factor input proportionately. It is not supposed to affect relative skill-demand in existing literature. However, it does affect skill-demand in this model.

Figure 1.15 illustrates the result of a TFP shock which increases A. The initial equilibrium is at point A, and the new equilibrium is at point B. The shock on $\bar{k}$ shifts the capital accumulation curve, but it does not shift other curves such as the motion of the number of product varieties.

Figure 1.15: steady states with a shock in TFP



In the top right quadrant, the motion of total capital stock, K_t, is shown. Initially, the steady state level of total capital stock is K^*. After the shock, the saving, which is an increasing function of output, jumps as the shock increases output given the capital stock. As saving increases at every level of capital stock, K_t, the curve of the motion of capital shifts upward, and the steady state level of capital stock increases to K^{**}.

The increase in the steady state level of capital stock also increases the number of product varieties, which is shown in the bottom right quadrant, as the fixed capital cost declines relative to the wage and the variable capital cost as capital accumulates. However, the curve of the motion of the number of product varieties does not shift, and the number of product varieties increases alongside the existing curve. Both the relative employment and the wage of white-collar workers increase as the number of product varieties increases, but the curves do not shift.

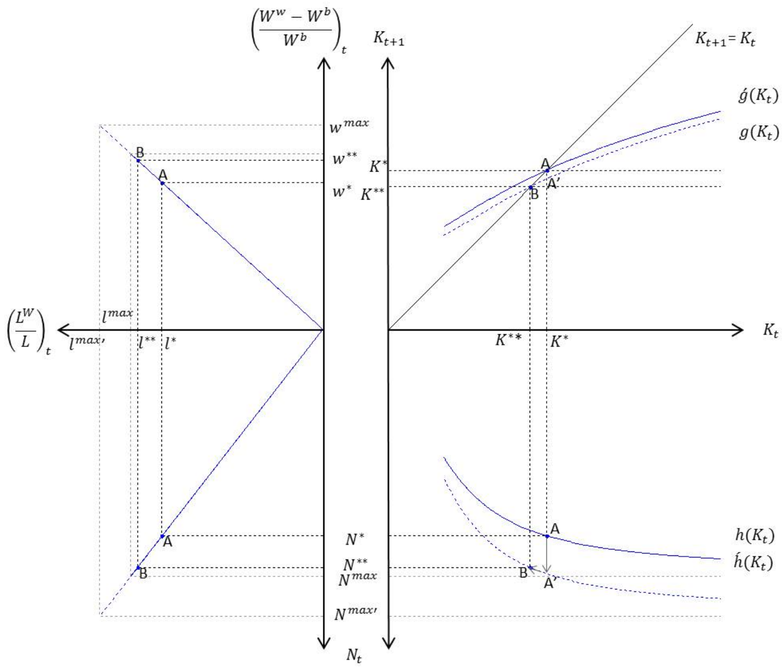
The maximum level of the number of product varieties, N^{max}, does not increase with the TFP, A. Therefore, the shift in the labour demand towards white-collar workers is upper-bounded even though the TFP increases towards infinity.

Taste shock

In this model, the price-cost mark-up is determined by the parameter, ρ, of the CES utility function, which represents the substitutability between goods. If there is a taste shock, probably due to product innovations, which makes consumers value differentiated goods more than before, the mark-up increases. The effect of the increase in mark-up due to such a taste shock is shown in the Figure 1.16.

As the mark-up increases, the gross-profit of the firms increases, and it induces more firm entry and increase in product variety. However, the production quantity per each variety decreases, and variable inputs are diverted to fixed inputs. Therefore, it reduces output, leading to a decreased level of saving and the steady state level of the total capital stock. The steady state level of capital stock decreases from K^* to K^{**}, and it negatively affects the number of product varieties.

Figure 1.16: steady states with a shock in mark-up



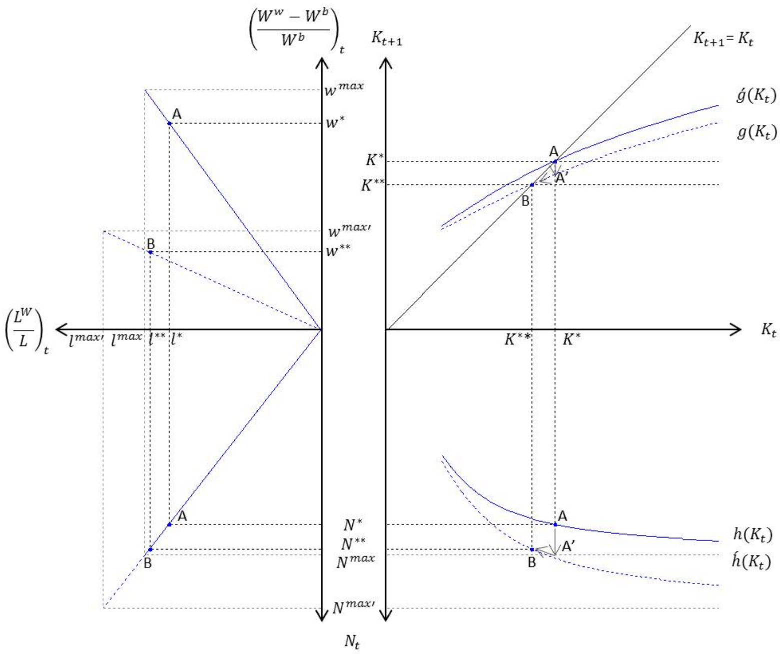
Therefore, there are two contrasting effects of the taste shock, which increases mark-up, on the steady state level of the product varieties. Given the level of total capital stock, the equilibrium number of product varieties increases, which is displayed as an upward shift of the curve of the motion of the number of product varieties in the bottom left quadrant of the graph. However, this increase in N_t is partly offset by the decrease in K_t. Both the relative employment and wage of white-collar workers increase accordingly in response to the increase in the number of product varieties.

However, a noteworthy point is that the maximum level of the number of product varieties, N^{max}, increases to $N^{max'}$ in response to the taste shock. As a response to the increase in N^{max}, the corresponding maximum level of the employment share of white-collar workers, l^{max}, increases to $l^{max'}$ accordingly, and the maximum level of the wage premium of white-collar workers, w^{max}, increases to $w^{max'}$ Therefore, as the level of mark-up goes toward infinity, which is very unlikely in the real world, the employment ratio of white-collar to the blue-collar workers goes towards infinity (in other words, the employment share of fixed white-collar workers converges towards 100%).

Labour supply shock

In this model, the labour supply of white-collar workers is endogenously determined, and increases with their wage premium over blue-collar workers. The decline in the education cost relative to wage, $sigma_e$, increases the labour supply of white-collar workers given the wage premium. The labour supply shock is endogenously generated by the shock in the exogenous parameter, $sigma_e$. The effect of a shock, which decreases the education cost, $sigma_e$, is shown in the Figure 1.17.

Figure 1.17: steady states with a shock in education cost



After a positive labour supply shock (due to the fall in education cost), the wage premium of white-collar workers decreases, appearing as the decrease in the slope of the curve in the upper left quadrant. As the relative wage of white-collar workers decreases, the fixed labour cost of introducing new product varieties decreases and the number of product varieties increases. Then, the employment share of white-collar workers increases with the number of product varieties.

These initial changes are amplified by the corresponding decrease in the level of total capital stock. As the number of product varieties jumps given the level of capital stock, due to the decreased cost of fixed labour input, more factor inputs are diverted toward fixed inputs. Therefore, both variable labour and capital inputs decrease, leading to the fall in output. This reduces saving and decreases the future capital stock, K_{t+1}, shifting the motion of capital curve downward in the upper right quadrant. As a result, the steady state level of capital decreases from K^* to K^{**}. It partly offsets the increase in the number of product varieties, and finally converges toward the new steady state level, N^{**}. Accordingly, the employment share of white-collar workers and the wage premium finally converges toward l^{**} and w^{**} each.

1.5 Conclusion

In this chapter, I have presented a dynamic general equilibrium model to explain the role of overhead labour in skill-biased technological change. In the model, it is the increasing ratio of the fixed labour input to the variable labour input that increases the demand for skill. It is because the overhead labour is assumed to be biased towards non-production workers, and non-production workers are usually those with a higher education level.

This model presents several predictions, which differ from the standard SBTC theory. Firstly, this model predicts that the employment share of white-collar workers interacts with the market structure. Evidence is provided suggesting that those industries with higher mark-up are likely to have higher employment shares of white-collar workers.

Secondly, it is predicted that there is an upper bound to the skill-biased change. Since the firms can pay for the fixed labour input only if the price exceeds the marginal cost, the wage-bill share of white-collar workers cannot increase indefinitely. Therefore, it is predicted that the growth of inequality between the white-collar workers and the blue-collar workers is likely to experience a slowdown in the long run.

