Essays on the Skill Premium and the Skill Bias of Technological Change

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A thesis submitted to the Department of Economics of the London School of Economics for the degree of Doctor of Philosophy, London.

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of about 40000 words.

Frankfurt, November 6, 2013

Barbara Richter

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Abstract

Using a two-sector model of production with potentially different capital shares in each sector, I show that the evolution of the skill premium from 1970 to 2005 is consistent with skill-neutrality and even a mild unskill-bias of technological change for plausible values of capital shares. The main channel of adjustment to changes in labor supply is instead via the reallocation of capital. New investment occurs predominantly in the skilled sector, to the detriment of the unskilled sector of the economy. This result is shown both theoretically in a simple model and in a quantitative exercise using data on the US economy.

Repeating the exercise with industry level data for the US reveals that there has indeed been skill-biased technological change in a number of industries (such as Business Activities and Health), while others have experienced skill neutral and unskill-biased technological change (e.g. Agriculture). This difference in results across industries is largely due to very different capital shares.

Finally, I look at the impact of the increasing importance of information and communication technology (ICT) on the production function and the skill premium in each industry. I estimate a translog price function with skilled and unskilled labor, ICT capital and non-ICT capital as factors of production and find that most industries exhibit ICT capital-skill complementarity. For most industries, technological progress has led to an increased use of both types of capital, but the results on skill-biased technological change are as mixed as in chapter two. ICT has affected the skill premium negatively in nearly two thirds of the industries studied.

Introduction

The evolution of the skill premium in the US is a well documented fact. The premium that a skilled worker can earn relative to an unskilled one has grown by more than 20 % in the period from 1970 to 2005. At the same time, however, the supply of skilled workers relative to unskilled workers has also increased, making the rise in the skill premium a bit of a puzzle. Remarkably, the rise in relative supply and relative wage has occurred in nearly all industries, though to differing degrees.

The solution to this puzzle is often attributed to skill-biased technological change (SBTC), technological progress that has enhanced the productivity of skilled labor more than the productivity of unskilled labor. One possible manifestation of this progress in technology is the rise in information and communication technologies (ICT).

In three essays, I check this solution to the puzzle against the data. First, I simulate a fairly standard model of SBTC, but allow for an additional channel of adjustment to changes in labor supply: the reallocation of capital investment from the unskilled to the skilled sector. I find that there are plausible parameter values for which this channel is strong enough to explain the evolution of the skill premium without resorting to SBTC.

For the second essay, I look at twenty-two US industries separately. Ten of these industries exhibit SBTC, twelve do not. Aggregating results to the sectoral level, the primary sector clearly has not seen SBTC, whereas the manufacturing and services sectors have, to varying degrees. For the most part, developments across industries have not been uniform, but for the subsample from 1990 onwards most of them have experienced some SBTC. As this is the period in which ICT, in the form of computers, has come to be widely used, the next logical step is to investigate the relationship between ICT and the skill premium.

Therefore, in the third essay, I estimate a translog production function, separately for each of twenty industries, to determine the role ICT capital plays in the production function and in the evolution of the skill premium. I find that ICT capital and skilled labor are complementary inputs in production for the majority of industries. In most industries, technological progress has led to more use of capital, both ICT and non-ICT, and to labor saving. The overall effect of ICT capital on the skill premium is negative in fourteen of the twenty industries.

Taken together, my results suggest that the increase in the skill premium in most industries and in the economy as a whole is only partly due to SBTC, if at all. Shifts in capital investment, and mostly non-ICT capital investment at that, also seem to be important.

Chapter 1

The Skill-Bias of Technological Change and the Evolution of the Skill Premium in the US Since 1970

1.1 Introduction

From 1970 to 2005, the premium that a college educated worker can earn relative to a worker without a college degree has risen by more than 20% in the US, even though the relative supply of college educated labor has also increased during that time. This is commonly attributed to skill-biased technological change (SBTC). I show that this rise in the skill premium[1] could also be the result of capital reallocation following the increase in the relative supply of skilled labor that can be observed in the data. Technological change would be close to neutral in that case, or biased towards the unskilled if anything.

Usually the line of reasoning to explain SBTC is as follows: the skill premium, i.e. the relative price of college educated labor, has increased at the same time as the relative supply of skilled labor. This is only possible if relative demand for skilled labor has increased more than supply. The demand increase is then

[1] The terms "skill premium" and "college wage premium" are used interchangeably here. Both refer to the relative price of college educated labor.

attributed to technological progress that favors skilled workers - i.e. SBTC.

By allowing for different capital shares in the skilled and unskilled sector of production, I open up an additional channel through which the demand for skilled labor can adjust to the observed increase in supply. If the initial level of capital in the skilled sector is low and the capital share of the skilled sector is higher than that of the unskilled sector, a large reallocation of capital is triggered by the increase in the relative supply of skilled labor, leading to an increase in payment to skilled labor relative to unskilled labor.[2] If the capital shares are different enough, it is even possible that there is so much capital reallocation that technological progress must favor unskilled workers to explain the skill premium.

This mechanism is, in brief, the driver behind the main result of this paper. I simulate a two-sector model like the one in Caselli (1999), focusing on the effect of an increase of the relative supply of skilled labor on the evolution of the skill premium. The effects of changes to the skill premium on the decision to become skilled are not considered here, nor is the origin of the increase in relative supply. With this model I answer the following: Given the relative supply of skilled labor observed in the data, how must skilled and unskilled capital and skilled and unskilled production efficiency have evolved to yield the skill premium we see in the data? I find that if the difference between skilled and unskilled capital shares is large, unskilled production efficiency must have grown at least as fast as skilled production efficiency for the model to be consistent with the wage and skill supply data. This would suggest that there was no ongoing SBTC in the period under study.

The analysis cannot capture one-off technology shocks that may have occurred prior to 1970, however. Thus, if changes in the skill premium and the skill supply since 1970 are consequences of a single technology shock before 1970 that affects skilled production efficiency more than unskilled production efficiency, the shock would not be picked up. The conclusion would still be that SBTC has

[2]Caselli (1999) points out that a fall in the wages of low-skilled workers, which also leads to an increase in the skill premium, can be explained by a fall in the capital they use.

played a small role at most in the changes to the skill premium.

That SBTC might not be the best explanation for the increase in the skill premium has been pointed out before, e.g. by Card and DiNardo (2002), who show that SBTC fails along several dimensions of the distribution of wages. Beaudry and Green (2002) show empirically that capital can play an important role. Still, the majority of previous work attributes the increase in the skill premium to SBTC. In empirical, mostly labor oriented, studies (e.g. Goldin and Katz (2007), Autor, Katz, and Kearney (2008), among others, Katz and Autor (1999) provide an overview), the change in labor demand is usually represented by a time trend that does not distinguish between changes in technology and changes in the allocation of capital. These shifts of labor demand can explain much of the evolution of the skill premium. While the shifts are usually attributed to SBTC, it is equally plausible to interpret them as an increase in skilled capital relative to unskilled capital.

In theoretical models capital is included explicitly, but either differentiated along a different dimension than "use by skill level" (e.g. equipment and structures as in Krusell, Ohanian, Rios-Rull, and Violante (2000) and Greenwood, Hercowitz, and Krusell (1997), among others) or assuming identical production functions for all sectors (Caselli (1999), Galor and Moav (2000), Acemoglu (2002a), and others). While the latter is a common assumption, it is not a priori certain that it should hold in this case. The sectors of production in my model are differentiated with regard to the skill level of the workforce. It is thus plausible to assume that the capital and labor intensities are different in these sectors. Dropping the assumption of equal capital shares across sectors can lead to very different implications with respect to SBTC.

There are other explanations for the evolution of the skill premium: it could be due to a decrease in the minimum wage, which affects mostly low-skilled workers and hence increases the premium (Fortin and Lemieux (1997), and more recently Barany (2011)), or to a decline in workers covered by unions, which increases the spread of wages paid (again, Fortin and Lemieux (1997), also mentioned in Gottschalk (1997)). One problem with the deunionization and minimum wage explanations, though, is that the majority of the increase in the skill premium is due to increases in wage inequality in the upper part of the wage distribution (i.e. comparing the 90th wage decile to the 50th), while these explanations mainly affect the lower end of the distribution (i.e. comparing the 50th decile to the 10th; Acemoglu (2002b), Acemoglu and Autor (2010)). Barany (2011) shows that a decrease in the minimum wage can have knock-on effects on the upper part of the distribution, too, but the overall effect she finds is not large enough to be the primary explanation.

Another possible explanation is an increase in trade openness, which leads low-skilled production to move to other countries, reducing domestic demand for low skilled workers (Johnson (1997), Topel (1997)). This explanation, while appealing, cannot explain the timing of the increase (Acemoglu (2002b)) and the overall effect is very small, as the US is not open enough to allow for a larger effect.[3] Burstein and Vogel (2010) find that international trade and multinational production together explain about $1/9th$ of the change in the skill premium.

Finally, the complementarity of skilled labor and capital (most famously Krusell, Ohanian, Rios-Rull, and Violante (2000)) is given as an explanation. While Krusell, Ohanian, Rios-Rull, and Violante (2000) claim it can account for virtually all of the change in the skill premium, Ruiz-Arranz (2003) finds that when allowing for the possibility of skill-biased technological change, capital-skill complementarity explains at most 40% of these changes. While my results show that skill-biased technological change is not necessarily present, doubts on the importance of capital-skill complementarity remain.

[3]The relevant measure of openness here is the share of imports in total GDP. Production that has moved to other countries should raise imports, as the goods that were produced domestically previously now have to be imported. The share of US imports in total GDP was 10.6% on average over the period studied. While it rose from 5.4% in 1970 to 16.1% in 2005, this is still very low compared to the EU27's share of imports from outside the EU27 (excluding all intra-EU trade), which was 32.5% on average between 1995 and 2005. (US data from the BEA, EU27 data from Eurostat)

Due to the assumption of different capital shares and the inclusion of an irreversibility constraint on capital investment, the model presented in section 1.2 is too complex to allow the derivation of a closed form expression for the equilibrium path of skilled and unskilled capital. I will therefore show my main result mathematically in a simplified version of the model in section 1.3 and then show quantitatively that this result can also hold for the full model, even when matching the model's parameters to the US economy. Section 1.4 gives details of the procedure and the derivation of these parameters, and the main results and robustness checks are presented in section 1.5. Section 1.6 concludes. Details on the algorithm are relegated to the appendix.

1.2 The Model

1.2.1 Production Function

There are two types of production, skilled and unskilled, that are perfect substitutes in producing the final good. Each type of production is Cobb-Douglass. Final output is given by:

$$Y_t = A_{s,t} K_{s,t}^{\beta} L_{s,t}^{1-\beta} + A_{u,t} K_{u,t}^{\gamma} L_{u,t}^{1-\gamma} \tag{1.2.1}$$

where s and u denote variables pertaining to skilled and unskilled production respectively, K is capital used in each type of production and L is hours worked. β is the skilled capital share, γ the unskilled one. A is a measure of production efficiency[4], and the relative growth rates of skilled and unskilled production efficiency determine the bias of technological change. This model nests the case of equal capital shares, but does not assume equality. In section 1.5 I look at the consequences of relaxing the assumption of perfect substitutability between skilled and unskilled production.

[4]Note that the A are not TFP: an increase in one of them would not lead to a parallel shift outwards of the production possibilities frontier.

Skilled production today includes pharmaceuticals and telecommunications equipment, where new production processes and very sensitive materials are handled by highly skilled workers. Examples of unskilled production are the textile and apparel industries, or food industries. Workers with college degrees are unlikely to be found on the floor of a meatpacking plant.

The production function can be normalized to output per hour worked

$$y_t = \frac{Y_t}{L_t} = A_{s,t} k_{s,t}^{\beta} \varphi_t^{1-\beta} + A_{u,t} k_{u,t}^{\gamma} (1-\varphi_t)^{1-\gamma} \tag{1.2.2}$$

with $\varphi \in (0,1)$ the fraction of hours worked by skilled workers, for which there is readily available data. In principle $\varphi = 0$ (only unskilled workers) and $\varphi = 1$ (only skilled workers) are possible, but as it is very unlikely that these extremes ever occur in reality, I ignore them. Lower case letters are the per-hour-worked equivalents to the elements of the final output production function.

1.2.2 Returns to Factors

The factors of production are paid their marginal products, so skilled wages are

$$w_{s,t} = (1-\beta) A_{s,t} k_{s,t}^{\beta} \varphi_t^{-\beta} \tag{1.2.3}$$

and the return to skilled capital is

$$r_{s,t} = \beta A_{s,t} k_{s,t}^{\beta-1} \varphi_t^{1-\beta} \tag{1.2.4}$$

and similarly for unskilled wages and return to capital. The skill premium is given by

$$\frac{w_{s,t}}{w_{u,t}} = \frac{1-\beta}{1-\gamma} \frac{A_{s,t}}{A_{u,t}} \frac{k_{s,t}^{\beta}}{k_{u,t}^{\gamma}} \frac{\varphi_t^{-\beta}}{(1-\varphi_t)^{-\gamma}} \tag{1.2.5}$$

Wages are increasing in both production efficiency and capital. An increase in the skill premium then requires that $A_{s,t} k_{s,t}^{\beta}$ grows faster than $A_{u,t} k_{u,t}^{\gamma}$, even more so as φ is increasing, too, which depresses the skill premium.

1.2.3 Irreversibility of Capital

The final good can be used for consumption or transformed into either type of capital without cost. Once it has been transformed into one type of capital however, it cannot be changed into the other type, i.e. investment in either type of capital is irreversible. Capital depreciates at a rate $\delta_j, j = s, u$, that may or may not be the same for both types of capital. The constraints can thus be written as $k'_s \geq (1 - \delta_s)k_s$ and $k'_u \geq (1 - \delta_u)k_u$.