Thirdly, while the increase in the employment share of non-production workers is expected to increase measured labour productivity through the composition effect in existing literature, this model predicts that the compositional effect on the measured productivity will be negative. Therefore, this model's prediction is consistent with such puzzling empirical facts as the rapid development of skill-biased technology coupled with stagnant productivity in the 1980s and the opposite pattern in the 1990s, wherein the slow down of skill-biased technological change was coupled with the resurgence of labour productivity growth.

Appendix. About mark-up ratio data

The mark-up ratio data comes from Oliveira Martins et al. [1996], who utilized Roeger [1995]'s method. Roeger [1995] utilises the gap between TFPs measured by different methods. Typically, TFP is estimated by calculating Solow residual as below:

$$SR = \Delta q - \alpha \Delta l - (1 - \alpha)\Delta k \tag{1.11}$$

Here, SR refers to Solow residual, and α is the share of labour income in the output. Δl, Δk, Δq are the differences in the logs of labour input, capital input and output. The contribution of each factor in production is equal to its income share under the assumption of perfect competition.

However, Roeger [1995] showed that TFP can also be estimated using a price-based Solow residual. It is defined by the difference between the increase in the weighted average of the factor price and the increase in the price of output as below:

$$SRP = \alpha \Delta w - (1 - \alpha)\Delta r - \Delta p \tag{1.12}$$

Here, SPR refers to price-based Solow residual. Δw, Δr, Δp are the difference in the logs of wage, rental rate of capital and output price. When there is a positive technology shock, the output price rises less than the increase in the factor prices as the factors are consumed less due to the productivity improvement. In theory, under the assumption of perfect competition, TFPs estimated by both methods should be the same in theory. However, they are rarely identical in practice.

The point is that the labour's income share of output is not an accurate measure of labour's contribution to production under imperfect competition. The exact contribution of labour is equal to its income share in the marginal cost, which is lower than the price. Therefore, labour's income share of output underestimates the contribution of labour and overestimates the contribution of capital under imperfect competition. As a result, both Solow residuals are biased, but in different directions. From the gap between these two types of Solow residuals, the mark-up ratio can be estimated as below:

$$SR_t - SRP_t = B\Delta x_t + u_t \tag{1.13}$$

$$\Delta x_t = (\Delta y_t - \Delta k_t) + (\Delta p_t - \Delta r_t)$$

Here, B is the Learner index defined as $B = \dfrac{P - MC}{P}$, or $B = 1 - \dfrac{1}{\mu}$, where μ is mark-up ratio. The mark-up ratio is derived by estimating B in equation (1.13). However, Oliveira Martins et al. [1996] modify Roeger's method to incorporate material inputs in equation (1.13). The estimation equation used in Oliveira Martins et al. [1996] is:

$$\Delta y_t = B \cdot \Delta x_t + \varepsilon_t \tag{1.14}$$

where,

$$\Delta y_t = (\Delta q + \Delta p) - \alpha \cdot (\Delta l + \Delta w) - \beta \cdot (\Delta m + \Delta p_m) - (1 - \alpha - \beta) \cdot (\Delta k + \Delta r)$$

$$\Delta x_t = (\Delta y_t - \Delta k_t) + (\Delta p_t - \Delta r_t)$$

Oliveira Martins et al.(1996) also adjust for the effect of indirect taxes on the estimated mark-up as below:

$$\mu = \frac{\mu^e}{1+\tau}$$

Here, μ^e is the estimated mark-up, and τ is indirect tax rate. Estimated mark-up ratios from Oliveira Martins et al. [1996] are shown in Table 1.1. The industrial classification system they use in Oliveira Martins et al. [1996] is ISIC rev.2. Data on payment, capital stock and material cost are based on NAICS 97 classification in this study. Therefore, only ISIC rev.2 industry groups with a clear correspondence to NAICS 97 classifications are used for estimation.

Table 1.1: The mark-up ratio in the US manufacturing, 1970-1992

Sector name	(ISIC rev.2)	Sector (Naics 97)	mark-up
Food Products	3112~	311000 ~ 312000	1.05
Beverages	3130~	-	-
Tobacco products	3140~	312200 ~ 313000	1.56
Textiles	3210~	313000 ~ 313000	1.08
Wearing apparel	3220~	315000 ~ 316000	1.10
Leather products	3230~	316000~321000	1.08
Wood products	3310~	321000~322000	1.22
Furniture	3320~	337000~339000	1.06
Paper products & Pulp	3410~	322000~323000	1.13
Printing & Publishing	3420~	323000~324000	1.19
Industrial chemicals	3510~	325130~325400	1.18
Drugs & Medicines	3522~	325400~325500	1.44
Chemical products	3529~	325500~326000	1.26
Petroleum refineries	3530~	324110	1.03
Petroleum & Coal products	3540~	324121~324199	1.11
Rubber products	3550~	-	-
Plastic products	3560~	326000~326200	1.07
Pottery & China	3610~	327000~327200	1.09
Glass products	3620~	327200~327300	1.17
Non-metal products	3690~	327300~331000	1.18
Iron & Steel	3710~	331000~331300	1.10
Non-ferrous metals	3720~	331300~332000	1.14
Metal products	3810~	332000~333000	1.09
Office & Computing mach.	3825~	334000~334200	1.54
Machinery & Equipment	3829~	333000~334000	1.06
Radio, TV & Comm. equip.	3832~	334200~334300	1.40
Electrical apparatus	3839~	-	-
Shipbuilding & Repair	3841~	-	-
Railroad equipment	3842~	-	-
Motor vehicles	3843~	336000~336400	1.09
Motorcycles & Bicycles	3844~	336991	1.13
Aircraft	3845~	-	-
Other transport equipment	3849~	-	-
Professional goods	3850~	-	-
Other manufacturing	3900~	339000~340000	1.08

Chapter 2

White-collar employment and firm scale

2.1 Introduction

There has been a secular rise in the share of white-collar workers, and this is usually attributed to the aggregate technological change. For example, the IT revolution, which had widespread effects on the economy, is considered to be the key factor driving skill-biased technological change. However, the pattern appears very different at firm level, especially at high frequency. In this chapter, firm level high frequency variation in the employment share of white-collar workers is empirically studied using the ARD firm level database on UK manufacturing industries.

A considerable level of heterogeneity between firms is found. Around 40% of firms decreased the employment share of white-collar workers from the previous year, although the aggregate share of white-collar workers was rising. At firm level, a large portion of high-frequency changes in the white-collar employment share cannot be fully explained by aggregate technological change, given that it is unrealistic to expect technology to deteriorate for such a large portion of firms[1], accounting for around 40 percent of total firms. As Dunne et al. [1996] have pointed out, there are unobservable factors, seemingly not related to technology, which generate high-frequency variation in white-collar employment share at firm level. This study suggests that the change in firm scale is one of those factors.

The level of production and employment fluctuates more at firm level than at aggregated level. I find that the labour demand for white-collar and blue-collar is not homothetic, so the change in firm scale affects the composition of employment as well as the scale of employment. There has been literature on the effect of firm size on a wide range of economic variables including firms' survival rate (Baldwin and Rafiquzzaman, 1995; Disney, Haskel and Heden, 2003), productivity (Leung, Danny, Meh, Cesaire and Terajima, Yaz, 2008), earning or job creation(Hijzen, Upward and Wright, 2010), but it is relatively rare to focus on its effect on relative demand for skilled (white-collar) workers.

In this chapter, the share of white-collar workers is found to be positively correlated with firm size across the cross-section. However, it is also found that the change in the share of white-collar workers is negatively correlated with the change in firm scale. So, the main aim of this study is to investigate why the positive relationship between white-collar employment share and firm size in the cross-section dimension is reversed in the time dimension.

As in the first chapter, it is also assumed that white-collar workers constitute fixed labour input. However, two assumptions in the previous chapter are relaxed here: some of the white-collar workers are variable in-

[1] This question is somewhat related to another question about RBC theory that how technology can deteriorate during recession.

put, and different products have different levels of fixed white-collar labour input. As it is assumed that the employment share of variable white-collar labour to blue-collar workers is homothetic, the non-homothetic property is supposed to come from the existence of fixed white-collar labour.

The empirical finding that the adjustment of white-collar employment is lumpier than the blue-collar workers is consistent with the hypothesis that white-collar labour is partially a fixed input. The employment of white-collar workers changes less frequently than that of blue-collar workers. However, when it changes, it changes more. This might be explained by the partial fixity of white-collar labour input. For example, the firm's employment of fixed labour is not supposed to change unless the firm changes its product variety to another one with a different minimum required level of fixed labour input. However, once the firm decides to change the product into another one with either higher or lower required level of fixed labour input, the employment of white-collar labour changes discontinuously, generating lumpy adjustment.

If a firm produces a more sophisticated product, which requires a higher level of fixed white-collar labour input, the firm is more likely to be large in size. Moreover, higher level of fixed input limits the number of firms and increases the price-cost mark-up. Therefore, firms with higher fixed labour input also would also show a higher employment share of white-collar workers. Therefore, the firm size is positively correlated with white-collar employment share as both of them are positively correlated with the size of fixed white-collar labour input, which is unobservable.