There are two reasons for including this constraint: it strengthens the central result of this paper, and it is realistic. The main mechanism I propose as an alternative to skill biased technological change works via a shift of new investment from unskilled capital to skilled capital as a consequence of an increase in the share of skilled hours worked. If the level of unskilled capital is higher than is optimal, there can be no reallocation of the existing unskilled capital to the skilled sector, only a reallocation of new investment. This slows down the shift of capital to the skilled sector. As the increase in the skill premium requires $A_{s,t}k_{s,t}^{\beta}$ growing faster than $A_{u,t}k_{u,t}^{\gamma}$, this brake on the growth of skilled capital means that skilled production efficiency must have grown faster than it would if there were no irreversibility constraint. Hence, the constraints bias the results towards concluding that there has been SBTC. If the results show an unskill bias of technological change nonetheless, this result is more robust as one important and realistic obstruction to the adjustment channel I propose is already accounted for.

The realism of irreversible investment has been observed before. Bertola (1998) notes that the market for used capital is thin or non-existent in most cases, as the capital used for a certain type of production is of no value outside of this production. As the two types of production in my model are very different, it is plausible that the capital used in one type of production is of no value in the other type. This also implies that a skilled worker cannot learn how to use unskilled capital and vice versa. Caballero (1999) provides empirical evidence on accumulation of capital that suggests the presence of an irreversibility constraint. In a simulated RBC model, Coleman (1997) shows that introducing an irreversibility constraint yields changes in the interest rate that better match the data than a model without this constraint.

The constraint imposed is a very generic form of irreversibility, it simply provides a lower bound on the units of capital available in any given period. Similar constraints have been used by Dixit (1995), Coleman (1997) and Bertola (1998).

There are other types of irreversibility, such as the vintage capital models used by Jovanovic (1998) and Jovanovic and Yatsenko (2012), and the putty-clay models based on Johansen (1959). Both types assume that new investment can be made in any type of capital, but once the investment is made, the installed capital is fixed in the sense that there is no technological progress that could improve existing capital. In vintage capital models, investment in new capital will always be in the latest vintage. An additional feature of putty-clay models is that the production function of each unit of installed capital becomes Leontieff, i.e. the amount of labor that can work with each unit of this capital is fixed. Putty-clay models were revived by Kehoe and Atkeson (1999) and Gilchrist and Williams (2000), who find that these models yield better predictions of the behavior of output and employment following a shock than the neoclassical model (without irreversibility).

These ways of modeling irreversibility are not useful for the purposes of this paper, however. As Bliss (1968) points out, technological progress in these models is fully embedded in new capital. This is counterproductive when trying to isolate the path of technological progress from aggregate data. It is also not wholly realistic, as innovation can take the form of an improvement of existing capital (an easy example would be a free software upgrade). This could not be captured via putty-clay and vintage models of capital. For the same reason, the assumption of an ex-post Leontieff production function for installed capital is unrealistic.

Innovations to existing capital can lead to changes in the units of labor required (again, software upgrades are a useful example: an improved version of the same software may mean work can now be done more efficiently by one person that was previously done by two).

1.2.4 Households

There is a mass one of identical households, each with a measure one of members who share all risks and income. Each household member inelastically provides one unit of labor. Households' per-period utility function is logarithmic and they discount the future with factor ρ. I check the robustness of my results to the choice of utility function later on.

A share φ_t of members of each household is skilled each period. At the beginning of each period, unskilled members of the household can choose to become skilled[5], then production occurs, incomes are earned, and investment decisions for the following period are taken. Each investor decides on their investment taking everyone else's decision on investment and the relative supply of skills as given.

The decision to become skilled or remain unskilled is not modeled explicitly, as I am not interested in the reasons determining skill acquisition, but only need to know the resulting relative skill supply. I can observe this relative skill supply in the data. Any explicit model of skill acquisition decisions would need to match this data and thus not affect the main results of this paper, therefore I simply use the data directly and treat labor supply as given.

[5]Only unskilled household members take this decision, as an education generally cannot be undone. This does not matter here, as the share of skilled labor is monotonously increasing over the period of interest. If this were not the case, each household member would need to have a finite lifespan and be replaced by a new, unskilled, member who could then decide not to become skilled.

1.2.5 Equilibrium

Households maximize lifetime utility subject to the resource constraint and the irreversibility constraints on investment. The model is in discrete time, each unit of time corresponding to a year.[6]

$$max_{\{k_{s,t+1},k_{u,t+1}\}_{t=0}^{\infty}} U = \sum_{t=0}^{\infty} \rho^t ln(c_t) \tag{1.2.6}$$

$$s.t. \quad c_t + k_{s,t+1} + k_{u,t+1} \leq y_t(k_{s,t}, k_{u,t}) + (1-\delta_s)k_{s,t} + (1-\delta_u)k_{u,t} \quad \forall t \geq 0$$

$$k_{j,t+1} \geq (1-\delta_j)k_{j,t} \qquad \forall t \geq 0, \quad j \in s, u$$

$$k_{j,t+1} > 0 \qquad \forall t \geq -1, \quad j \in s, u$$

$$k_{s,0}, k_{u,0} \quad \text{given}$$

Households know their future paths of labor supply and the evolution of production efficiency, there is no uncertainty in the model.

In equilibrium, the following first order conditions must hold:

$$\frac{1}{c_t} + \mu_{j,t} = \rho \frac{1}{c_{t+1}}(1 - \delta_j + r_{j,t+1}) + \rho \mu_{j,t+1}(1-\delta_j) \tag{1.2.7}$$

where $j = s, u$ and $\mu_{j,t}$ is the Lagrange multiplier on the irreversibility constraint for capital of type j at time t.

As long as the irreversibility constraint is not binding, the rates of return on both types of capital are equal and determine consumption growth.

$$\frac{c_{t+1}}{c_t} = \rho(r_{s,t+1} - \delta_s + 1) = \rho(r_{u,t+1} - \delta_u + 1) \tag{1.2.8}$$

Whenever the constraint becomes binding for one type of capital, consumption growth is determined by the rate of return to that type of capital for which the constraint is not binding.

[6] To improve readability, the index denoting households is suppressed.

1.2.6 Balanced Growth Path

Let $\bar{g}$ be the growth rate of output on the balanced growth path, and let $\bar{g_s}$ and $\bar{g_u}$ be the BGP growth rates of A_s and A_u, respectively.

Proposition 1. *If* $\bar{g} = \frac{1}{1-\beta}\bar{g_s} = \frac{1}{1-\gamma}\bar{g_u}$, $0 < \varphi < 1$ *is constant and the irreversibility constraint is not binding, then there exists a Balanced Growth Path on which* y, c, k_s *and* k_u *grow at constant rates.*

Proof. The proof proceeds in three steps: first, I use the Euler equation to establish the relationship between the production efficiency and capital growth rates of each type of production. Next, I derive the growth rate of total output and finally I show that for the economy to be on the BGP the above equality has to hold.

Starting from the Euler equation

$$1 + g_c = \rho(\beta A_s k_s^{\beta-1}\varphi^{1-\beta} + 1 - \delta_s) = \rho(\gamma A_u k_u^{\gamma-1}(1-\varphi)^{1-\gamma} + 1 - \delta_u), \quad (1.2.9)$$

I look at the change in the growth rate of consumption g_c from one period to the next, keeping in mind that δ_s, δ_u, ρ are constants, and that φ is also constant on the BGP:

$$\frac{1+g_c'}{1+g_c} = \frac{\beta A_s' k_s'^{\beta-1}\varphi^{1-\beta} + 1 - \delta_s}{\beta A_s k_s^{\beta-1}\varphi^{1-\beta} + 1 - \delta_s} = \frac{\gamma A_u' k_u'^{\gamma-1}(1-\varphi)^{1-\gamma} + 1 - \delta_u}{\gamma A_u k_u^{\gamma-1}(1-\varphi)^{1-\gamma} + 1 - \delta_u} \quad (1.2.10)$$

BGP requires that $\frac{1+g_c'}{1+g_c} = 1$, so (1.2.10) leads to

$$\beta A_s' k_s'^{\beta-1}\varphi^{1-\beta} = \beta A_s k_s^{\beta-1}\varphi^{1-\beta} \quad (1.2.11)$$

and further to

$$1 + g_s = (1 + g_{ks})^{1-\beta}. \quad (1.2.12)$$

The same process yields

$$1 + g_u = (1 + g_{ku})^{1-\gamma}. \quad (1.2.13)$$

The growth rate of total output is simply

$$\frac{Y'}{Y} = 1 + g = \frac{(1 + g_{ys})Y_s + (1 + g_{yu})Y_u}{Y_s + Y_u}. \tag{1.2.14}$$

The growth rate of skilled output in turn is

$$1 + g_{ys} = (1 + g_s)(1 + g_{ks})^{\beta} = 1 + g_{ks}, \tag{1.2.15}$$

making use of (1.2.12) in the second equality, and similarly for the growth rate of unskilled output, making use of (1.2.13).

Next, using the fact that on the BGP $\frac{1+g'}{1+g} = 1$ together with (1.2.15) and the equivalent equation for unskilled output and capital, it can be shown that $g_{ks} = g_{ku}$. Plugging this result back into (1.2.14) yields $1 + \bar{g} = 1 + g_{ks} = 1 + g_{ku}$. Using (1.2.12) and (1.2.13) and approximating by taking logs yields the conditions stated. □

Note that the condition is an approximation only in the discrete case. It holds exactly in continuous time. This result, excepting the irreversibility constraint, is also used in Caselli and Coleman (2001).

The condition of a constant share of skilled hours worked must always hold on a balanced growth path. If φ were growing at a constant rate on the balanced growth path, as $\varphi \to 1$, $w_u \to \infty$, providing an incentive for some individuals to remain unskilled and thus stopping the growth in skilled hours worked. This would be inconsistent with a constant growth rate. For the same reason, φ cannot be growing at a negative constant rate on the balanced growth path.

As there will always be an incentive for someone to become skilled if φ goes to zero and to remain unskilled if φ approaches one, the corner cases of only skilled and only unskilled labor can only occur as a consequence of a discrete jump. Such a jump is extremely unlikely to occur.

The irreversibility constraint on investment cannot be binding on the balanced growth path. If the constraint were binding on investment in unskilled capital, for example, k_u would decrease at rate δ_u. This would raise the rate of return on unskilled capital, r_u. At some point, $r_u \geq r_s$ would be reached, at which point investment in k_u is worthwhile again. Thus, a binding irreversibility constraint on investment in unskilled capital cannot be part of a balanced growth path. Following the same reasoning on k_s leads to the conclusion that the irreversibility constraint cannot be binding for skilled capital on the balanced growth path either. A binding irreversibility constraint on both types of capital at the same time would lead to a decline in total capital and is equivalent to a binding irreversibility constraint in a one sector economy. Sargent (1980) and Olson (1989) show that this is not possible on the BGP.

In order to assess local stability of the BGP consider, without loss of generality, a one time shock to k_s. A negative shock will cause the level of skilled capital to fall below its BGP level. This leads to an increase of r_s relative to r_u, leading to more investment in k_s and thus a growth rate of skilled capital above the BGP growth rate. Eventually, the difference between the rates of return disappears and the two types of capital grow at constant rates again. If there is a positive shock, k_s will rise above its BGP level. r_s falls below r_u and investment in k_s slows or even ceases altogether if the irreversibility constraint becomes binding. This will continue until the rates of return equalize and both types of capital grow at constant rates again.

1.3 An Illustration of the Central Mechanism

To illustrate the channel through which a higher share of skilled labor can lead to an increase in the skill premium, I use a simplified version of the model to show the main result analytically: An increase in the skill premium can be consistent with an increase in relative labor supply even absent any bias in technological change.

1.3.1 The Simplified Model

The economy is now a one period, two sector economy, with one sector skilled and the other one unskilled. There is no irreversibility constraint and no intertemporal problem. An endowment of total capital K is given exogenously, as are the levels of production efficiency. The only decision to be taken in this economy is how to allocate this endowment of total capital between skilled and unskilled capital.

Of particular interest is a comparative statics analysis of what happens to the equilibrium skill premium when there is an infinitesimal change in the relative supply of skilled labor, i.e. if φ increases.

1.3.2 The Main Result

Let $\frac{k_s^*}{k}$ be the initial equilibrium share of skilled capital in the economy.

Proposition 2. *Iff $\beta > \gamma$ and $\varphi > \frac{k_s^*(\beta,\gamma,\varphi,k)}{k}$ or $\beta < \gamma$ and $\varphi < \frac{k_s^*(\beta,\gamma,\varphi,k)}{k}$, then $\frac{d(\frac{w_s}{w_u})}{d(\varphi)} > 0$.*

Proof. First, find the total differential of the skill premium with respect to skilled labor share. This differential will be greater than zero iff

$$(\beta k_s^{-1} + \gamma k_u^{-1})\frac{dk_s}{d\varphi} > \beta\varphi^{-1} + \gamma(1-\varphi)^{-1} \tag{1.3.1}$$

Finding the total differential of skilled capital with respect to the skilled labor share and plugging into the inequality above yields

$$\beta(1-\gamma)k_s^{-1}(1-\varphi)^{-1} + \gamma(1-\beta)k_u^{-1}\varphi^{-1} > \beta(1-\gamma)k_u^{-1}\varphi^{-1} + \gamma(1-\beta)k_s^{-1}(1-\varphi)^{-1}. \tag{1.3.2}$$

This can be simplified further to

$$\beta(1-\gamma)(k_s^{-1}(1-\varphi)^{-1} - k_u^{-1}\varphi^{-1}) > \gamma(1-\beta)(k_s^{-1}(1-\varphi)^{-1} - k_u^{-1}\varphi^{-1}) \tag{1.3.3}$$

which is true whenever the conditions stated in the proposition hold. □

The first set of conditions states that it is possible to observe an increase in the skill premium following an increase in the relative supply of skilled labor, if the skilled sector is more capital intensive but its equilibrium share of capital is lower than its share of labor. This suggests that the increase in the skill premium with an increase in the relative supply of skilled labor is more likely if the skilled sector is small initially, where the indicator of sector size is the share of capital in the sector relative to total capital in the economy. As capital is used more intensively in the skilled sector (which is what the first condition tells us), a lower level of capital can produce a lot of output. When the availability of the other input increases, however, it becomes desirable to substantially increase capital as well.

The second set of conditions reverses the inequality signs and the intuition behind it: now, if the less capital intensive sector (the skilled sector now) sees an increase in labor, the large share of skilled capital in total capital increases further. This is because the more labor intensive sector now gets more of the production factor it uses more intensively anyway, making it optimal to also give it more of the less-intensively used factor.

Note that if $\beta = \gamma$, $\frac{d(\frac{w_S}{w_U})}{d(\varphi)} > 0$ is impossible. Assuming equal capital shares ex ante thus automatically leads to the conclusion that skill demand must have increased due to SBTC.

1.3.3 Relationship to Specific Factors Model

The simple model described here is a version of the specific factors model well-known in the trade literature (see Jones (1971)). Here, the specific factors are skilled and unskilled labor, and capital is the common factor.

Note that having $\beta > \gamma$ means that production in the skilled sector is more capital intensive than in the unskilled sector. One result for specific factor models is that if the amount available of the factor specific to a sector increases, this leads to a more than one-for-one increase in the common factor used in this sector in equilibrium. In my version this result means that an increase in the amount of skilled labor leads to a more than one-for-one increase in skilled capital in equilibrium, as each additional worker will be able to use capital more efficiently than in the other sector, providing higher returns to the owner of capital. By analogous reasoning, if the amount of unskilled labor decreases, this leads to a more than one-for-one decrease in unskilled capital. If the initial equilibrium level of skilled capital is low enough, the reallocation of capital will be so large as to overcome the downward pressure on the skill premium due to the increase in skilled labor.

1.4 The Quantitative Exercise

The full dynamic model cannot be solved analytically. This section describes the quantitative exercise, the data series used, and the choice of parameters.

1.4.1 The Idea

I perform a growth accounting exercise that allows me to back out the unobservable paths of skilled and unskilled capital and skilled and unskilled production efficiency from the observed paths of skilled and unskilled wages and skilled and unskilled labor supply. Finding capital in this way is a departure from standard growth accounting, where capital is taken from national accounts data. Here, capital is determined endogenously for three reasons. First, while it is easy to separate skilled and unskilled labor in the data, the distinction is much less clear for capital. Is all capital used in a sector dominated by skilled labor automatically skilled capital? Or only a constant fraction? What exactly is the difference between skilled and unskilled capital? Letting the model determine the allocation of capital circumvents these issues. Second, capital data in the national accounts is imperfectly adjusted for quality changes and hence technological progress. Using these data might lead to an understatement of the increase in production efficiency. Third, capital data in the national accounts is aggregated under the assumption of reversible investment. This assumption is violated whenever the irreversibility constraint on investment is binding for one type of capital. Ignoring this violation introduces a bias into the sectoral capital data.[7]

The optimization problem in 2.6 can be solved either by Lagrangian or by value function iteration. The former is more useful in illustrating the formal equilibrium and hence was used in section two. Value function iteration on the other hand is easier to implement quantitatively, especially when dealing with the additional irreversibility constraints on investment. The results are the same using either method.

The exercise starts with an initial guess on a sequence for A_s and A_u. With this guess I can recursively solve

$$V(k_s, k_u, A_s, A_u) = \max_{k_s', k_u'} \left\{ \ln(c) + \rho V'(k_s', k_u', A_s', A_u') \right\} \tag{1.4.1}$$
$$s.t. \qquad k_s' \geq (1-\delta_s)k_s, \quad k_u' \geq (1-\delta_u)k_u$$

with $c = y(k_s, k_u, A_s, A_u, \varphi) + (1-\delta_s)k_s + (1-\delta_u)k_u - k_s' - k_u'$, and φ as taken from the data as described below. This yields optimal paths for k_s and k_u which are then combined with the sequences for A_s and A_u guessed previously and φ as taken from the data to derive the wage sequences w_s and w_u that are implied by the model. These sequences of wages are then compared to the actual wage data. If the sum of squared differences between the wages in the model and in the data is above a critical value, the sequences of k_s and k_u and the data on wages and φ are used to update the guess for A_s and A_u via $A_s = \frac{w_s \varphi^\beta}{(1-\beta)k_s}$ and $A_u = \frac{w_u (1-\varphi)^\gamma}{(1-\gamma)k_u}$. With this new guess, the value function iteration starts over. This process is repeated until the sum of squared differences between model-generated wages and wage data falls below the critical value.

In order to run this exercise, I need data series for φ, w_s and w_u, and parameter

[7] More specifically, this bias is introduced through the aggregation weights. One assumption in the construction of these weights is that returns to assets are equal within an industry. If the irreversibility constraint is binding on one asset in that industry, this assumption is violated, leading to the wrong weights and hence the wrong number for aggregated capital.

values for β, γ, δ_s, δ_u, and ρ. Their derivation is described in the next section. More detail on the algorithm can be found in the appendix.

1.4.2 The Data

The data used in this paper is either directly taken or derived from the EU KLEMS dataset (EUKLEMS (2008), also see Timmer, O'Mahony, and van Ark (2007)) on the US economy. The dataset builds on Jorgenson, Ho, and Stiroh (2003)'s work in growth accounting and collects data on, among other things, wages, different types of capital and output by industry.[8]

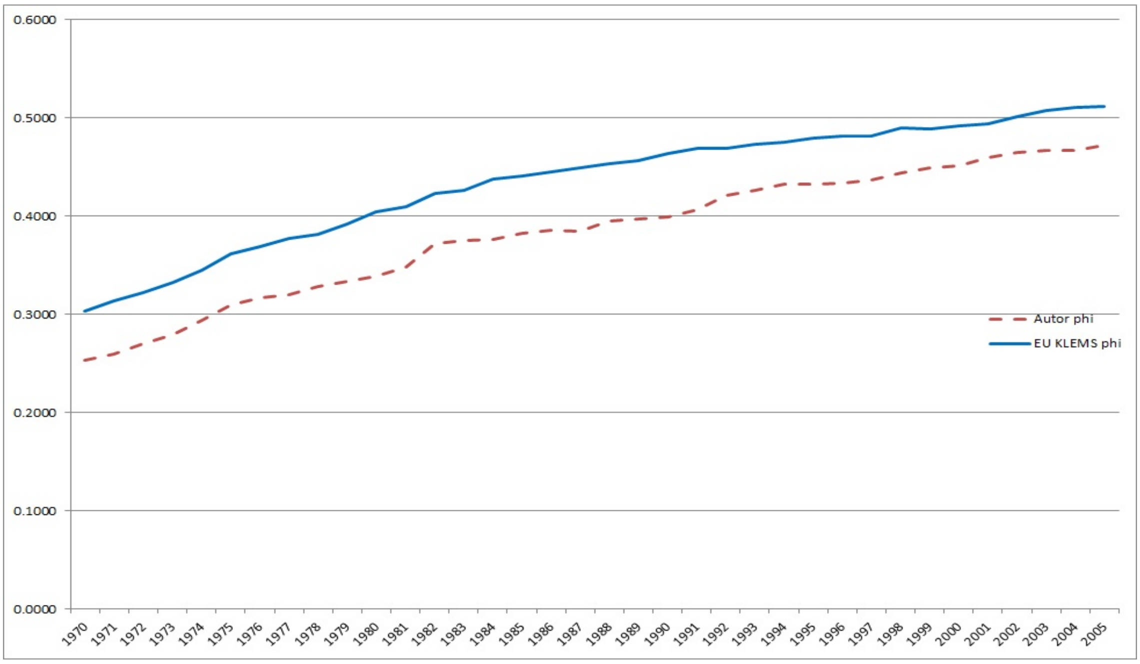
1.4.2.1 Labor Supply and Wages: φ, w_s, and w_u

Labor market data by skill is available in three categories in the dataset: high-skilled (college graduate and above), medium-skilled (high school graduate and some college) and low-skilled (did not complete high school). As the model requires two types of skill, one third of the medium-skilled values in labor compensation and hours worked data are added to the corresponding high-skill values to yield the *skilled* variables and two-thirds of the medium-skilled values are added to the low-skill values to deliver *unskilled* variables. This is to reflect the fact that someone who dropped out of college just before graduation will have considerably more education than someone who left after the first term, even though both are classified as medium-skilled. Using one third and two thirds to separate them yields a skill premium that is close to what others have found.

The share of skilled hours worked φ is simply hours worked by skilled workers divided by hours worked by all workers, and similarly for unskilled labor.

[8] Most empirical studies of the skill premium use data from the Current Population Survey (CPS). In contrast to the EU KLEMS dataset, CPS does not have data on output. As I need output data to construct some of my parameters, the EU KLEMS dataset is preferable for me. Furthermore, the labor market data in EU KLEMS are derived from the CPS, so the results would be very similar using CPS. For the US, there are two sets of data in EU KLEMS: one based on the old SIC industry classification and extrapolated to 2005, and one focusing on capital, based on the new NAICS classification, extrapolated backwards. Detailed labor data are only included in the SIC version, which I use for most data. I use the NAICS data only for the derivation of depreciation rates.

Figure 1.1 Comparing the Share of Skilled Hours Worked from EU KLEMS Data and from Autor, Katz, and Kearney (2008)



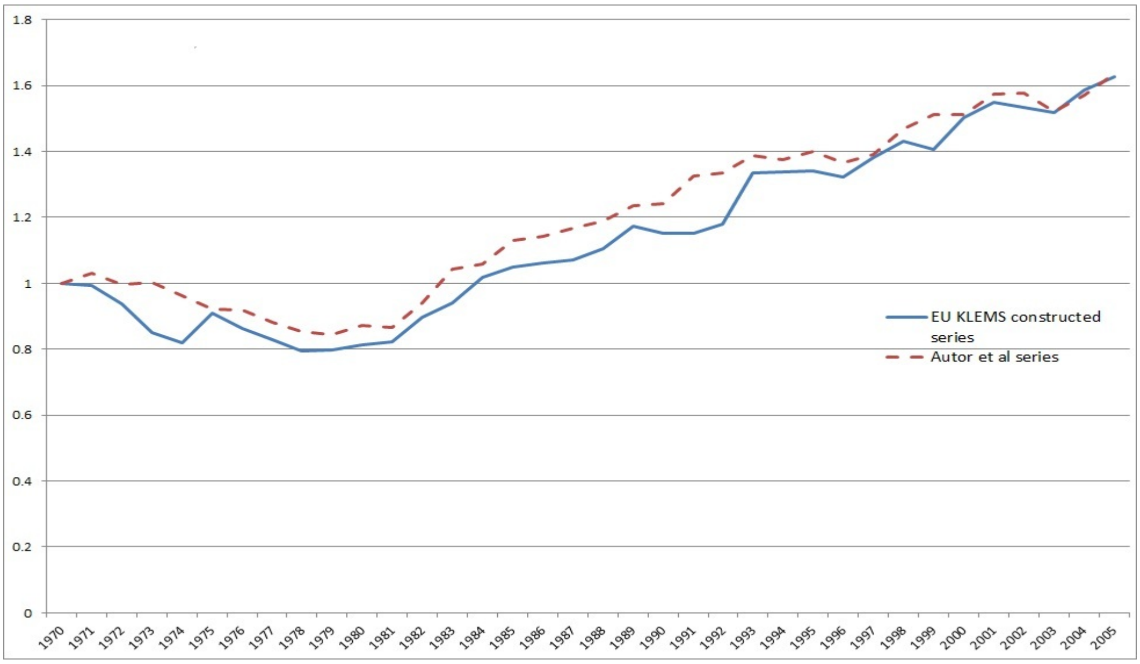
Skilled hourly wages are derived by multiplying the skilled workers' share in labor compensation with total labor compensation and dividing the total by skilled hours worked (share of skilled hours worked times total hours worked).[9] The analogous procedure is used for unskilled hourly wages.

Figure 1.1 compares the share of skilled hours worked according to my derivation and using the data from Autor, Katz, and Kearney (2008). The series move in parallel, and Autor, Katz, and Kearney (2008)'s share of skilled hours worked is slightly lower throughout. As a robustness check I run the simulation with the Autor, Katz, and Kearney (2008) values and find that there is virtually no difference in the results.

Figure 1.2 shows the log of the skill premium my procedure yields and compares it to the log of the skill premium used in Autor, Katz, and Kearney (2008), both normalized to one in 1970. Similarly to the skill share in hours, my data series is below Autor, Katz, and Kearney (2008)'s series, and they move in parallel

[9]The data series by name and formulas used are: H_HS+1/3 H_MS for high skilled hours worked, 2/3 H_MS+H_LS for low skilled hours worked, and $\frac{(LAB\_HS+1/3LAB\_MS)*COMP}{(H\_HS+1/3H\_MS)*H\_EMP}$ for the skilled hourly wage.

Figure 1.2 Comparing the Log Wage Premium from EU KLEMS Data and from Autor, Katz, and Kearney (2008)



for most of the period under consideration.

Labor compensation may also include non-wage payments to the worker and other benefits, so it is not a perfect measure from which to derive wages. This may go some way towards explaining the remaining difference from Autor, Katz, and Kearney (2008)'s series. Eckstein and Nagypal (2004) find however that labor compensation data and wage data move largely parallel. In any case, as the present study is an accounting exercise at heart, total labor compensation is the more appropriate measure.

1.4.2.2 Initial Values for Skilled and Unskilled Capital and the Production Efficiencies

The initial levels of skilled and unskilled production efficiencies are normalized to one. In order to find model-consistent initial values I have to either assume equal production efficiencies in the first period or equal rates of return on capital, implying a non-binding irreversibility constraint. The first alternative is less restrictive[10].

To start the iteration, I need to specify a first guess for the full sequence of skilled and unskilled production efficiency. The initial guess sets the first period's skilled and unskilled production efficiency equal to one. For all further periods it is simply assumed that both types of production become more efficient at the same constant rate, the long run growth rate.

The initial values for skilled and unskilled capital are obtained from the equations for the skilled and unskilled wage respectively. The values for capital are the only unknowns in the wage equations $w_{s,0} = (1-\beta)A_{s,0}k_{s,0}^{\beta}\varphi_0^{-\beta}$ and $w_{u,0} = (1-\gamma)A_{u,0}k_{u,0}^{\gamma}(1-\varphi_0)^{-\gamma}$, so $k_{s,0}$ and $k_{u,0}$ can be found by simply solving for them.