However, short-run expansions of output due to positive demand shock usually do not involve such an upgrading towards more sophisticated product. In such a case, only the variable part of labour input increases with firm output scale, and the total employment share of white-collar workers , including both fixed and variable part, decreases.

The remainder of the chapter is structured as follows: Section 2.2 shows the analytical frame work. Section 2.3 explains the data and implements empirical estimations. Section 2.4 concludes.

2.2 Theoretical Framework

In this section, a theoretical framework for empirical estimation is presented. It is also assumed that firms are producing differentiated goods, and fixed cost is required to produce any goods. The fixed cost consists of white-collar labour. However, each good has different minimum requirement level of fixed labour input and firms can select which goods to produce. For example, developing a new car requires more fixed labour than developing a new T-shirt.

As the main focus of this chapter is on the empirical analysis of high-frequency movement of the employment of white-collar workers, it is beyond the scope to explain what makes a firm choose a specific product. It is assumed for simplicity that fixed input includes only white-collar labour.

2.2.1 Production function

There is a fixed labour input associated with producing product variety i, $\bar{L}_i$, which is exogenously given. As it is assumed that white-collar workers constitutes fixed labour input, the employment of variable white-collar workers, $L^W_{v,i}$, is :

$$L^W_{v,i} = L^W_i - \bar{L}_i$$

The production follows CES function as below:

$$Y_{i,t} = A_i \cdot K_i^{\alpha} \cdot \left[\beta \cdot \left(a^W \cdot (L^W - \bar{L}_i)\right)^{\rho} + (1-\beta) \cdot \left(a^B \cdot L_i^B\right)^{\rho}\right]^{\frac{1-\alpha}{\rho}} \tag{2.1}$$

Y_i is the production quantity of firm i. A_i is skill-neutral technology level. a^W is high-skilled or white-collar labour augmenting technology, and a^B is blue-collar labour augmenting technology. K_i is capital stock. L_i^B is low-skilled or blue-collar workers' employment. Among total white-collar labour input of firm i, L_i^W, only variable part, $L_{v,i}^W$, enters into the production function.

However, Y_i is not directly observable, and what we can observe directly from the data is $P_i \cdot Y_i$, the nominal value added output of the firm. Although the nominal output is converted to real output using existing price indices, whether it is aggregate price index or industry level price index, the difference in the price level across individual firms cannot be accounted for fully.

Usually, the real ouput variable of each firm is constructed from the observed nominal value added output of each firm, $P_i \cdot Y_i$, which is deflated not by individual price , P_i, but by more aggregated price index, P. Then, what we get as a result is not exactly Y_i, but $\frac{P_i}{P} Y_i$. Let us denote the relative price of firm i compared with the aggregate price level as $p_i = \frac{P_i}{P}$. Then, the production function we actually observe is:

$$p_i \cdot Y_{i,t} = A_i \cdot p_i \cdot K_i^{\alpha} \cdot \left[\beta \cdot \left(a^W \cdot L_{v,i}^W\right)^{\rho} + (1-\beta) \cdot \left(a^B \cdot L_i^B\right)^{\rho}\right]^{\frac{1-\alpha}{\rho}} \tag{2.2}$$

The above equation (2.2) implies that observed productivity at firm level reflects not only pure or physical technology but also the relative price of the good, p_i. If a firm i produces a good which is highly appreciated by consumers, the relative price of the good, p_i, will be higher and contribute to the growth of observed real output, $p_i \cdot Y_i$. Therefore, the effect of the rise in p_i is hard to distinguish from the effect of the rise in physical technology, A_i.

This explains why some firms choose to produce goods with higher required level of fixed input. Although higher level of fixed labour input decreases output quantity by lowering the variable input part of white-collar labour, it may increase the price of the good which the firm produces. The reason why the relative price of the good is positively related with the size of fixed input will be explained later in this chapter.

2.2.2 Fixed white-collar labour

It is assumed firms need to hire certain number of white-collar workers as fixed input to produce a new variety of good.[2] However, the employment of white-collar workers is rather quasi-fixed and not completely fixed in the long-run. Sutton (1991) has proposed that firms endogenously select the level of sunk cost such as advertisement cost. In this study, firms are supposed to be able to change the level of fixed input by changing to another variety with different level of fixed input.

As it is assumed that the employment of fixed part of white-collar labour, $barL_i$, is exogenously determined by the characteristic of the variety, the employment of fixed white-collar labour does not change until the

[2]Fair (2008) also mentions that the demand for non-production worker is fixed in the short run.

firm changes the product variety into another one.

However, firms produce more than one product variety in reality, and even the same product variety sold in different regions or countries are imperfect substitutes for each other. Therefore, the good can be interpreted as a composite good, which consists of multiple differentiated goods sold in different markets. Either adding a new product variety or entering into a new market with existing product variety can also be interpreted as changing into another composite good, which requires higher fixed cost.

$$L_i^W = L_{v,i}^W + L_{f,i}^W$$

What is observable from data is only the total white-collar labour input for firm i, which is the sum of white-collar fixed labour input,$L_{f,i}^W$, and variable labour input, $L_{v,i}^W$, both of which are not observable from data. Only the variable part of white-collar labour enters into the CES production function in the equation (2.2). As the fixed part of white-collar labour input is considered as sunk-cost, it does not affect the optimization decision based on the CES production function.

$$\frac{L^{W_v}}{L^B} = \left(\frac{a^W}{a^B}\right)^{\frac{\rho}{1-\rho}} \cdot \left(\frac{w^B}{w^W} \cdot \frac{\beta}{1-\beta}\right)^{\frac{1}{1-\rho}} \tag{2.3}$$

The relative employment ratio of variable white-collar labour and blue-collar labour is shown in equation (2.3). It is derived from the optimization of the CES production function in (2.2). As the CES product function is homothetic, the relative employment ratio is not directly affected by firm scale, either in terms of employment or output.

$$\frac{L^H}{L^B} = \frac{L^{H_v}}{L^B} + \frac{L^{H_f}}{L^B} \tag{2.4}$$

The observed employment ratio of white-collar workers and blue-collar workers, $\frac{L^H}{L^B}$, is the sum of the employment ratio of variable white-collar to blue-collar workers and the ratio of fixed white-collar to blue-collar workers. Therefore, the observed employment share of white-collar workers can rise even without any increase in the ratio of variable white-collar to blue-collar labour, if the ratio of fixed white-collar to blue-collar labour increases. This implies that it is possible for the relative employment ratio of white-collar workers to change without any change in the production technology as represented by the CES production function. If the ratio of fixed white-collar labour to blue-collar labour is affected by firm scale, then firm scale can affect the employment share of white-collar workers, although the production function is homothetic.

2.2.3 firm size and white-collar share

$$\begin{array}{ll} & \nearrow number\,of\,firms \downarrow \Rightarrow price\,\&\,markup \uparrow \Rightarrow \frac{L_f^W}{L^B} \uparrow \Rightarrow \frac{L^W}{L^B} \uparrow \\ \bar{L}_i \uparrow & \\ & \searrow firm\,size \uparrow \end{array}$$

If a group of products in a market require larger fixed input, $\bar{L}_i$, fewer firms will be able to enter the market. There will be a smaller number of firms, and the degree of competition will be decreased. On the contrary, if a group of varieties requires smaller fixed input, more firms will be able to operate, and this will increase the number of firms and the competition between them. We can express the number of firms in the market j as a function of the level of fixed input : $N_j = N(\bar{L}_i)$.

Unlike the previous chapter, this chapter does not assume constant elasticity of substitution as Dixit and Stiglitz [1977], but assumes that the elasticity of substitution increases as the number of firms in the market increase as is suggested in a number of studies (Manez and Waterson [2001], Krugman [1979a], Lancaster [1980] and Hummels and Lugovskyy [2005]).

For example, Hummels and Lugovskyy [2005] assume that 'all varieties can be represented by points on the circumference of a circle, with the circumference being of unit length.' Then, the utility of consumer consuming a product variety with a property represented by a point ω decreases with the distance of ω from the consumer's most desired ideal variety with a property of $\tilde{\omega}$, $v_{w\tilde{w}}$. As more entrance of firms crowd the variety space and make goods more similar each other, it leads to higher elasticities of substitution and lower mark-up and price. Therefore, both the price and mark-up is negatively correlated with the number of firms (products) in the market. We can express the mark-up as a function of the number of firms: $markup = \mu(N)$.

As a result, the size of fixed input, $\bar{L}_i$, which is exogenously given to each product, also determines mark-up through its effect on the number of firms : $markup = \mu(N(\bar{L}_i))$. Here, $\dfrac{\partial \mu}{\partial N} > 0$ and $\dfrac{\partial N}{\partial \bar{L}_i} < 0$.