1.4.2.3 Capital Shares: β and γ

As the model has two sectors, skilled and unskilled, I classify the industries in the dataset into skilled and unskilled. To that end, I rank all industries at the highest-digit level for which data are available[11] by the average of the share of high-skilled (in the three-skill-level definition) hours worked in 1970 and 2005.

Over the period studied, the share of high-skilled labor has increased in all industries, sometimes substantially. This trend has been observed first by Berman, Bound, and Griliches (1994) for manufacturing industries from 1979 to 1989. Autor, Levy, and Murnane (2003) and Spitz-Oener (2006) (for Germany) show that this trend is not due to a change in the type of jobs available, but to an increase in skill requirements for the same job. They attribute the increased skill requirements to SBTC. As this increase has been observed across all industries, the fact that it might be due to SBTC should not bias my results. One further indication that this method of finding capital shares should not introduce a bias is that using

[10] Assuming equal rates of return in the first period results in skill neutral to unskill-biased technological change for a wider range of values for the capital shares. Normalizing production efficiencies thus also is the more conservative assumption.

[11] If I only have data for the one-digit industry, I use that; if there is data for three-digit industries I throw out the one-digit aggregation of these industries

either the 1970 high-skill shares or the 2005 shares would not change the ranking substantially.

All industries with an average share of hours worked by high-skilled labor of 20% or higher are considered part of the "skilled" sector, the rest forms the "unskilled" sector. Appendix 3 shows the industries' ranking and their average high-skill share of labor, along with the 1970 and 2005 shares. The cutoff of 20% ensures that there are roughly the same number of industries in the skilled and unskilled sector.

I start by calculating the labor share, i.e. the ratio of labor compensation and value added in a sector ($1 - \beta_i = \frac{LAB_i}{VA_i}$), for each industry every five years. Then I take the unweighted average of each industry over time (also given in Appendix 3) and then the average over all industries classified as skilled or unskilled respectively, weighted by their average value added. The skilled and unskilled capital shares are then derived as one minus the labor shares.

The resulting capital shares are $\beta = 0.39$ for skilled production and $\gamma = 0.29$ for unskilled production, meaning the skilled sector is more capital intensive than the unskilled sector. As the values for the capital shares are sensitive to the definition of sectors and the cutoffs chosen, I check the robustness of the simulation results to different values of β and γ.

1.4.2.4 Depreciation Rates: δ_s and δ_u

EU KLEMS breaks down the data on capital stock into eight types of capital: *Information Technology*, *Software*, *Communication Technology*, *Transport Capital*, *Other Machinery*, *Other Construction*, *Residential Structures*, and *Other Capital*. Each type of capital has its own depreciation rate that is constant across industries. Differences in depreciation rates between industries thus arise from differences in the composition of their capital stocks. To find each industry's depreciation rates at one point in time, I take the average of the different depreciation rates, weighted by the corresponding capital type's share in the industry's capital stock.

As capital stock data are not available at the same level of detail as labor and output data, the level of capital stocks must be imputed for some industries. In these cases, I assume that a three-digit industry's share of capital in the one digit-capital stock is the same as the three-digit industry's share in value added.

Once I have each industry's depreciation rate for every five years, I follow the same sector division and averaging procedure as for capital shares. The resulting depreciation rates are $\delta_s = 0.091$ for skilled capital and $\delta_u = 0.079$ for unskilled capital.

1.5 Quantitative Results and Robustness Checks

1.5.1 Main Results

The main parameter specification uses the values derived in section 1.4.2 and presented in table 1.1. The long run growth rate, which is needed for the algorithm, is set to $g = 0.025$ to correspond to the historic average US growth rate. The results are not sensitive to this choice, however. Some more technical parameters need to be specified for the algorithm. These are given in table 1.5 in the appendix. The robustness of results to different parameter specifications will be discussed later.

The simulation results for production efficiency growth and capital are shown in Figures 1.3 and 1.4 respectively. Both production efficiency growth rates are very high until about 1980 and considerably lower after that, consistent with the productivity slowdown observed by others (see for example Nordhaus (2005)). Until 1980 the growth rate for unskilled production efficiency is above the one for skilled production efficiency, after 1980 the growth rates are much closer. Skilled production efficiency grows 0.27 percentage points slower on average than un-

Table 1.1: Main Parameter Specification

Parameter	β	γ	δ_s	δ_u	ρ
Value	0.39	0.29	0.091	0.079	0.95

Figure 1.3 Simulation Results on Growth Rates of Skilled and Unskilled Labor Efficiency

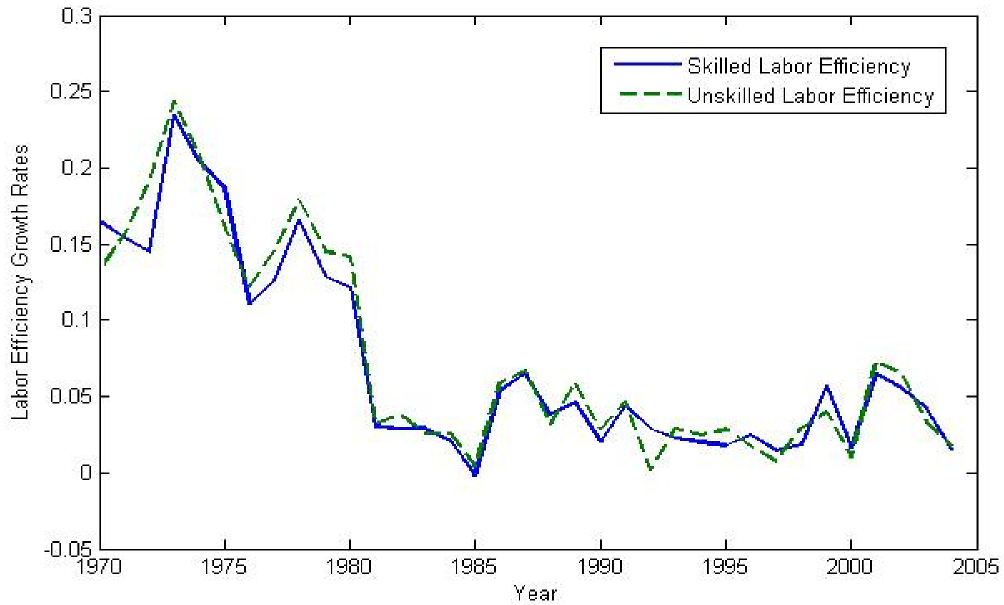
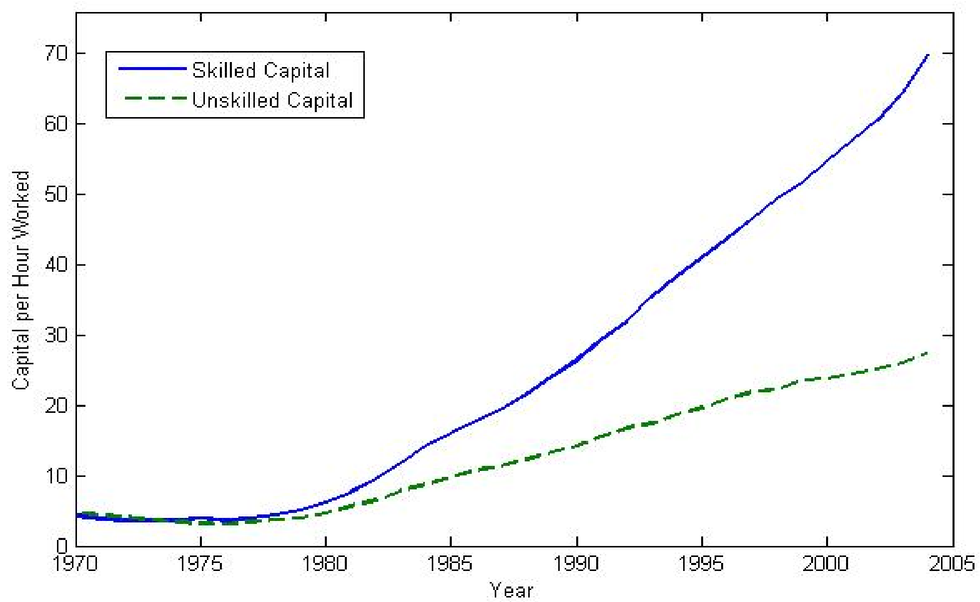


Figure 1.4 Simulation Results on Evolution of Skilled and Unskilled Capital per Hour Worked



skilled production efficiency, though the difference is 0.53 percentage points in the first fifteen years and only 0.04 percentage points after 1985.

SBTC is said to be present if the growth of relative skilled production efficiency leads to an increase in the relative marginal product of skilled labor (see, eg, Caselli and Coleman (2001)), in which case the skill premium is increasing in $\frac{A_s}{A_u}$. For this ratio to increase, skilled production efficiency needs to grow faster than unskilled production efficiency. The higher growth rate for unskilled production efficiency here suggests then that there is unskill-biased technological change if anything, though given the differences are small throughout, considering technological change as skill-neutral is more appropriate. This result can be attributed to the combination of different capital shares in the two sectors and very low initial levels of skilled capital. Part of the difference pre- and post-1985 stems from a period between 1974 and 1982 in which the skill premium was actually decreasing. In that time period, higher unskilled production efficiency growth would be predicted by most models.

Both types of capital increase over the 35 years under consideration. Skilled capital stays roughly constant in the early 1970s, grows very rapidly in the early 1980s and continues growing at a slightly lower rate. The average growth rate for skilled capital is 8.84%. Unskilled capital decreases for the first few years as the irreversibility constraint is binding. After that, unskilled capital grows consistently. Overall, the average yearly growth rate for unskilled capital is 5.6%.

The reasons for slow capital growth in the 1970s can only be speculated on. It could simply be a consequence of low economic growth following the oil shocks. I could also be due to the 1970s being the early period of a new general purpose technology (GPT, see, e.g. Aghion, Howitt, and Violante (2002)). This nascent technology could have led to deferred investment, to be able to take advantage of the new technology once it is better developed.

These results illustrate the additional adjustment mechanism present in the model: the increase in skilled labor supply induces a shift of investment from unskilled to skilled capital. The magnitude of this shift depends on the relative size of the capital shares in the two sectors.

1.5.2 Robustness Checks

The skill premium can be explained in absence of SBTC for plausible values of the capital shares. This is need not be true universally, however. The overarching question in this section is: If the wages and skill supply observed in the data were generated by an economy not governed by the parameters used in section 1.5.1, but by different ones, would the implications of these other parameters for SBTC be the same? A number of robustness checks in this section show how the values of capital shares matter, while other parameters are less important.

1.5.2.1 Different Capital Shares

There are two margins along which different capital shares might have an impact: changes to the levels of β and γ and changes to the difference between the two capital shares.

Table 1.2 provides a summary of the results using a wide array of values for β and γ. The first two columns give the values for capital shares in the skilled and unskilled sector and the third gives the difference between the two capital shares. The fourth column shows the average difference between the skilled and unskilled production efficiency growth rates over the whole sample period, and the last two columns give the average difference for the two sub-periods from $1970 - 1985$ and $1985 - 2005$. The first row shows the values for the preferred specification discussed in the previous section.

Looking at the difference in growth rates for the whole period, two observations are striking. First, SBTC is observed for $\beta - \gamma \leq 0.08$, and the skill bias is larger the smaller the difference between the capital shares. Second, the degree of skill-bias is decreasing in the skilled capital share, even holding the difference between capital shares constant. The difference between skilled and unskilled

Table 1.2: Results for Different Values of β and γ

β	γ	$\beta - \gamma$	$\overline{g_s - g_u}$ 1970-2005	$\overline{g_s - g_u}$ 1970-1985	$\overline{g_s - g_u}$ 1985-2005
0.39	0.29	0.1	-0.0027	-0.0053	-0.0004
0.42	0.32	0.1	-0.0035	-0.0069	-0.007
0.36	0.26	0.1	-0.0018	-0.0039	-0.0001
0.44	0.32	0.12	-0.0066	-0.0121	-0.0021
0.40	0.28	0.12	-0.0055	-0.0099	-0.0017
0.39	0.30	0.09	-0.0014	-0.0032	0.0002
0.38	0.29	0.09	-0.0011	-0.0028	0.0003
0.39	0.31	0.08	-0.0001	-0.0011	0.0008
0.38	0.30	0.08	0.0001	-0.0008	0.0009
0.37	0.31	0.06	0.0030	0.0040	0.0022
0.42	0.38	0.04	0.0046	0.0065	0.0030
0.40	0.36	0.04	0.0050	0.0072	0.0031
0.38	0.34	0.04	0.0054	0.0079	0.0033
0.36	0.32	0.04	0.0059	0.0087	0.0035
0.34	0.34	0	0.0014	0.0177	0.0061
0.32	0.36	-0.04	0.0169	0.0267	0.0087
0.29	0.39	-0.1	0.0252	0.0401	0.0127

capital shares determines the direction of the bias, the level of β the degree, as can be seen from looking at the results for $\beta - \gamma = 0.1$ and $\beta - \gamma = 0.04$ with different values for β. The positive value for the growth rate differential for $\beta = 0.29$ and $\gamma = 0.39$ shows that the results are not symmetric in the capital shares. The turning point is at $\beta - \gamma = 0.08$, where the bias is very close to zero.

The results differ markedly across the two sub-periods under consideration as well. The difference in growth rates is consistently closer to zero in the second part of the sample. This is a bit puzzling in some cases, as the decline in the skill premium in the early part of the sample would suggest a stronger unskilled production efficiency growth rate and thus a narrowing of the difference. Two possible explanations come to mind. The first is that the capital investment channel works in the opposite direction there, too, and the second that these values for the capital shares are less likely to be correct.

The presence and degree of SBTC thus depends both on the level of the capital shares and the difference between them: the higher β and the larger the difference between β and γ, the smaller is the degree of SBTC. This is consistent with the additional mechanism I propose, as the degree of capital reallocation will be larger for larger differences between the capital shares. As the previous sections have shown, values for which SBTC plays no role can be derived plausibly.