Therefore, higher mark-up leads to higher share of fixed white-collar labour as the ratio of the fixed input to the variable input is still positively correlated with the mark-up although the elasticity of substitution is not constant unlike in the Dixit-Stiglitz type model.[3]

However, if a group of varieties requires higher level of fixed input, only

[3]The existence of fixed cost result increasing return to scale even under constant marginal cost. Under increasing return to scale, those firms with higher mark-up reaches break-even production quantity earlier, and the equilibrium production quantity which corresponds to zero-profit equilibrium is lower. Therefore, the lower output quantity leads to lower employment of variable factor, which is biased toward blue-collar workers, relative to the fixed factor, which is biased toward white-collar workers.

large firms which have financial ability to afford large fixed cost expenditure can enter into the market.[4] Therefore, there is a positive correlation between the employment share of fixed white-collar labour, $\bar{L}_i$, and the firm size.

As higher level of fixed white-collar labour, $\bar{L}_i$, results in both the increase in the share of white-collar workers and the firm size, a positive correlation is predicted between the share of white-collar workers and the firm size even though there is no direct causality between them. As the positive correlation is due to an endogenity caused by the unobservable, $\bar{L}_i$, following empirical analysis aims to detect the existence of the endogeneity, rather than eliminating it.

2.2.4 the growth of firm size and white-collar share

The employment ratio of white-collar workers to blue-collar workers is the sum of the ratio of the fixed part,$\frac{L^{H_f}}{L^B}$, and the ratio of the variable part, $\frac{L^{H_v}}{L^B}$, as in the equation (2.4). The employment of fixed white-collar labour input is determined by the size of fixed labour input, $\bar{L}_i$, which does not change with the output unless the firm changes its product variety. The increase in production quantity due to demand shock is not supposed to increase the demand for fixed white-collar labour input. Only the increase in output caused by the exogenous increase in the fixed labour input, $barL_i$, is positively correlated with the growth of fixed part of white-collar employment, L^H_f.

Any increase in firm size which is not caused by the increase in the size of fixed input, $\bar{L}_i$, does not increase the demand for fixed white-collar labour,

[4] Cabral and Mata [2003] have argued that the limit to financial access is the main obstacles of the firm growth, and many firms, especially young firms, have less than desirable size due to financial constraint.

L_f^W, but only increases the demand for variable labour inputs. Therefore, the ratio of fixed white-collar labour to blue-collar labour, $\frac{L^{H_f}}{L^B}$, declines as a result. However, the ratio of the variable part of white-collar to blue-collar labour, $\frac{L^{H_v}}{L^B}$, remains unchanged as the CES production function is homothetic. Therefore, the ratio of white-collar labour to blue-collar labour, $\frac{L^W}{L^B}$, declines with the growth of firm size.

In sum, the growth in firm size is positively correlated with white-collar employment share if it is driven by an exogenous increase in the fixed labour input, L_f^W, and negatively correlated if it is driven by other factors such as positive demand shock. However, for a high-frequency output variation, the case of output variation due to a change in product variety is likely to be rarer as it takes time for firms to change product variety.

2.3 Empirical Results

2.3.1 Data

The Annual Respondent Database (ARD) by ONS (Office for National Statistics, UK) will be used for empirical analysis in this chapter. The ARD is the micro data, which is based on annual business surveys in the UK. The dataset includes data on total sales, value added, industrial classification (SIC) and employment. The sources of the dataset were ACOP (Annual Census of Production) and ACOC (Annual Census of Production and Construction) until 1997, but changed to the ABI (Annual Business Inquiry) from 1998 onwards as the former business surveys were merged into the ABI in 1998.

A merit of the ARD dataset is that it provides wide coverage with very disaggregated level data. The business surveys underlying the ARD are sampled from the ONS business register. Until 1993, the CSO business register, which was based on VAT register and other sources, was used and covered manufacturing and other production industries (e.g. construction). However, the IDBR register replaced the CSO register after 1994, and the coverage expanded to the majority of the all the businesses in Great Britain (the total turn over of firms in the register accounts for the 98% of the whole country).

The unit of reporting in the ARD dataset is at three different level of aggregation. First, the "Local unit" is the most disaggregate level of reporting unit (e.g. a workshop, factory or warehouse, etc) and is defined based on its location. Second, "Establishment" is the most disaggregated unit, which responds to the business survey. Most local units are too small to fully respond to the survey, and the parent unit of several local units, which is called "Establishment" reports full information on behalf of every local unit. "Enterprise group" includes all the establishments and local units under common control. The unit of analysis of this study will be the establishment.[5] However, the problem is that the change in the register in 1994 caused discontinuity in the identifier of the establishments, and the mapping by ONS is not perfect. This can be an serious issue when the annual changes in several variables (e.g. employment and value-added) are calculated because the values of the difference can be greatly mis-measured if the observations with the same establishment identifier actually indicate different establishments.[6]

However, not all establishments are sampled to report full survey forms.

[5] The definition of "establishment" does not exactly match with that of a firm, but an establishment will be considered as a firm in this chapter, for simplicity.

[6] This issue becomes more serious if annual changes, rather than levels, are analysed.

According to Griffith [1999], every establishment with the employment size of over one hundred reports in the survey, while smaller ones with the employment less than one hundred are randomly selected every year (at the probability between 1/5 to 1/2). The data on those sampled establishments are in the selected file with full information, while the data on other non-sampled establishments and non-reporting local units (although they belong to the sampled establishments) are in the non-selected file with limited information, such as establishment identifier, industry classification, and imputed employment.

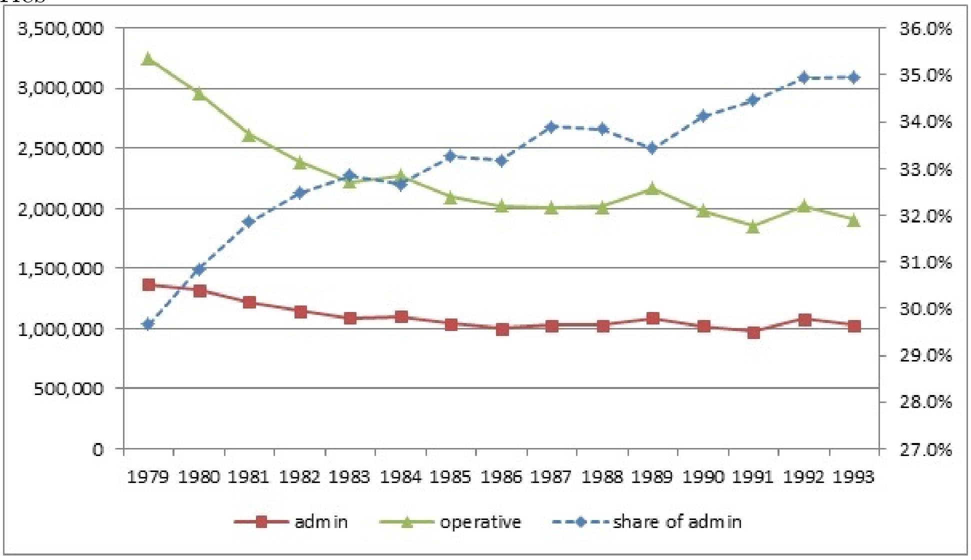
Another very important advantage of this dataset is that the data on employment offer a helpful categorization, namely that of the employees as administrative, technical and clerical workers (ATC) and operative workers (OP). The administrative workers are roughly equivalent to white-collar workers or non-production workers, who are supposed to have a higher educational level. The operative workers are roughly equivalent to blue-collar workers or production workers. However, distinction in the employment categories is maintained only until 1995. Since 1995, the dataset does not distinguish between the two types of workers.

Therefore, the empirical analysis will be limited to the observations in the period of between 1978 and 1993, in the selected file and within manufacturing industries, as they include all the variables needed and are not affected by the change in the register in 1994.

2.3.2 Overview

The employment trends of both administrative and operative workers in the dataset are shown in Figure(2.1). The share of administrative workers in 1979 (amongst the sampled UK manufacturing firms) was 29.7%.

Figure 2.1: Employments by type of workers in UK manufacturing industries



Source: Annual Respondent Database, 1979-1993

It began to rise gradually and reached the level of 35.0% in 1993. However, the absolute number of administrative workers did not rise for the same period but decreased gradually. The total employment of the administrative workers decreased by 24.9% from 1,368,887 in 1979 to 1,027,418 in 1993. It is the further decline in the employment of operative workers which increased the share of administrative workers in the manufacturing sector. The operatives' employment dropped by 41.1% from 3,244,708 to 1,911,580 for the same period.

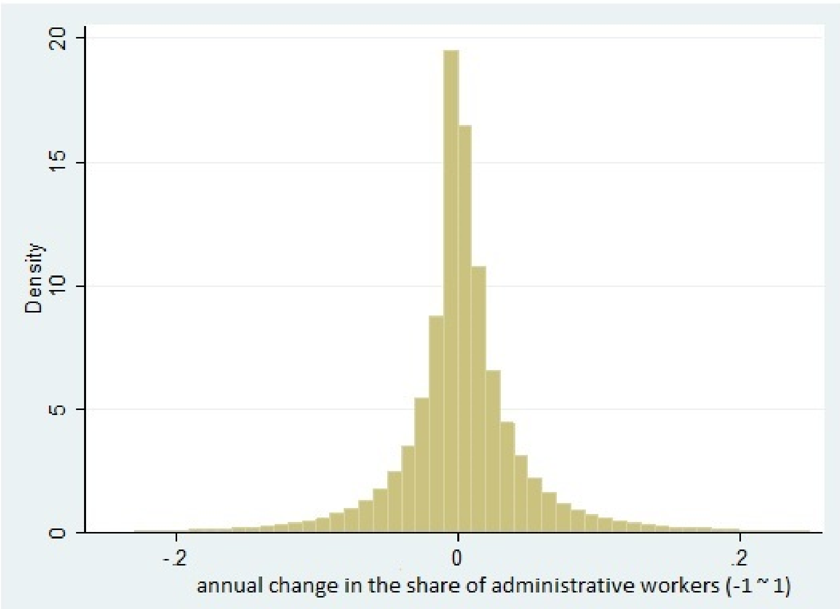
However, such a trend is not homogeneous for every firm. Firms show heterogeneous patterns in terms of the annual change in the share of administrative workers. Table 2 shows that 44.6% of firms decreased the share of administrative workers from the previous year, while 51.8% of firms increased the share and 3.6% of firms did not change the share from the previous year.

Table 2.1: Employment growth by type of workers

year	Share of admin	total	administrative	operative
1979	29.7%	4,613,595	1,368,887	3,244,708
1980	30.8%	4,280,101	1,320,054	2,960,047
1981	31.9%	3,835,123	1,221,934	2,613,189
1982	32.5%	3,537,837	1,148,747	2,389,090
1983	32.9%	3,313,091	1,088,522	2,224,569
1984	32.7%	3,382,610	1,104,948	2,277,662
1985	33.3%	3,138,484	1,044,024	2,094,460
1986	33.2%	3,028,121	1,004,833	2,023,288
1987	33.9%	3,036,721	1,029,228	2,007,493
1988	33.8%	3,046,362	1,030,752	2,015,610
1989	33.4%	3,258,172	1,089,298	2,168,874
1990	34.1%	3,005,449	1,025,229	1,980,220
1991	34.5%	2,828,766	974,746	1,854,020
1992	34.9%	3,103,535	1,084,632	2,018,903
1993	35.0%	2,938,998	1,027,418	1,911,580

Note: The sum of all sampled manufacturing firms in the ARD data.

Figure 2.2: The annual changes in the share of administrative workers



Note: All sampled manufacturing firms in 1979-1993

2.3.3 Lumpy adjustment for non-production workers

There has been empirical research on firms' employment adjustment. For example, Davis and Haltiwanger [1992] have reported that 29% of job cre-

Table 2.2: The annual changes in the share of administrative workers

$\Delta(\frac{L^w}{L})$	share	obs.
> 0	51.8%	44,069
$= 0$	3.6%	3,049
< 0	44.6%	37,954

ation and 23% of job destruction are due to modest employment growth of individual firms.

All firms in the sample are grouped into three categories, namely firms with no employment change, firms with moderated change, firms with large change, and the firms which did not change employment level at all from the previous year.[7]

The growth rate of employment is determined as below followingDavis and Haltiwanger [1992]:

$$g_{i,t} = \frac{L_{i,t} - L_{i,t-1}}{\frac{1}{2} * (L_{i,t} + L_{i,t-1})}$$

$g_{i,t}$ is the employment growth rate of type i at year t. The type is either white-collar workers, blue-collar workers or total number of workers including both white-collar workers and blue-collar workers. $L_{i,t}$ is the employment of type i at year t. If $|g| \leq 0.2$, the employment change is counted as moderated change. If $|g| > 0.2$, it is counted as large change.

In Table 2.3, the share of firms according to the employment growth rate is shown. The administrative workers are roughly equivalent to non-production workers or white-collar workers or skilled workers. The operative workers are roughly equivalent to production workers, blue-collar workers or unskilled workers.

[7] Different years of the same firm are counted as different observations.

The share of firms without any employment change in total employment is 5.8%. It is 17.2% for administrative workers, which is significantly higher than the 7.2% for operative workers. This result is consistent with the findings of Hamermesh [1993] and Pfann and Palm [1993] that the adjustment of non-production workers is more rigid than that of production workers.

However, the share of firms with large employment change, either positive or negative, is higher for administrative workers than the operative workers. The share of firms with large total employment growth rate,$|g|$, exceeding 0.2, either positive or negative, is 15.6%. It is 24.7% for administrative workers, which is higher than 21.3% of operative workers. The share of firms with moderate employment change rate, $|g| \leq 0.2$, is 78.5% for total workers. It is 58.1% for Administrative workers, which is lower than 71.5% for operative workers.

Table 2.3: Employment growth by type of workers

Employment growth	Administrative	Operative	Total
$\|g\| > 0.2$	24.7%	21.3%	15.6%
$\|g\| < 0.2$	58.1%	71.5%	78.5%
$\|g\| = 0$	17.2%	7.2%	5.8%

Note: Annual growth of firms in 1979-1993

Table 2.4: Employment growth by type of workers - positive change

Employment growth	Administrative	Operative	Total
$\|g\| > 0.2$	29.6%	20.4%	14.3%
$\|g\| < 0.2$	70.4%	79.6%	85.7%

In terms of employment growth, if a distinction is made between the positive and negative growth, then the share of large change for the negative

Table 2.5: Employment growth by type of workers - negative change

Employment growth	Administrative	Operative	Total
$\lvert g\rvert > 0.2$	30.1%	24.7%	18.3%
$\lvert g\rvert < 0.2$	69.9%	75.3%	81.7%

change is higher than for the positive change for every type of worker as shown in Table 2.4 and Table 2.5.

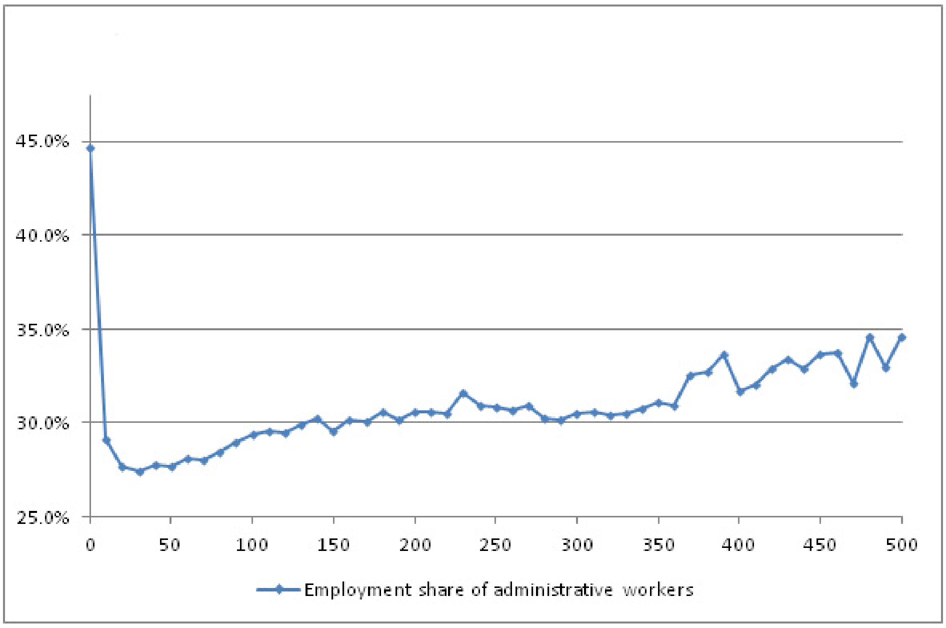
This implies higher adjustment cost for firing than hiring. However, the share of large change is higher for white-collar workers for both positive change and negative change although the share of no change is higher for white-collar workers as well. For every case, the share of moderate employment change of total workers is shown to be higher than that for both administrative workers and operative workers.

My model suggests that the firm's employment of fixed part of white-collar workers does not change until the firm changes its product variety. This explains the high share of firms that do not change the employment of white-collar workers. However, once firms change the product variety or add another product variety, then they need to change the employment of white-collar workers discontinuously. That creates lumpy adjustment of white-collar labour.

2.3.4 The effect of firm size

The share of non-production workers is initially very high remaining stable at 44.7% for firms with total employment between 1 and 9 but then beginning to fall until the total employment of the firms reaches 30-39. The share of non-production workers is the lowest, 27.5%, for firms with the total employment between 30 and 39. Then, the share of non-production workers

Figure 2.3: Employment share of administrative workers by firm size



Note: The average employment share between 1979 and 1993

increases with the firm size continuously. When the employment size is higher than 500 employees, the average share of non-production workers is 34.6%.