1.5.2.2 Different Depreciation Rates

For my main specification, the depreciation rates for the two types of capital are different. It is possible that the initially binding constraint is due to this difference, and it is likewise possible that the higher production efficiency growth rate in the unskilled sector is due to the irreversibility constraint being binding early on. I therefore check how results change when the depreciation rates are equal in both sectors. Ex ante I would expect largely the same result as before. The main channel from which my result derives is the reallocation of capital investment, with different depreciation rates and the irreversibility constraint as possible blockages of this channel. Including these blockages in the model strengthens the main result, as two important potential obstructions are already accounted for. As the blockages do not narrow the main channel enough to qualitatively affect the results, removing either one or both of them should not alter the main result, though the precise values might be different.

This turns out to be true, as the production efficiency growth rates with equal depreciations rates track the ones from my preferred specification. Only in the earlier years is the skilled growth rate larger than in the main specification. This is true whether I assume that both depreciation rates are equal to the skilled rate or the unskilled rate, the results are nearly identical (-0.0032 for the higher rate, -0.0033 for the lower one).

I also check results for a larger difference between the depreciation rates ($\delta_s = 0.12$ compared to $\delta_u = 0.06$) to see if results are sensitive to an understatement of the difference in depreciation rates. The growth rate differential in this case is -0.0002, suggesting that a very large difference in depreciation rates might change results.

Finally, I also consider much smaller depreciation rates, $\delta_s = 0.039$ and $\delta_u = 0.033$. These are the values of the skilled and unskilled depreciation rates as calculated for 1970. The depreciation rates are increasing over time, as they form the weighted average of the depreciation rates of skilled and unskilled capital used at each period. Over time, the types of capital with higher depreciation rates increase, which leads to an overstatement of the depreciation rate for the early periods. This matters, as depreciation rates determine the irreversibility constraint, which is binding for several periods early on in the baseline scenario. With these lower depreciation rates, I can test whether the binding constraint is an artifact of taking the average depreciation rate. It turns out that with the lower rates, the irreversibility constraint binds for one period only. The difference in the growth rate of skilled and unskilled labor efficiency stays negative (-0.0039). The main results are not affected.

1.5.2.3 Equal Depreciation Rates and Capital Shares

A further check is whether the results change if I assume equal capital shares and equal depreciation rates in both sectors. This is the standard assumption in the SBTC literature, and I would therefore expect the same result as in that literature, namely that skilled production efficiency grows faster than unskilled production efficiency.

In this case, with $\beta = \gamma = 0.34$, skilled production efficiency indeed grows faster than unskilled production efficiency on average, with a difference of 1.07 percentage points. This indicates that with the assumption of equal capital shares intact, the conclusion that SBTC drove the increase in the skill premium is valid.

1.5.2.4 Leaving Out the Irreversibility Constraint

Ignoring the irreversibility constraint should lead to a faster decrease in unskilled capital and hence to a higher growth rate for unskilled production efficiency. This is exactly what I observe. Without the constraint, unskilled capital drops rapidly.

As this has knock-on effect on skilled capital, the overall result changes little. The growth rate of unskilled production efficiency is larger than the skilled growth rate, with a difference of 0.0027.

1.5.2.5 Alternative Utility Function

So far, I have assumed that individuals have logarithmic utility, mostly because I am interested in the capital reallocation process between sectors and less in people's overall investment decision. Log utility is convenient, as changes in the interest rate do not affect the consumption allocation over time.

As consumption allocation, via the budget constraint, has effects on investment decisions, it is prudent to check that the results do not depend on the choice of utility function. Therefore, I also look at the results from using a CRRA utility function $u(c) = \frac{c^{1-\eta}-1}{1-\eta}$, with $\eta = 2$. On average, unskilled production efficiency grows faster by 0.1 percentage points. The difference here is smaller in value, but points in the same direction.

1.5.2.6 Alternative Data Derivation

I also test a different way of constructing the data for skilled and unskilled wages and shares in hours worked. Choosing as a cutoff at least 30% highly skilled workers in 2005 yields a wage premium and total skilled labor with the same movements as in the data used above, but with slightly different absolute values. This time, I take the initial values for skilled and unskilled capital directly from the data. The caveats as to the appropriateness of the capital data remain.

In this version of data derivation, I leave out *Real Estate Activities*. It would classify as skilled given the cutoff I use, but is the sector with the largest change in labor composition. To avoid the results swinging on the choice I make for this sector, I prefer to leave it out altogether.

The capital shares in this case are slightly different: $\beta = 0.3$ and $\gamma = 0.29$, closer together than in my main specification. Nonetheless, the qualitative results remain the same: skilled capital increases fourfold, unskilled capital does not quite double and skilled production efficiency grows slower than unskilled production efficiency in more than half the periods. The average difference in the growth rates is very small with unskilled production efficiency growing 0.3 percentage points faster.

1.5.2.7 A Different Production Function

The assumption of perfect substitutability of both types of production is fairly restrictive, and it is not a priori obvious why it is a reasonable assumption to make. Indeed, generalizing the production function to a CES function would open another channel of adjustment to changes in labor supply via the change in the relative price of the two kinds of output.

A more general production function would be

$$Y = [\eta(A_s k_s^{\beta} \varphi^{1-\beta})^{\alpha} + (1-\eta)(A_u k_u^{\gamma}(1-\varphi)^{1-\gamma})^{\alpha}]^{\frac{1}{\alpha}} \tag{1.5.1}$$

where $\sigma = \frac{1}{1-\alpha}$ is the elasticity of substitution between skilled and unskilled production and $\alpha \in (-\infty, 1)$. Setting $\alpha = 1$ yields the perfect substitutability case.

The relative growth rate of labor efficiencies then is

$$\frac{g_s}{g_u} = \frac{g_{ks}^{-\beta}}{g_{ku}^{-\gamma}} \left(\frac{w_{s,t+1}/w_{u,t+1}}{w_{s,t}/w_{u,t}}\right)^{\frac{1}{\alpha}} \left(\frac{\varphi_{t+1}}{\varphi_t}\right)^{\frac{1}{\alpha}-1+\beta} \left(\frac{1-\varphi_{t+1}}{1-\varphi_t}\right)^{1-\frac{1}{\alpha}-\gamma}. \tag{1.5.2}$$

It is decreasing in the absolute value of α. Skilled production efficiency grows faster relative to unskilled production efficiency the poorer the substitutability between the two sectors of production: With decreasing α the weight given to growth in the wage premium and growth in relative labor supply increases, whereas the weight given to the relative capital growth rates stays the same. As both wage premium and relative labor supply increase over the sample, a smaller α suggests a higher growth rate of skilled production efficiency relative

Table 1.3: Simulation results for different values of α

α	η	median $\frac{g_s}{g_u}$
1	NA	0.98419
0.91	0.474	1.0065
0.8	0.48	1.0559
0.73	0.484	1.1154
0.576	0.49	1.2303

to the growth rate of unskilled production efficiency. Changing α changes the capital growth rates, too, as lower α leads to higher growth rates of skilled capital relative to unskilled capital, but this effect seems to not be strong enough to keep the relative labor efficiency growth rates the same. A good and reliable estimate of α is therefore very important to check the validity of the perfect substitution assumption and the robustness of the central results.

To further illustrate the importance of having the correct α, I report simulation results for different values of α below. To be able to run the simulation, I also need a value for the dispersion parameter η, which depends on relative prices, α and the ratio of skilled and unskilled value added: $\frac{p_s}{p_u} = \frac{\eta}{1-\eta}(\frac{Y_s}{Y_u})^{\alpha-1}$. Using the specification from the previous subsection, rather than my main specification, means I have data on relative prices and the ratio of skilled and unskilled value added. The value for η is not constant over time, so I simply use the average.

Table 1.3 shows the median relative production efficiency growth rates for different values of α.[12] A ratio greater than one suggests skilled production efficiency grows faster, a ratio less than one suggests unskilled production efficiency does. This is a rule of thumb only, however, since it is possible for the median ratio of growth rates to be greater than one (suggesting skilled production efficiency grows faster), while the difference of the averages of the growth rates is negative (suggesting unskilled production efficiency grows faster).

As can be seen from table 1.3, the choice of α is crucial for the results on pro-

[12]For this production function I cannot derive the growth rates separately. Growth rates here are $g_s = \frac{p_s}{p_s'}\frac{w_s'}{w_s}(\frac{\varphi'}{\varphi})^{\beta}(\frac{k_s'}{k_s})^{-\beta}$ and $g_u = \frac{p_u}{p_u'}\frac{w_u'}{w_u}(\frac{1-\varphi'}{1-\varphi})^{\gamma}(\frac{k_u'}{k_u})^{-\gamma}$. To calculate the growth rates I would need the growth rates of skilled and unskilled prices. The model can only determine relative prices, hence I only show the ratio of the growth rates.

duction efficiency growth rates and hence for the decision of whether there is skill-biased technological change or not. The smaller α, the larger the relative growth rate of skilled production efficiency needed to be consistent with the wage and labor data. For any $\alpha = 0.91$ or smaller, the results suggest SBTC, any value above that threshold suggest unskilled production efficiency grew faster.

Simply using a value for the elasticity of substitution between skilled and unskilled labor from the range that the labor literature considers most likely (between $\sigma = 1.5$ and $\sigma = 2$, see e.g. Acemoglu (2002a), Autor, Katz, and Kearney (2008), corresponding to α between $\frac{1}{3}$ and $\frac{1}{2}$) is not an option. I need the elasticity of substitution between skilled and unskilled production, whose exact relationship with the elasticity of substitution between skilled and unskilled labor is not straightforward to determine. In fact, for any value of α the simulation results would be consistent with the labor literature consensus: the standard way of finding σ is from a regression of the wage premium on the relative supply of skilled and unskilled labor and a time trend, $log(\frac{w_s}{w_u}) = \rho + \frac{1}{\sigma}log(\frac{L_s}{L_u}) + \delta t + \epsilon$. In the simulation, I take both $\frac{w_s}{w_u}$ and $\frac{L_s}{L_u}$ from the data, so that no matter which α I choose and no matter the simulation results, the estimated σ remains the same. There is a one-to-one relationship between the elasticity of substitution between skilled and unskilled labor and the elasticity of skilled and unskilled production only if $\beta = \gamma$. If the capital shares are not equal, as is the case in my parameter specification, α cannot be determined algebraically from standard values of σ.

Instead, I try to estimate α from the expression for the log wage premium

$$\begin{aligned} log(\frac{w_{s,t}}{w_{u,t}}) =& c + \alpha\beta log(k_{s,t}) - \alpha\gamma log(k_{u,t}) + \\ & (\alpha(1-\beta)-1)log(\varphi_t) - (\alpha(1-\gamma)-1)log(1-\varphi_t) + \epsilon_t \end{aligned} \tag{1.5.3}$$

where $\frac{w_{s,t}}{w_{u,t}}$ is the hourly wage premium at time t and ϵ_t is an i.i.d. normally distributed error term.

I use the data as derived in the previous section, as relative price data is read-

Table 1.4: Estimation results for α

	Trend	No Trend
Constant	-1.299***	-1.568***
	(0.1903)	(0.0633)
α	0.576*	1.007***
	(0.2880)	(0.0374)
Trend	0.400	
	(0.2652)	
* indicates	significance	at 10%
** indicates	significance	at 5%
*** indicates	significance	at 1%

ily available for that derivation and will be needed later. The values for β and γ are thus the same as for the simulation in the previous section ($\beta = 0.3$ and $\gamma = 0.29$). To find α, I estimate two versions of the model: one as given in equation 1.5.3 and one with a time trend, to capture other time variant effects on the wage premium (e.g. technological progress). Model selection criteria disagree on whether the model with or without trend is better. The results of the OLS estimation are shown in table 1.4. The point estimate for α in the model without trend is 1.007 and highly significant, suggesting that the perfect substitutes case is realistic[13]. Including a positive time trend reduces this point estimate to $\alpha = 0.576$,[14] though it is only significant at the 10% level, and a Wald coefficient test cannot reject the null hypothesis that $\alpha = 1$.

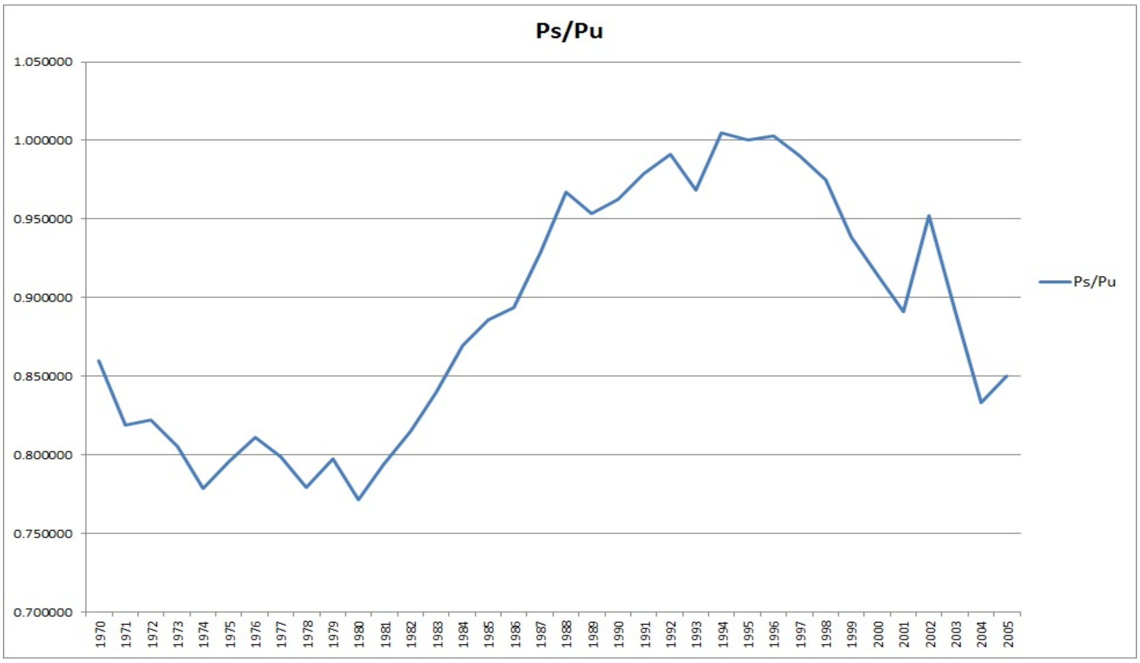
The estimation without trend does not reveal a long-running trend in the residuals, and the coefficient on the trend parameter is not significant at any conventional level. This suggests that there is no need for the trend parameter, and the assumption of perfect substitutability, $\alpha = 1$, is warranted.