It is interesting that the share of white-collar workers is seen to decrease in scale among small firms. One possible reason is that there might be a lower bound of white-collar employment. For example, firms need to hire at least one white-collar worker - manager of the firm - although it is very small. Then, the share of white-collar workers would increase as firm size decreases.

Several questions arose. The first question was whether the relative employment share of white-collar workers in the total employment was affected by firm size, either in terms of employment or value added output. The second question was whether the relative employment of white-collar workers was increasing to scale or decreasing to scale and, lastly, whether there was any endogeneity behind such relationship between firm scale and white-collar employment share. To address these, OLS, Fixed-Effect and Between-effect regressions were implemented and compared to each other.

$$ln\left(\frac{L_{i,t}^{H}}{L_{i,t}^{B}}\right) = \alpha + \beta \cdot ln\left(Y_{i,t}\right) + trend + \varepsilon_{i,t} \tag{2.5}$$

The dependent variable, $ln\left(\frac{L_{i,t}^{H}}{L_{i,t}^{B}}\right)$ is the log of the ratio of white-collar workers to blue-collar workers in firm i at time t. It is regressed for both the log of value added output, $ln\left(Y_{i,t}\right)$. A linear time trend dummy is also included.

The firm size can be defined in terms of both output and employment. Therefore, it is regressed for $ln(L)$, the log of total employment as well.

$$ln\left(\frac{L_{i,t}^{H}}{L_{i,t}^{B}}\right) = \alpha + \beta \cdot ln\left(L_{i,t}\right) + trend + \varepsilon_{i,t} \tag{2.6}$$

Table 2.6: The effect of firm size - OLS

$ln(\frac{L^W}{L^B})$	(1)	(2)	(3)	(4)
$ln(Y)$	0.163***(0.005)	0.162***(0.005)	-	-
$ln(L)$	-	-	0.098***(0.007)	0.098***(0.007)
trend	-	0.004***(0.001)	-	0.008***(0.001)
Obs.	112,800	112,800	112,800	112,800

Note:
1) L^W: the employment of white-collar (Administrative) workers in the firm
2) L^B: the employment of blue-collar (Operative) workers in the firm
3) ***: significant at 1% error level
4) standard errors in the parenthesis are clustered at firm level

The OLS results are shown in Table 2.6. Both output and total employment are very highly significant (at 1% significance level) and positively correlated with the share of non-production workers. One percent increase in the firm output is associated with the increase of the relative employment ratio of white-collar workers to blue-collar workers by approximately 0.163 percent. However, there must be a caution to interpreting this result for it does not necessarily indicate that the white-collar employment share increases by 0.163 percent when a firm increases its output, as will be shown later. The scale effect also appears with respect to the employment size as well. One percent increase in the total employment of the firm is associated with the increase of the ratio of white-collar workers by 0.098 percent. The result remains qualitatively the same after including the time trend dummy. The coefficients on the trend dummy are positively significant for both regressions : 0.004 for output and 0.008 for employment. It implies that there exists an upward trend in white-collar employment share.

Panel analysis

OLS estimation result includes both direct effect of firm size on white-collar employment share and the indirect effect due to endogeneity. The firm size is positively correlated with the unobserved requirement level of fixed white-collar workers, L_f^W, which is also positively correlated with the white-collar employment share (including both variable part and fixed part of white-collar employment). As significant part of the positive correlation in OLS might come from such endogeneity, panel analysis is also implemented. Because the size of fixed white-collar employment requirement is specific to the characteristic of the product which the firm is producing, it is unlikely to change in short-term although it is not entirely fixed. Therefore, a significant part of the effect from the size of fixed white-collar labour, L_f^W, is supposed to be captured by the time-invariant firm-specific fixed effect.

Fixed-effect estimation shows completely different results. The result is shown in Table 2.7. The coefficient of the firm size, both in terms of

Table 2.7: The effect of firm size - FE

$ln(\frac{L^W}{L^B})$	(1)	(2)	(3)	(4)
$ln(Y)$	-0.045***(0.006)	-0.053***(0.006)	-	-
$ln(L)$	-	-	-0.183***(0.014)	-0.174***(0.015)
trend	-	0.010***(0.001)	-	0.008***(0.001)
Obs.	112,800	112,800	112,800	112,800

output and employment, turns to negative. The coefficient of the log of value added output is -0.045 and that of the log of employment is -0.183. The values remain qualitatively unchanged after time trend dummy is included. The coefficients on time trend are positive for fixed-effect case as well. These contrasting patterns imply that a large part of the positive correlation between firm scale and relative demand for white-collar labour comes from between-firm effect. Therefore, between-effect panel estimation is also implemented.

Table 2.8: The effect of firm size - BE

$ln(\frac{L^W}{L^B})$	(1)	(2)	(3)	(4)
$ln(Y)$	0.173***(0.004)	0.172***(0.004)	-	-
$ln(L)$	-	-	0.098***(0.005)	0.097***(0.005)
trend	-	0.004***(0.002)	-	0.010***(0.002)
Obs.	112,800	112,800	112,800	112,800

The between-effect estimation result is shown in Table 2.8. The coefficient of log output is 0.173, which is slightly larger than the OLS estimate. The coefficient of log employment is 0.098 and also significant at 1% significance level. The coefficients of time trend for log output equation is 0.004 and that of log employment is 0.010. Both are significant at 1% significance level.

2.3.5 The change in administrative workers' employment share

Table 2.9: The effect of the change in the firm output

$\Delta ln(\frac{L^W}{L^B})$	(1)	(2)	(3)
$\Delta ln(Y)$	-0.040***(0.004)	-0.036***(0.004)	-0.022***(0.007)
$\Delta ln(Y) * D_{neg}$	-	-	-0.025***(0.010)
year dummies	No	Yes	Yes
Obs.	84,046	84,046	84,046

Note: $D_{neg} = 1$ if $\Delta ln(Y) < 0$

$$\Delta ln\left(\frac{L^H_{i,t}}{L^B_{i,t}}\right) = \alpha + \beta_1 \cdot \Delta ln\left(Y_{i,t}\right) + D_{year} + \beta_2 \cdot D_{negY} \cdot \Delta ln\left(Y_{i,t}\right) + \varepsilon_{i,t} \quad (2.7)$$

$$D_{negY} = 1\, if\, \Delta ln\left(Y_{i,t}\right) < 0$$

$\Delta ln\left(\frac{L^H_{i,t}}{L^B_{i,t}}\right)$ is the annual change in the log of the ratio of white-collar workers to blue-collar workers in firm i between time t and $t-1$. $\Delta ln\left(Y_{i,t}\right)$ is the annual change in the log of output. D_{year} is set of dummies for each year. Each year dummy corresponds to any common disturbance specific to that year, affecting the white-collar employment share across all firms. Aggregate skill-biased technology shock, which is specific to the year, is supposed to be captured by the year dummy. However, the positive and negative changes in output might have heterogeneous effect on the white-collar employment share. Therefore, the interaction dummy term is included. $D_{negY} = 1$ if the change in output is negative.

$$\Delta ln\left(\frac{L^H_{i,t}}{L^B_{i,t}}\right) = \alpha + \beta_1 \cdot \Delta ln\left(L_{i,t}\right) + D_{year} + \beta_2 \cdot D_{negL} \cdot \Delta ln\left(L_{i,t}\right) + \varepsilon_{i,t} \quad (2.8)$$

$$D_{negL} = 1\, if\ \Delta ln\left(L_{i,t}\right) < 0$$

The regression results on the annual differences are shown in Table 2.9 and Table 2.10. The difference in the log employment share of white-collar workers is negatively correlated with the difference in the log of output. One percent increase in value added output from the previous year decreases the relative employment ratio of white-collar workers by 0.040 percent. The inclusion of year dummies decreases the absolute size of coefficient slightly from -0.040 to -0.036.

However, if the interaction dummy, which becomes 1 if the change in value added is negative, is included, the coefficient changes from -0.036 to -0.022. The coefficient on the interaction dummy term is negative, which is -0.025, and this means that the negative correlation between the change in firm size (in terms of value added output) and the employment share of administrative workers is stronger for negative change than positive change.

Table 2.10: The effect of the change in the firm employment

$\Delta ln(\frac{L^W}{L^B})$	(1)	(2)	(3)
$\Delta ln(L)$	-0.249***(0.017)	-0.245***(0.017)	-0.284***(0.033)
$\Delta ln(L) * D_{neg}$	-	-	0.069*(0.040)
year dummies	No	Yes	Yes
Obs.	84,046	84,046	84,046

Note: $D_{neg} = 1$ if $\Delta ln(Y) < 0$

The negative correlation is even larger for employment change. One percent increase in the employment from the previous year decreases the relative employment ratio of white-collar workers by 0.249 percent. The inclusion of year dummies just slightly decrease the magnitude of the coefficient from -0.249 to -0.245. The coefficient of the interaction dummy for negative change is positive, which is 0.069. This is in contrast with the result for the change in output. This implies that the negative relationship between the change in firm size and the employment share of white-collar workers is weaker for negative firm size change if the firm size is measured in terms of employment.

This result is also in line with Dunne et al. [1996], who report that white-collar employment share is negatively correlated with the business-cycle in the US manufacturing industries.

2.3.6 Potential alternative explanations

It is also possible to explain the above result, namely the negative correlation between the change in the employment share of white-collar workers and the change in firm size, under the conventional assumption that both types of workers are variable factors. For example, it is usually presumed, including by Dunne et al. [1996] and Hamermesh [1993], that adjustment costs (hiring and firing costs) of skilled workers are greater than those for unskilled workers. If so, firms which increase employment to meet the demand during expansion hire blue-collar workers first and fire blue-collar workers first when they have to decrease production. This also generates the negative correlation between the change in firm output (or employment) and the change in the employment share of white-collar workers (skilled workers).

The underlying assumption of such an explanation is that the optimal employment of white-collar workers changes flexibly in response to output fluctuations, but the actual employment does not follow up the optimal employment due to the labour rigidity. Therefore, such a rigid adjustment of white-collar employment would disappear if the rigidities (in terms of hiring and firing costs) are removed. In contrast, what this study suggests is that the optimal employment (for white-collar labour) itself is rigid. Therefore, one implication of this study is that the adjustment of the employment of white-collar workers will still remain less responsive to the output fluctuations, although the hiring and firing costs approach zero.

The implications on productivity are also different between the two explanations. If white-collar labour is regarded as entirely variable input, the employment ratio of white-collar to blue-collar workers would deviate from the optimal level both during the boom time and recession time, leading to lower productivity, certeris paribus. To explain the pro-cyclical productivity, an exogenous technology shock, which is large enough to offset such a negative compositional effect, is required. However, under the assumption of this thesis that white-collar labour is an overhead input, such a compositional effect of labour force is likely to contribute to the pro-cyclicality of labour productivity. Therefore, implied size of positive technology shock to match the observed pro-cyclicality of productivity would be significantly smaller under the framework of this study.

To test which of the contrasting predictions are true requires identification of whether the expansion of each firm is due to a demand shock or a supply shock (productivity shock). However, it is beyond the scope of this study and remains to be further studied.

2.4 Conclusion

The share of administrative workers is found to be positively correlated with firm scale in UK manufacturing industries. However, this positive correlation is due to the between-firms effect, and a negative correlation is found in time dimension. This implies that firm size is positively correlated with only the firm-specific, time-invariant effect.

This study suggests that this is due to the positive correlation between the minimum required level of white-collar workers to produce the product, which the firm is producing and the size of the firm. High frequency variations in output changes affect only the demand for variable inputs and do not affect fixed labour input, which is biased towards fixed input, leading to the negative correlation between firm size and the employment share of white-collar workers over time.

Chapter 3

The effect of firm entry and exit on skill demand and productivity

3.1 Intro

Firm entry and exit have significant influences over job creation and job destruction, and this is also considered to be an important source of productivity growth. (Wheeler [2005]; Dunne et al. [1996]); Aghion et al. [2004]; Foster et al. [1998]) Then, the next question, which arises, is whether firm entry and firm exit are also related with the shift in skill demand. In this chapter, the effects of firm entry and exit on the employment of white-collar workers and the labour productivity are empirically tested using firm level data on UK manufacturing industries.

It is found that entering firms have significantly higher labour productivity, but this is due to the fact that firm entry is more concentrated in the industries with higher labour productivity. However, exiting firms have lower labour productivity. This is consistent with the theory that negative productivity shock leads firms to exit (Hopenhayn [1992]).

It is found that entering firms have a significantly higher share of administrative workers than incumbent firms. It is not surprising given that new firms are supposed to embody the latest technology. However, it is found that not only entering firms but also exiting firms have higher share of administrative workers than incumbent firms. It is rather surprising considering the fact that exiting firms are declining firms with lower labour productivity. It means that this pattern cannot be explained simply as a result of technological progress.

It might be due to that exiting firms lay off operative workers before they lay off administrative workers, who are supposed to constitute fixed labour input. The negative correlation between the change in firm scale and the change in the share of administrative workers found in the previous chapter is consistent with the finding that both entering and exiting firms have higher share of administrative workers. Upon entry, the firms experience positive change in firm scale, while firms experience negative change in firm scale before exit.

However, the main assumption of this study that skilled workers mainly constitute overhead labour implies that at least part of the decline in the labour productivity of exiting firms comes from the scale effect. The decrease in the share of variable factors decreases labour productivity even further, amplifying the exogenous productivity shock.

The remainder of the chapter is structured as follows: Section 3.2 shows the outline of the data. Section 3.3 implements empirical estimations. Section 3.4 concludes.

3.2 Data

The same ARD database is used as in the previous chapter. An entrant is defined as the firm which did not exist at t-1 but appears at t. An exitor is defined as the firm which exists at t but does not exist at t+1. Stayers are those firms which have existed over t-1, t and t+1. Those firms entering at t and directly exiting at t+1 are excluded.

To determine which firms are entering, exiting or staying firms, the non-selected files are used as well as the selected files following Disney et al. [2003]. Not all firms are sampled every year; larger firms report every year, but smaller firms are sampled randomly.[1] Therefore, as only selected firms reported data on the employment of administrative workers and operative workers, looking at only selected files can cause bias as unsampled firms might be counted as exit firms although they actually did not exit but were just not sampled. Therefore, both selected and non-selected files are combined. If a firm which appeared on the selected files at time t did not appear at t+1 on the same file but still appears on the non-selected files, it is not counted as firm exit. Table 3.1 presents descriptive statistics on the firm entry and exit in UK manufacturing industries between the years 1979 to 1995.

The average number of total employees per firm, emp_{tot} is 156.23 for entering firms, 266.67 for exiting firms and 280.58 for incumbent firms. The entrant firms are the smallest in employment size, and the incumbent firms are the largest. However, the entering firms have the largest employment share of administrative workers, $\frac{emp_{admin}}{emp_{tot}}$, 32.52%, while the incumbent

[1]According to Oulton [1997], from 1986 to 1988, firms employing more than 100 workers reported every year, but only half of firms with an employment size of between 50 and 100 were sampled/

Table 3.1: Firm entry and exit

	Entrant	Exitor	Stayer
emp_{tot}	156.23	266.67	280.58
emp_{admin}	54.77	89.81	92.57
emp_{op}	101.46	176.86	188.00
$\frac{emp_{admin}}{emp_{tot}}$	32.52%	31.30%	30.01%
Obs.	6,421	6,583	191,485

firms have the smallest share, 30.01%. Nevertheless, the exiting firms also show higher share of administrative workers, 31.30%, than the incumbent firms.

3.3 The effects of firm entry and exit

To capture the effect of firm entry and exit on the skill demand, a regression is implemented including dummy variables representing firm entry and exit:

$$s^w_{i,t} = \alpha + \beta_1 \cdot D_{entry,i,t} + \beta_2 \cdot D_{exit,i,t} + \gamma_1 \cdot ln(emp_{tot,i,t}) + \gamma_2 \cdot ln(emp_{tot,i,t})^2 + \varepsilon_{i,t} \tag{3.1}$$

$$s^w_{i,t} = \frac{emp_{admin}}{emp_{tot}} * 100$$

$s^w_{i,t}$ is the employment share of administrative workers of firm i, at year t. The effects of firm entry and exit are captured by the coefficients of the dummy variables, $D_{entry,i,t}$ and $D_{exit,i,t}$.

As shown in Chapter 2, the employment share of non-production workers is positively correlated with firm size across the cross-section. As both entering firms and exiting firms are smaller than incumbent firms, the coefficients on the dummies of entrance and exit might be downward biased. Therefore, the log of the employment size, $ln(emp_{tot,i,t})$, is included in the regression equation (3.1). To capture the non-linearity of the effect of firm size, the square of the variable, $ln(emp_{tot,i,t})^2$, is also included.

Table 3.2: The effects on the share of administrative workers

	(1)	(2)	(3)	(4)
Dependent:	s^w		$\tilde{s}^w$	
$D_{Entrant}$	2.632***	2.901***	1.328***	1.554***
	(0.317)	(0.313)	(0.257)	(0.256)
D_{Exitor}	1.289***	1.292***	1.163***	1.178***
	(0.266)	(0.265)	(0.213)	(0.212)
$ln(emp_{tot})$	-	-4.151***	-	1.245***
		(0.552)		(0.101)
$ln(emp_{tot})^2$	-	0.537***	-	0.389***
		(0.0572)		(0.0486)
Constant	30.02***	36.87***	-0.0918	0.0380
	(0.119)	(1.279)	(0.0836)	(0.106)
Observations	203,970	203,970	203,970	203,970
R-squared	0.001	0.010	0.000	0.006

Note:
1) standard errors are in parenthesis and clustered at firm level
2) over the period of 1979-1995 in UK manufacturing industries

The regression result is shown in Table 3.2. The dependent variable is the employment share of administrative workers, $s^w_{i,t}$, in 0-100% scale for the first two columns. In the first column, the coefficient for the dummy variable for entrant firm is 2.632 and significant at 1% error level before controlling the effect of firm size. It means that the entering firms in UK manufacturing showed 2.632 %p higher employment share of administrative workers than the incumbent firms. However, what is rather surprising is that the exiting firms also showed significantly higher employment share of administrative workers. The coefficient for the dummy variable of firm exit is 1.289 and significant at 1% error level.