There is, however, a problem in the estimation. The production efficiencies are part of the error term, and the model suggests that the production efficiencies depend on capital. Thus, the errors correlate with one of my exogenous variables, muddying the estimation result. As I do not have a good solution to this problem,

[13]Constraining the estimation to ensure $\alpha \leq 1$ would lead to a point estimate of $\alpha = 1$, as this is the closest permissible value to the unconstrained optimum.

[14]This value of α suggests an elasticity of substitution between skilled and unskilled production of 2.35, somewhat above the consensus in the labor literature of between $\sigma = 1.5$ and $\sigma = 2$.

Figure 1.5 Price of Skilled Output Relative to Unskilled Output, normalized to one in 1995, Source: EUKLEMS (2008)



I can only acknowledge its presence, and caution to not place too much reliance on the estimation results.

As an alternative, I also try to find the right α by matching the model's relative prices to the relative prices for goods produced by the skilled and unskilled sector found in the data. For all $\alpha < 1$, the model results in steadily decreasing relative prices, while the relative price data shown in figure 1.5 indicate that the relative price in 2004 was only slightly lower than in 1970, with movement in both directions in between. Given these divergent results on prices, the assumption of perfect substitutability seems reasonable, as the constant relative prices it implies are closer to observed data than the prices implied by equation 1.5.1.

As this section shows, relaxing the assumption of perfect substitutability of production can have considerable effects on my main result. However, deriving a value for the elasticity of substitution between skilled and unskilled production, both via direct estimation and via matching of data on relative prices, suggests that $\alpha = 1$ is a reasonable choice, and the assumption of perfect substitutability thus warranted.

1.6 Conclusions

Dropping the common assumption of equal capital shares, I show that the increase of the skill premium between 1970 and 2005, despite the concurrent increase of the relative supply of skilled labor, can be explained by a reallocation of capital and neutral to unskill-biased technological change. This is a departure from most of the literature on the topic, yet my result is not inconsistent when compared to other work. If I impose the condition of equal capital shares I get the standard result of SBTC as an explanation of the change in the skill premium. This suggests that a more frequent departure from this simplifying and admittedly very convenient assumption might be advisable.

The results depend crucially on the capital shares of the two sectors, especially on their relative sizes. These vary depending on the definition of sectors and the kind of averaging procedure chosen. They can also be very different when considering different periods of time. Two issues for further research are to find the "best" way of deriving capital shares, and the consequences of allowing these shares to vary over time.

Of course, this paper leaves many more questions unanswered. I have nothing to say on the origins of the increase in the supply of skilled labor. It is possible, indeed likely, that there is some feedback mechanism involved, by which changes in capital allocation and technology lead to changes in education decisions, which in turn lead to changes in capital allocation, and so on. Nor do I claim to know what drives skilled and unskilled production efficiency. There may be factors completely unrelated to technology that caused a higher efficiency of unskilled production, but my model has no way of distinguishing these from genuine improvements in efficiency.

1.7 Appendix

1.7.1 Notes on the Algorithm

As there is very little previous numerical work involving irreversibility constraints (one notable exception being Coleman (1997)), the algorithm is developed from scratch. There are two parts to it: a value function iteration for given production efficiencies and an update mechanism for the guess of the production efficiencies.

Value function iteration with irreversibility constraint, given production efficiencies

At its core is a finite horizon value function iteration that incorporates an irreversibility constraint. I am interested in a period of $T = 35$ years, corresponding to the period from 1970 to 2005. The terminal value is the steady state value towards which the economy converges, given that all values grow at their BGP rates from the final period of interest onwards. Between the last period of interest and the terminal value are m periods at which the production efficiencies grow at their BGP rates and relative labor supply stays constant. m is chosen large enough so that the choice of terminal value does not affect the results in the period of interest, a method known as tatonnement. An assumption implicit in this method is that the model converges to a steady state (see Judd (1998)), hence it is important to ascertain theoretically that a steady state indeed exists and that the model converges to it, to be able to trust the results. My model converges to a balanced growth path with both production efficiency growth rates uniquely determined by the overall growth rate of the economy, and the capital shares β and γ.

Each value function iteration takes as given the $(T + m \times 2)$-matrix of skilled and unskilled production efficiencies. Using a vector of n values for unskilled capital, I derive the corresponding values for k_s for which rates of return to capital are equalized each period. I use these values for skilled and unskilled capital to derive the optimal choice of next period's capital, given each k_s-k_u combination possible in the current period.

As the irreversibility constraint might be binding somewhere along the optimal path, running the value function iteration under the binding constraint is also necessary. For this, a separate grid is introduced for next period's values of unskilled capital under the binding constraint. Then the value function iteration is used to find the optimal choice of next period's skilled capital, given that the irreversibility constraint on unskilled capital is binding.

Given the initial values for k_s and k_u, it is straightforward to pick the optimal paths for both types of capital for 35 periods. If the unconstrained optimal choice violates the irreversibility constraint, the optimal value will be that from the constrained choices.

Updating the guess for production efficiency

With the optimal paths for the two types of capital and the values of production efficiency, I calculate skilled and unskilled wages as implied by the model. The next step calculates the difference between these wages and the actual wages as given in the data. If the sum of squared errors implied by this difference is above the convergence criterion specified, the efficiency matrix is updated. The new matrix will be a weighted average of the old matrix used to derive the latest optimal paths for capital and the values for skilled and unskilled production efficiency that would yield the wages from the data, given the paths for capital. The weights on the old and new efficiencies, λ and $1 - \lambda$, are chosen such that convergence is as smooth as possible, as giving too much weight to the new solution can lead to overshooting the true solution and slow down convergence (Judd (1998)). Some values of λ may also send the algorithm into an infinite loop that repeats the same few guesses over and over. If this happens, λ is decreased or increased to escape the loop.

With the new efficiency matrix, the value function iteration described above starts again until the sum of squared errors of the model's wages compared to actual wages is below a critical value. Note that as there is no uncertainty whatsoever in the model, it is possible in principle to arrive at the exact solution, provided the grid on capital is infinitely fine. This would, however, come at a large cost in computing time.

Effects of changing the initial guess of production efficiency, years to terminal value, or steady state growth rates

As mentioned in section 1.4.2, the initial guess for production efficiency is chosen to be one in the first period and grow at a certain constant rate afterwards. I also run the program for a variety of other growth rates, equal for both production efficiencies and different, constant and changing. The first period production efficiency however stays the same throughout.

Changing the initial growth rate for production efficiency does not affect results. This is true whether the same growth rate is used for all periods or the growth rate varies for blocks of time. As an example, changing the growth rate for the initial guess from 0.025 to 0.08 for five periods yields the same final production efficiency growth rates as the uniform growth rate for the initial guess.

The choice of m, years until terminal value, depends on the number of grid points chosen. The finer the grid, the larger m needs to be for the results to be unaffected by the exact choice of terminal value. Increasing the number of years between the last period of interest and the terminal value beyond the point where results are constant will only lead to increased computing times. Of course, it is important to check that the number of years is large enough in the first place.

The parameter g is the steady state growth rate to which the economy converges eventually. It does not appear in the period of interest, but is needed to provide a terminal value for the value function iteration. It also pins down, together with β and γ, the growth rates of skilled and unskilled production efficiency after T. I assume that in the long run the economy will converge to its past long run growth rate of 2.5%.

As this is only an assumption, it is very desirable that the results do not depend on the exact choice of this value. Decreasing the steady state growth rate

Table 1.5: Preferred Parameter Specification, Part 2

Parameter	T	n	m	g	λ	Convergence criterion
Value	35	1500	100	0.025	0.09	$10 * e^{-6}$

by one percentage point, increases both production efficiency growth rates in the last ten periods by less than one percent (not percentage point), while earlier periods are not affected. Since most of the larger differences between the production efficiency growth rates occur before 1990, the main results do not depend on the choice of steady state growth rate.

Table 1.5 shows the parameter values used for the algorithm. λ gives the weights of the new and old values of production efficiencies for the updated guess and the next value function iteration. Finally, the convergence criterion determines how small the sum of squared differences between the model's wages and wage data must be for the program to stop updating.

1.7.2 Derivation of Capital Shares

The following table shows the skill classification of industries. Each industry is classifies as skilled if the average of its 1970 and its 2005 share of hours worked by high skilled labor is at least 20%, and classified as unskilled otherwise.

Table 1.6: Skilled Industries

Industry	Skill Share avg.	Skill Share 1970	Skill Share 2005	Capital Share avg.
Education	63.56	58.79	68.33	0.22
Research and development	56.20	40.42	71.98	0.18
Legal, technical, advertising	51.13	41.56	60.70	0.08
Computer, related activities	50.48	35.29	65.67	0.36
Chemicals ex pharma	46.95	31.76	62.14	0.50
Office, accounting, computing	40.75	21.00	60.49	0.25
Activities of membership org	38.29	35.40	41.17	0.06
Insurance, pension funding	32.63	21.20	44.05	0.20
Telecommunication eq.	32.49	12.12	52.86	0.44
Radio and television receivers	31.52	12.14	50.90	0.25
Health and social work	30.18	22.13	38.23	0.16
Financial intermediation	30.10	15.74	44.46	0.51
Publishing	29.62	9.96	49.28	0.26
Aircraft and spacecraft	29.18	14.61	43.74	0.08
Electronic valves and tubes	29.17	10.58	47.77	0.27
Other instruments	29.11	15.38	42.84	0.16
Scientific instruments	28.64	15.20	42.09	0.15
Media activities	28.46	12.93	43.98	0.22
Pharmaceuticals	27.50	18.42	36.58	0.47
Real estate activities	27.21	17.09	37.33	0.90
Other air transport	24.06	11.91	36.22	0.23
Coke, petroleum, nuclear fuel	23.84	15.62	32.06	0.63
Other business activities	23.74	17.37	30.12	0.32
Post and telecoms	22.77	7.39	38.15	0.54
Public administration	21.71	12.18	31.24	0.32
Crude petroleum, natural gas	21.17	14.61	27.72	0.77
Other electrical machinery	20.52	10.59	30.44	0.25
Wholesale, commission trade	20.28	12.02	28.53	0.26

Table 1.7: Unskilled Industries

Industry	Skill Share avg.	Skill Share 1970	Skill Share 2005	Capital Share avg.
Renting of machinery and eq.	19.36	8.43	30.29	0.79
Other water transport	18.88	6.81	30.96	0.30
Electricity supply	18.75	8.13	29.38	0.68
Gas supply	18.12	8.48	27.76	0.66
Other recreational activities	17.94	5.81	30.06	0.26
Tobacco	17.82	7.01	28.64	0.61
Printing and reproduction	16.64	12.56	20.72	0.24
Machinery	15.67	6.87	24.47	0.24
Supporting transport act	15.65	10.29	21.01	0.37
Mining of metal ores	15.43	6.23	24.63	0.47
Motor vehicles and trailers	14.12	6.14	22.09	0.34
Retail trade household goods	13.70	7.10	20.29	0.16
Railroad and transport eq.	13.56	4.62	22.49	0.45
Pulp and paper	12.17	5.82	18.52	0.35
Building, repairing of ships	11.82	6.94	16.69	0.15
Manufacturing nec	11.77	5.84	17.71	0.26
Food and beverages	11.66	5.87	17.45	0.39
Insulated wire	11.26	6.41	16.11	0.48
Basic metals	11.26	6.41	16.11	0.31
Other non-metallic mineral	10.60	5.34	15.85	0.26
Rubber and plastics	10.43	5.00	15.87	0.22
Fabricated metal	10.12	6.54	13.71	0.27
Agriculture	9.80	3.10	16.50	0.53
Other service activities	9.50	1.97	17.02	0.11
Sewage and sanitation	9.45	0.27	18.62	0.62
Wearing apparel, fur	9.12	2.89	15.36	0.18
Hotels, restaurants	8.58	4.01	13.15	0.22
Other mining, quarrying	8.36	6.55	10.16	0.50
Sale of motor vehicles, fuel	8.14	4.87	11.41	-0.08
Construction	7.48	3.74	11.23	0.14
Forestry	7.48	0.70	14.27	0.64
Fishing	7.48	0.70	14.27	0.45
Textiles	7.04	2.46	11.61	0.25
Other inland transport	6.79	2.75	10.82	0.30
Wood and cork	6.63	4.01	9.24	0.30
Mining of coal, lignite; peat	6.32	3.12	9.52	0.48
Leather and footwear	6.31	3.75	8.88	0.29

Chapter 2

Industry Differences in the Skill-Bias of Technological Change

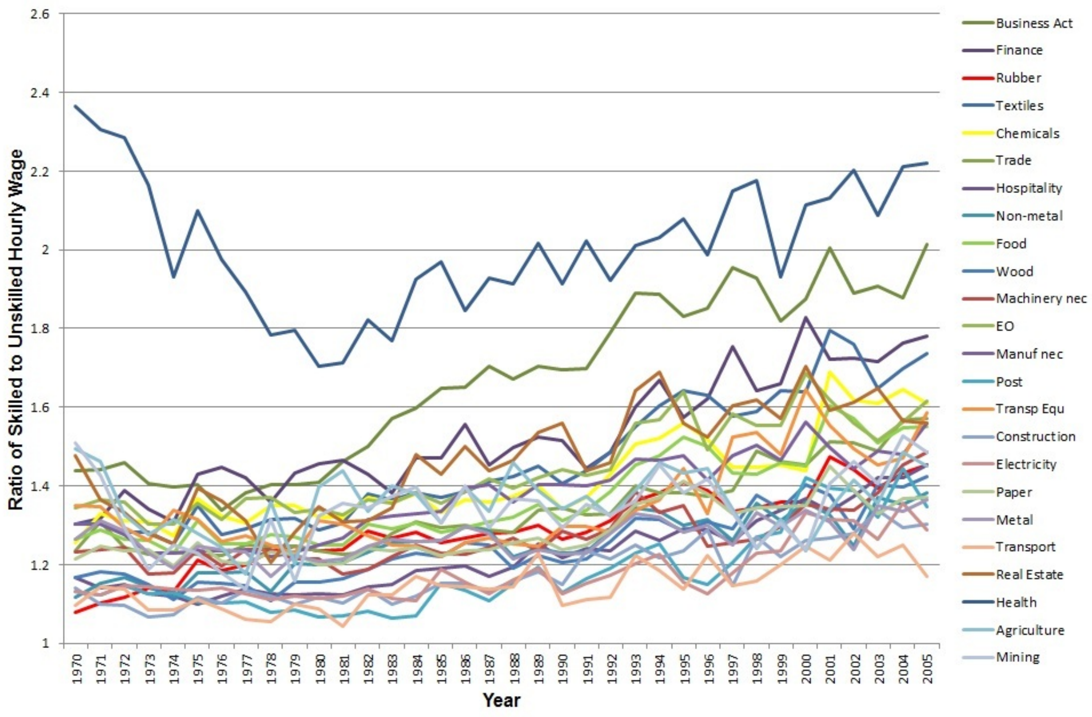
2.1 Introduction

In the previous chapter I look at the skill bias of technological change in the aggregate US economy over the 35 years from 1970 to 2005 and find that technological change has largely been skill neutral. This could either be the result of uniform effects of technological change across all parts of the economy, or the averaging out of very different developments. Adapting the model from chapter one, I repeat the exercise at the industry level for 24 US industries in the same period and find that the latter is the case.