In the second column, the regression result which includes variables representing firm size is shown. The coefficients for firm entry and exit increases slightly after controlling the effect of firm size and remains significant at 1% error level. This implies firm size is positively related with the employment share of administrative workers. However, the coefficients for the dummies of firm entry and exit not only remain significant but also increase in the size. This might reflect the fact that both the entering firms and exiting firms are smaller than incumbent firms.

However, it is possible that the year-specific and industry-specific factors have caused a bias in the estimate. For example, firm entry or exit might have been more frequent in some industries than others, while those industries are different with respect to the employment share of administrative workers. Therefore, it will be examined whether the employment share of administrative workers in the entering or exiting firms is higher than the average of the same industry in the same year.

$$\tilde{s}^w_{i,t} = \alpha + \beta_1 \cdot D_{entry,i,t} + \beta_2 \cdot D_{exit,i,t} + \gamma_1 \cdot ln(e\tilde{m}p_{tot,i,t}) + \gamma_2 \cdot ln(e\tilde{m}p_{tot,i,t})^2 + \varepsilon_{i,t} \tag{3.2}$$

$$\tilde{s}^w_{i,j,t} = s^w_{i,j,t} - \bar{s}^w_{j,t}$$

$$e\tilde{m}p_{tot,i,t} = emp_{tot,i,t} - e\bar{m}p_{tot,j,t}$$

$\bar{s}^w_{j,t}$ is the average employment share of white-collar workers (administrative workers) of all the firms in the industry j, categorized by 5-digit SIC code, at time t. $\tilde{s}^w_{i,j,t}$ is the difference between a firm's own employment share of white-collar workers and $\bar{s}^w_{j,t}$, the average of the 5-digit SIC industry to which the firm belongs. The variables controlling for firm size effect are also replaced by the difference from the average firm size of the industry, $\tilde{emp}_{tot,i,t}$.

The regression result is shown in the 3rd and 4th column of Table 3.2. Although the size of the coefficients decreases slightly, the pattern remains qualitatively the same. Both the entering and exiting firms show a significantly (at 1% error level) higher share of administrative workers than the average of the firms in the same industry in the same year.

The effect on the labour productivity

In literature, firm entrance is considered as an important source of technological innovation. New firms are expected to bring new technology to the economy. However, exiting firms are supposed to have lower level of productivity. Therefore, it has been tested whether entering firms have higher level of labour productivity.

$$lnz_{i,t} = \alpha + \beta_1 \cdot D_{entry,i,t} + \beta_2 \cdot D_{exit,i,t} + \gamma_1 \cdot ln(emp_{tot,i,t}) + \gamma_2 \cdot ln(emp_{tot,i,t})^2 + \varepsilon_{i,t} \tag{3.3}$$

$$z_{i,t} = \frac{Y_{i,t}}{emp_{tot,i,t}}$$

The dependent variable of the regression equation (3.3) , $lnz_{i,t}$, is the log of the labour productivity of the firm i at year t. The labour productivity is defined as the value added output per employee. The nominal value-added output is converted to the real value added output using GDP deflators.

The regression result is shown in Table (3.3). In column (1), the coefficient for the firm entrance is 0.046 and significant at 1% error level. The coefficient for the firm exit is -0.097 and significant at 1% error level. This result shows that entering firms have higher labour productivity than incumbent firms, while exiting firms have lower labour productivity.

Table 3.3: The effects on the labour productivity

	(1)	(2)	(3)	(4)
Dependent:	$ln\, z$		$\widetilde{ln\, z}$	
$D_{Entrant}$	0.0461***	0.0880***	-0.0319***	0.0110
	(0.00902)	(0.00900)	(0.00782)	(0.00779)
D_{Exitor}	-0.0966***	-0.0949***	-0.139***	-0.133***
	(0.00889)	(0.00879)	(0.00771)	(0.00764)
$ln\, emp_{tot}$	-	-0.0776***	-	0.0781***
		(0.00752)		(0.00148)
$(ln\, emp_{tot})^2$	-	0.0160***	-	0.00382***
		(0.000735)		(0.000721)
Constant	3.334***	3.317***	-0.153***	-0.112***
	(0.00159)	(0.0187)	(0.00138)	(0.00166)
Observations	201,485	201,485	201,485	201,485
R-squared	0.001	0.023	0.002	0.020

Note:
1) standard errors are in parenthesis and clustered at firm level
2) over the period of 1979-1995 in UK manufacturing industries

However, the fact that both entering and exiting firms are smaller than incumbent firms could bias the estimates downward as the firm size is positively correlated with labour productivity. Therefore, variables representing the log of the number of employees per firm are included in the second column. To capture non-linearity, the square term of the log of employment size is also included. With the inclusion of firm size dummies, the coefficients for both entrance and exit increased.

Nevertheless, it is also possible such a relation appeared because firm entrance was more frequent in more productive sectors, such as IT industries. Table 3.4 shows that those industries with higher labour productivity also have higher rates of both entry and exit. The correlation between the log of the labour productivity of the 5 digit SIC industry and the rate of annual firm Entry of the industry (percentage point) is 0.126, and the correlation with the exit rate of the industry is 0.196.

To deal with this issue, the dependent variable of the equation (3.3), the firm's own labour productivity, $lnz_{i,t}$, is replaced with the difference between the firm's own labour productivity and the average labour productivity of the 5 digit SIC industry j, $ln\, z_{i,t} - ln\, \tilde{z_{j,t}}$. The results are shown in the column (3) and (4) of the table 3.3. The coefficient for firm entrance turns to negative, -0.0319, and significant at 1% error level. The coefficient for firm exit also decreases to -0.139 and significant at 1% error level. After the firm size effect is controlled, in the column (4), the coefficient for firm entry is insignificant, and the coefficient for firm exit still appears negative and still significant at 1% error level.

Table 3.4: The correlation between avg. productivity and entry and exit rates

	Entrant (%)	Exitor (%)	Stayer (%)
$ln(labour\, productivity)$	0.126	0.196	-0.201

In summary, firm exit is negatively correlated with labour productivity in all specifications. However, firm entrance is shown to be positively correlated, but the positive correlation is supposed to come from the fact that firm entrance is more common in more productive industries. It appears that entering firms are not more productive than incumbent firms in the same industry in the same year.

3.3.1 The channel between firm entry and exit and skill demand

The finding that entrant firms have higher share of administrative workers does not seem to be strange as new firms need to hire them to initiate the new business. It is consistent with the assumption of this study that white-collar labour is quasi-fixed or overhead labour input rather than variable input.

However, it is a rather surprising finding that exiting firms, with lower productivity, also show higher share of administrative workers. As the employment share of more educated workers is supposed to be positively correlated with the aggregated labour productivity, it is rather puzzling that firms exiting the market due to lower productivity actually show a slightly higher share of administrative workers.

A possible explanation is that declining firms fire operative workers earlier than administrative workers, leading to an increase in the share of administrative workers. If administrative workers constitute variable input, this compositional change is expected to increase labour productivity. However, if, instead, they constitute quasi-fixed input, it would decrease the labour productivity by decreasing the share of variable input in the total factor inputs. The result discussed earlier favours the latter view that administrative workers constitute quasi-fixed input, although the factor that exiting firms suffered a huge negative productivity shock, which offset the increase in productivity due to compositional effect of labour force cannot be excluded.

Firm exit is usually explained as result of negative exogenous productivity shock. However, increasing return to scale due to the existence of overhead labour implies that part of the decline in the productivity of exiting firms is not due to the exogenous productivity shock, but, rather, due to the amplification effect of negative productivity shock via increasing return to scale.

3.4 Conclusion

It has been empirically examined whether firm entry and exit have significant effect on productivity and skill-demand in UK manufacturing industries. It has been found that entering firms have higher level of productivity, but this might be due to the fact that firm entrance is concentrated in more productive industries, and no firm evidence is found that new firms are more productive. However, exiting firms are found to be less productive as is to be expected.

Entering firms are found to have a higher share of non-production workers than incumbent firms even after controlling for other factors, such as firm scale, year and industry. However, exiting firms are also found to have higher share of administrative workers even after controlling for other factors, including firm scale, year and industry, and this fact is noteworthy, considering that these exiting firms are also found to have lower labour productivity. This appears rather puzzling, but, in fact, is consistent with this study's hypothesis that non-production workers constitute overhead labour.

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