This result is not surprising given that the changes in the skill premium, i.e. the ratio of skilled to unskilled hourly wage, vary across industries as well, as figure 2.1 shows. The skill premium increased in all industries in the sample in the period under consideration, apart from *Health and Social Work*, *Agriculture and Fishing*, and *Mining and Quarrying*, but the degree of change ranges from a 5% increase in *Real Estate Activities* to a rise of more than 40% in *Other Business Activities*[1]. Other industries with strong growth of the skill premium are *Financial*

[1] This is probably due to the industry being the catch-all for service industries that do not fit in any other category. Thus it includes activities as diverse as legal services and business consulting

Figure 2.1 Skill Premium by Industry, 1970-2005



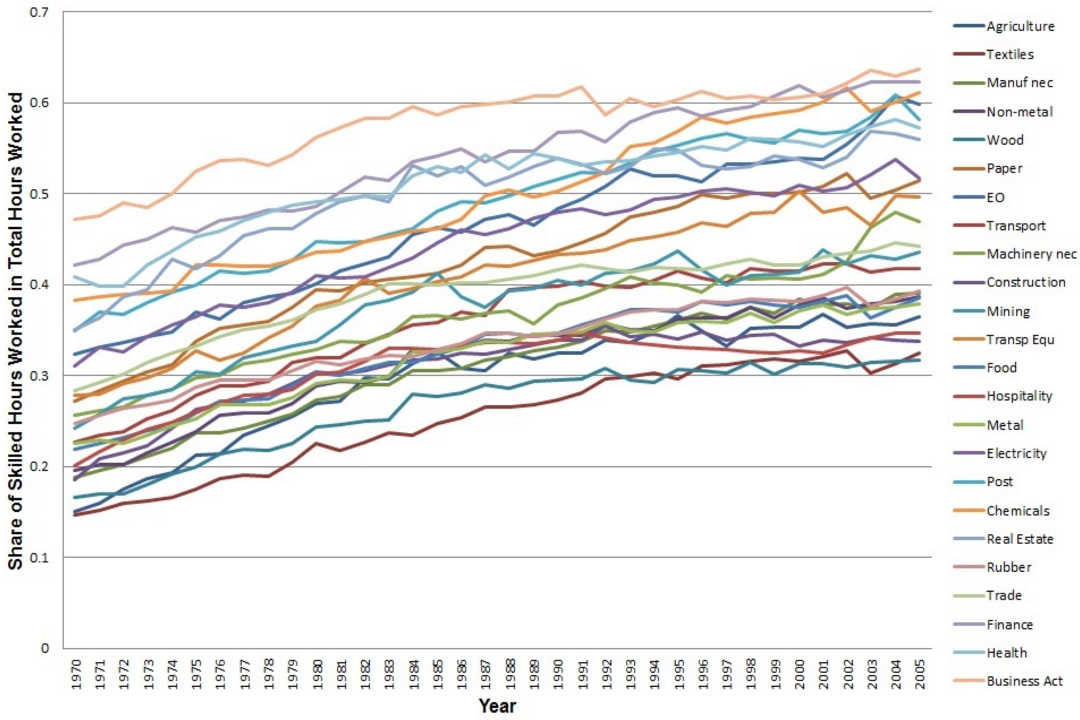
Intermediation, *Rubber and Plastics*, and *Textiles and Leather*. The reasons for the increase in the skill premium are likely different across industries as well. In some of them the increase is probably due to increased investment in capital predominantly used by skilled labor, in others to skill-biased technological change.

The increase in the skill premium is observed despite the relative decline in unskilled hours worked, as can be seen from the evolution of the ratio of skilled to unskilled labor in figure 2.2.[2] The share of hours worked by skilled labor has increased in all industries. The increase varies from 35% in *Other Business Activities* and 40% in *Health and Social Work* to more than 100% in *Agriculture and Fishing*, *Textiles and Leather* and *Manufacturing not elsewhere classified (nec)*. These three industries have very low shares of skilled labor initially, so that even after doubling

at the highly skilled end and call centers and cleaning services at the lower skilled end.

[2]Skilled and unskilled labor are defined as in the previous chapter: skilled labor is a composite of hours worked by people with a college degree and one third of hours worked by people with at least some college education, unskilled labor is the remaining hours worked. Skilled wages are derived as labor compensation to people with a college degree plus one third of labor compensation to people with some college education divided by skilled hours worked. Unskilled wages are the remaining labor compensation divided by unskilled hours worked. Data are again taken from the EUKLEMS (2008) dataset.

Figure 2.2 Share of Skilled Hours Worked by Industry, 1970-2005



this share, they are still comparatively low-skilled sectors. *Health and Social Work* is a special case among the industries studied, as it combines a drop in the skill premium with a large rise in skilled labor - different from what is observed in all other industries. One would not expect a role for technology in explaining the skill premium, although it turns out that skilled production efficiency increased substantially.

Looking beyond the economy as a whole, and seeing whether all industries that make up this economy developed in parallel or there were large differences is interesting in itself, as it explores the origins of the result in chapter one. It is also useful to know when designing a policy to offset some potential negative effects of biased growth of production efficiencies. A policy that wanted to boost unskilled wages, e.g. by encouraging investment in unskilled capital, would require more resources in *Textiles and Leather*, where skilled production efficiency outgrows unskilled production efficiency, than in *Wood and Cork*, where the production efficiency growth rates also work to decrease the skill premium by raising unskilled wages. Furthermore, looking at whether there is a systematic difference between one group of similar industries and another (say manufacturing and services) or whether the difference is random could be helpful when looking for the source of the biases: if similar industries show similar biases, production efficiency biases are more likely due to a common characteristic of these industries; if the biases follow no obvious pattern, the causes of bias need to be found elsewhere. Unfortunately, the latter seems to be the case.

The analysis is very similar to chapter one, but there are some new issues to resolve for this chapter. One issue involves finding a plausible method of deriving the share of skilled and unskilled production in value added from existing data. This is a prerequisite for finding skilled and unskilled capital shares, which turn out to vary considerably across industries. The simulation algorithm remains unchanged, though there is a conceptual difference between the first chapter model of the whole economy and the industry model in this chapter. This difference requires some additional assumptions to keep the model tractable.

There are a number of studies on productivity growth by industry, but to my knowledge none that try to differentiate production efficiency effects by skill level. Nordhaus (2005), for example, finds that productivity growth was largest in *Finance* and *Computers and electronic products*, but only the latter exhibits skill-biased technological change in my analysis. Nordhaus distinguishes neither labor nor productivity by skill level. He also uses a different industry classification, so that his results and mine are not comparable for all industries. Jorgenson, Ho, and Stiroh (2003) look at productivity growth by industry. Their dataset provides the basis for the EUKLEMS (2008) dataset (see also Timmer, O'Mahony, and van Ark (2007)) I use in this paper. Differentiating labor by skill, they find that productivity growth is largest in *Electronic components* and *Computers and office equipment*, but they do not try to distinguish different types of labor efficiency either. Wolff (2002) includes different measures of skill in his study of productivity growth in 44 industries. He uses the industry data in a regression analysis, however, and thus has nothing to say on individual industries or labor efficiency by skill level.

To derive my results, I proceed as follows: section 2.2 describes the changes to the model of chapter one that are necessary to adapt it to a multi-sector environment. In section 2.3, I explain how I obtain the data and parameters I need, again focusing on changes from chapter one. The main results and some robustness checks are described in section 2.4, and section 2.5 concludes.

2.2 The Model

This section briefly recapitulates the model from chapter one (which is an extension of the model in Caselli (1999)), and explains the changes necessary to be able to look at industries within an economy separately.

2.2.1 Production and Factor Payments

Each industry produces one good using two types of production: skilled and unskilled. Each type of production uses a Cobb-Douglass technology and the two technologies are perfect substitutes. There is perfect competition in each industry, so that the factors of production are paid their marginal products. Industry i's production function per hour worked at time t is

$$y_{it} = A_{sit} k_{sit}^{\beta_i} \varphi_{it}^{1-\beta_i} + A_{uit} k_{uit}^{\gamma_i} (1 - \varphi_{it})^{1-\gamma_i}. \tag{2.2.1}$$

Note that the capital shares β and γ can be different for each industry.

This production function is used for reasons of feasibility and consistency with chapter one. There may be more realistic production functions, e.g. one that does not assume perfect substitutability between skilled and unskilled production, or one that has both types of labor in both skilled and unskilled production:

$$Y_{it} = A_{sit} K_{sit}^{b_{1,i}} L_{s,sit}^{b_{2,i}} L_{u,sit}^{1-b_{1,i}-b_{2,i}} + A_{uit} K_{uit}^{c_{1,i}} L_{s,uit}^{c_{2,i}} L_{u,uit}^{1-c_{1,i}-c_{2,i}}. \tag{2.2.2}$$

The results from chapter one suggest that perfect substitutability between both types of production is not too strong an assumption. Equation 2.2.2 is more realistic at the industry level, as any type of production tends to involve both types of labor to some degree. It is, however, impossible to separate skilled labor in skilled production from skilled labor in unskilled production in the data, so that the quantitative exercise of this paper is not feasible with the production function represented in 2.2.2.

The economy's total output is the sum of all n industries' output:

$$Y = \sum_{i=1}^{n} Y_i.$$

Factor payments in industry i then are

$$w_{sit} = (1 - \beta_i) A_{sit} k_{sit}^{\beta_i} \varphi_{it}^{-\beta_i} \tag{2.2.3}$$

and

$$r_{sit} = \beta_i A_{sit} k_{sit}^{\beta_i - 1} \varphi_{it}^{1-\beta_i} \tag{2.2.4}$$

for the skilled sector in industry i. Factor payments for the unskilled sector are obtained analogously.

2.2.2 Consumption

As in chapter one, there is a measure one of identical households, with measure one of members who share all risks and incomes. Households consume the aggregate consumption good $C = \sum_{i=1}^{n} c_i$, where n is the number of industries in the economy and c_i the units of output of industry i used for consumption. The consumer's utility function is logarithmic:

$$u(C) = log(C) = log(\sum_{i=1}^{n} c_i). \tag{2.2.5}$$

Assuming this form of aggregation across goods allows me to keep all prices normalized to one and to compare results with those in chapter one. It is a strong assumption, so I also consider aggregation of consumption via a CES aggregator as a robustness check. Using the CES aggregator, however, requires strong and unrealistic assumptions with respect to the future development of relative prices, which is why I keep the perfect substitutability aggregation as the main model.

One unit of labor is supplied inelastically. Each worker assigns a value $L_i(w_i, x_i)$ to working in industry i, based on the wage w_i to be earned in that industry and a vector x_i of other, non-wage, characteristics that may govern the worker's preferences for a particular industry.

The vector x_i is necessary for two reasons: In an overview of sociological research on various parameters that determine an individual's choice of occupation and change of occupation, Levine (1976) shows that there are factors other than wage that matter for this decision (e.g. personal interest and family expectations, among others). Additionally, including this vector is a crude, but effective, way of explaining wage differentials across industries in equilibrium. These differences can be observed in the data, and they are not consistent with industry choice based purely on wages earned each period, as wages equalize across industries in that case. Prohibiting industry mobility would result in wage differentials across industries, but this is not realistic either. Kambourov and Manovskii (2008) show that between 1968 and 1997 on average 10% of workers moved from one one-digit industry to another every year.

At the beginning of each period t, before production begins, workers decide in which industry to work that period[3], choosing the industry with the highest value of L_i attached and taking everyone else's choice as given. This results in a certain number of hours worked by skilled and unskilled labor in each industry. Normalizing by total hours worked in each industry yields $\varphi_{i,t}$ and $1 - \varphi_{i,t}$, the share of skilled and unskilled hours worked in industry i in period t.

Explicitly specifying a functional form for L_i is not necessary, as I observe the

[3]The full sequence of events: skill acquisition by the unskilled, then industry choice, then production occurs and finally the investment decision.

outcome of this decision process for each period in the data. Taking this shortcut will not affect the main results, as the exact specification of L_i would need to be calibrated to match this data. Additionally, the decision on the choice of industry takes place before production begins each period, so L_i does not affect the equations used to back out A_s and A_u, other than via $\varphi_{i,t}$.

2.2.3 Wage Differentials Across Industries

As mentioned in the previous section, in a basic model of endogenous labor choice between industries, workers would keep moving to the industry paying the highest wage until wages are equalized across industries. This is not what we observe in the data, however. Industry wage differentials have been very persistent over time and across countries, as has been noted in the literature (e.g. Krueger and Summers (1986), Krueger and Summers (1988), Blanchflower, Oswald, and Sanfey (1996), Thaler (1989)).

There are various possible explanations for why there are wage differentials across industries (all of them possible elements of the vector x_i), most of them rooted in the question of why people do not move to another industry to equalize wages. A number of explanations are consistent with perfect competition in the labor market, some more explanations are not[4]. While I am agnostic as to which is the "correct" explanation, I need to consider the impact on my variables of interest, as these explanations affect the A_s and A_u I am interested in differently.

My main results are determined by looking at the difference in average growth rates of skilled and unskilled production efficiency. The results are therefore affected if the explanation for the wage differentials has effects on skilled and unskilled production efficiency that are non-constant and not growing at the same rate for both types of workers over time.

[4]The assumption of perfect competition ensures that workers are paid their marginal product, thus providing a convenient mathematical relationship between wages and the production inputs. If the assumption of perfect competition does not hold and wages paid are above workers' marginal products, the results on growth rate differentials of this paper still go through, as long as both types of wages surpass marginal products to a similar degree.

The explanation requiring least discussion is that there are exogenous barriers to mobility across industries. These would not affect A_s and A_u at all. It is, however, hard to think of any barriers that affect a large share of the labor force. There are barriers to entry into certain professions, e.g. a law degree and the bar exam for lawyers, but this is not true for most industries.

Another explanation concerns unobserved differences in ability, which would be reflected in the backed out values of A. If the effect is increasing (constant) over time for skilled labor, but constant (decreasing) for unskilled labor, or vice versa, this is a problem. Krueger and Summers (1986) show that industry differentials are the same for different types of workers, though, i.e. an industry A that pays highly skilled workers more than industry B also pays more to low skilled workers than industry B. Effects from unobserved ability, if they exist, thus go in the same direction for both types of labor and do not affect the sign of the growth rate differential. For skilled and unskilled wages by industry in my data, the rank correlation is 0.85 or higher, depending on which wage I look at: the average wage over time, 1970 wages, or 2005 wages. This suggests that if the wage differentials exist due to unobserved differences in ability between workers in different industries, this applies to both types of workers similarly.

Yet another explanation is that people include variables in their labor supply decision that are unrelated to money, e.g. the location of the job, the reputation of the industry, overall working conditions, flexibility of hours, etc. This would not change the values of A, as they are similar to exogenous barriers and thus do not directly affect production.

Krueger and Summers (1986) argue that the reason for wage differentials across industries is neither unobserved ability nor differences in non-financial job characteristics, as neither explanation can match all features of the data (see also Krueger and Summers (1988)). They conclude that the wage differentials across industries are due to some form of rent sharing, most likely from considerations of fairness, between firm and worker. The high rank correlation between different types of workers again suggests that this is industry specific, but not specific to a type of labor.

This explanation, however, is not consistent with the assumption of perfect competition and labor being paid its marginal product. Under my model, which assumes the wage data are the results of profit maximization, wage determination via rent sharing will lead to an overstatement of A_s and A_u. Crucially, both terms will be overstated to the same extent, as rent sharing seems to depend on industry, not on the type of labor. Therefore I can still answer the central question - do we observe SBTC or not - for each industry.[5]

2.2.4 Equilibrium

As I am working with yearly data in the quantitative exercise, the model is set up in discrete time. The irreversibility constraint discussed in chapter one is maintained here, too. It is even more likely to hold for specific industries than for the economy as a whole, irrespective of whether the firm owns the capital or rents it every period: as most capital is specific to each industry, a leasing company could not cross-lease to other industries. Therefore, the constraint would only shift from the producing to the leasing company.

[5]One could argue that rent sharing has a stronger effect on skilled wages than on unskilled wages, as skilled workers have better outside options, but in that case we should observe stronger wage differentials for skilled workers than for unskilled workers, which Krueger and Summers (1986) disprove. If this were true, then A_s would be overstated by more than A_u, and the difference in production efficiency growth rates my model finds would be the upper bound of the actual growth rate differential: if the result shows no SBTC, this would be true; if the result for an industry shows SBTC, this result would be subject to the caveat that the actual difference in growth rates might be smaller. Overall, this would make SBTC as an explanation of the wage developments in individual industries less likely.

Each household solves

$$
\begin{aligned}
& max_{k_s,k_u} \quad U = \sum_{t=0}^{\infty} \rho^t ln(C_t) \qquad (2.2.6)\\
& s.t. \quad C_t = \sum_{i=1}^{n} c_{it} = \sum_{i=1}^{n} C_{it}\\
& \sum_{i=1}^{n} C_{it} + \sum_{i=1}^{n} k_{sit+1} + \sum_{i=1}^{n} k_{uit+1} \leq\\
& \sum_{i=1}^{n} y_{it}(k_{sit}, k_{uit}) + \sum_{i=1}^{n} (1-\delta_{si}) k_{sit} + \sum_{i=1}^{n} (1-\delta_{ui}) k_{uit} \quad \forall t \geq 0\\
& k_{jit+1} \geq (1-\delta_{ji}) k_{jit} \qquad \forall t \geq 0, \quad j \in (s,u), \quad i \in (1,n)\\
& k_{si0}, k_{ui0} \quad \text{given} \quad \forall i
\end{aligned}
$$

where n is the number of industries in the economy, and C_{it} the amount of the aggregate consumption good consumed at time t from the proceeds of industry i.

Solving the optimization problem yields the following set of optimality conditions:

$$
\rho \frac{1}{C_{t+1}} (r_{jit+1} + 1 - \delta_{ji}) + \rho \mu_{jit+1} = \frac{1}{C_t} + (1-\delta_{ji}) \mu_{jit} \qquad \forall i, j, t \qquad (2.2.7)
$$

where $j = s, u$, i denotes industry, and the μ are the Lagrange multipliers on the irreversibility constraints. Whenever the irreversibility constraint is not binding,

$$
\frac{C_{t+1}}{C_t} = \rho (r_{jit+1} + 1 - \delta_{ji}) \qquad (2.2.8)
$$

must hold. Equation 2.2.8 implies that the rate of return on either type of capital less depreciation must be equal across all industries.

2.3 The Quantitative Exercise

The quantitative exercise is analogous to the one in chapter one. The detailed description of the exercise can be found in section 1.4.1, more detail on the algorithm is in the appendix of chapter one. The model in section 2.2 is constructed to work the same way. This requires one additional assumption: each industry is small enough that a change in C_i does not noticeably affect C_j, $j \neq i$. With this assumption, finding the optimal use for the income from one industry does not affect all other industries. This is a rather strong assumption given the limited number of industries, but it is necessary to make the model tractable.

There are, however, some differences with regard to the derivation of data and parameters which I explain in this section. In particular, it is not possible to separate the *skilled* and *unskilled* portions of value added within each industry in the data. Depreciation rates and capital shares therefore need to be handled differently.

2.3.1 Data Source and Industry Choice

I look at the data for twenty-four US industries. Table 2.1 shows the industries covered and gives the EUKLEMS (2008) industry code (for a more detailed description of the data used see chapter one, the description of the whole dataset is in Timmer, O'Mahony, and van Ark (2007)). The main criterion for choosing these industries is the availability of data. If more disaggregated industry data is available, but very similar across subgroups, I choose the more aggregated industry. Industries that are by their nature not profit maximizing are dropped (e.g., *Public Administration* or *Education*).

Table 2.1: List of Industries Covered and the Main Parameters

Industry	SIC	δ	β	γ	x
Agriculture and Fishing	AtB	0.07	0.57	0.47	0.36
Mining and Quarrying	C	0.042	0.73	0.68	0.44
Food and Tobacco	15t16	0.079	0.42	0.34	0.40
Textiles and Leather	17t19	0.08	0.27	0.21	0.33
Wood and Cork	20	0.087	0.34	0.26	0.31
Paper and Publishing	21t22	0.096	0.37	0.26	0.48
Chemicals	24	0.087	0.53	0.47	0.58
Rubber and Plastics	25	0.095	0.29	0.20	0.39
Non-Metallic Minerals	26	0.088	0.38	0.26	0.37
Metal Products	27t28	0.082	0.36	0.29	0.37
Machinery nec	29	0.097	0.21	0.27	0.42
Electrical & Optical Eq.	30t33	0.095	0.27	0.23	0.55
Transport Equipment	34t35	0.097	0.22	0.19	0.48
Manufacture nec	36t37	0.089	0.29	0.23	0.38
Electricity and Gas	E	0.045	0.71	0.66	0.48
Construction	F	0.13	0.30	0.12	0.34
Trade	G	0.086	0.26	0.17	0.46
Hotels and Restaurants	H	0.064	0.34	0.27	0.35
Transport and Storage	60t63	0.069	0.42	0.31	0.39
Post and Telecommunications	64	0.073	0.58	0.51	0.53
Financial Intermediation	J	0.125	0.44	0.33	0.63
Real Estate Activities	70	0.013	0.90	0.90	0.59
Other Business Activities	71t74	0.151	0.30	0.26	0.69
Health and Social Work	N	0.064	0.16	0.19	0.68

The first two columns show industries covered and the industry codes as used in EUKLEMS (2008).
The third column shows each industry's depreciation rate of capital.
Columns four and five show skilled (β) and unskilled (γ) capital shares.
x is the share of skilled value added in total value added in each industry.

2.3.2 Construction of Parameters

2.3.2.1 Initial Values for Production Efficiency and Capital

As in chapter one, I assume that the initial value for both skilled and unskilled production efficiency is equal to one. This amounts to a normalization of the level of production efficiency across all industries to be the same in 1970. Skilled and unskilled capital are then derived from the wage and employment data for the first period: $k_{si} = (\frac{w_{si}}{1-\beta_i})^{\frac{1}{\beta_i}} \varphi_i$ and $k_{ui} = (\frac{w_{ui}}{1-\gamma_i})^{\frac{1}{\gamma_i}} (1 - \varphi_i)$.

2.3.2.2 Wages and Share of Skilled Labor: w_{si}, w_{ui}, and φ_i

Skilled and unskilled wages are derived from the shares of labor compensation paid to skilled and unskilled labor, divided by the number of hours worked by skilled and unskilled labor in that industry. As in chapter one, to reduce the three skill levels in the dataset to the two skill levels I need, I add one third of the hours worked by medium skilled labor and of medium skilled labor compensation to the values for high skilled, and the rest to the values of low skilled hours worked and labor compensation. The share of skilled labor φ_i is the share of hours worked by skilled labor in industry i in total hours worked in that industry.

2.3.2.3 Depreciation Rates: δ_i

For the depreciation rates, I assume they are equal for skilled and unskilled capital. This is necessary as I cannot subdivide the industry data further to differentiate capital according to skill and calculate the respective rates. In chapter one it turned out that assuming equal depreciation rates did not qualitatively alter the results, so losing this source of differentiation should not affect the main results here either. The depreciation rate used for each industry is given in table 2.1.

2.3.2.4 Capital Shares: β_i and γ_i

To derive skilled and unskilled capital shares, β_i and γ_i respectively, I need data on skilled and unskilled labor compensation (LAB_{si} and LAB_{ui}) and skilled and unskilled value added (Y_{si} and Y_{ui}). Labor compensation by skill level is available in the data, but there is no direct information on skilled and unskilled value added within each industry. The share of skilled value added in total value added in industry i is x, such that $Y_i = xY_{si} + (1-x)Y_{ui}$. x turns out to be equal to the share of skilled labor compensation in total labor compensation:

Proposition 3. *If Y_i is produced using a constant returns to scale production function and $\frac{w_s L_s}{Y_s} \neq \frac{r_u K_u}{Y_u}$, the share of skilled value added in total value added is either $x = \frac{1}{2}$ or $x = \frac{w_s L_s}{w_s L_s + w_u L_u}$, the share of skilled labor compensation in total labor compensation.*

Proof. As $\frac{w_j L_j + r_j K_j}{Y_j} = 1$, for $j = s, u$,

$$\frac{w_s L_s + r_s K_s + w_u L_u + r_u K_u}{Y} = \frac{1}{2}\left(\frac{w_s L_s}{Y_s} + \frac{r_s K_s}{Y_s} + \frac{w_u L_u}{Y_u} + \frac{r_u K_u}{Y_u}\right). \tag{2.3.1}$$

Provided that $\frac{w_s L_s}{Y_s} \neq \frac{r_u K_u}{Y_u}$ (and thus automatically that $\frac{w_u L_u}{Y_u} \neq \frac{r_s K_s}{Y_s}$), equation 2.3.1 implies $\frac{w_s L_s + w_u L_u}{Y} = \frac{1}{2}(\frac{w_s L_s}{y_s} + \frac{w_u L_u}{Y_u})$.[6] Equation 2.3.1 can be rewritten as $\frac{1}{2}\frac{w_s L_s}{xY} - \frac{w_s L_s}{Y} = \frac{w_u L_u}{Y} - \frac{1}{2}\frac{w_u L_u}{(1-x)Y}$, where x is the share of skilled value added, and with some algebra transformed into a quadratic equation:

$$2\left(\frac{w_s L_s}{Y} + \frac{w_u L_u}{Y}\right)x^2 - \left(3\frac{w_s L_s}{Y} + \frac{w_u L_u}{Y}\right)x + \frac{w_s L_s}{Y} = 0 \tag{2.3.2}$$

Solving out this quadratic yields $x = \frac{w_s L_s}{w_s L_s + w_u L_u}$ or $x = \frac{1}{2}$. □

For each industry, I calculate x each period and take the unweighted average over time. With this average x, I calculate skilled and unskilled value added, Y_s and Y_u.

[6] To show this is the case, note that for $z \neq 0$, $(\frac{1}{2} + z)(\frac{w_s L_s}{Y_s} + \frac{w_u L_u}{Y_u}) + (\frac{1}{2} - z)(\frac{r_s K_s}{Y_s} + \frac{r_u K_u}{Y_u}) = \frac{w_s L_s + r_s K_s + w_u L_u + r_u K_u}{Y}$ implies $\frac{1}{2}(\frac{w_s L_s}{Y_s} + \frac{w_u L_u}{Y_u} + \frac{r_s K_s}{Y_s} + \frac{r_u K_u}{Y_u}) + z(\frac{w_s L_s}{Y_s} + \frac{w_u L_u}{Y_u} - \frac{r_s K_s}{Y_s} - \frac{r_u K_u}{Y_u}) = \frac{w_s L_s + r_s K_s + w_u L_u + r_u K_u}{Y}$. Unless $\frac{w_s L_s}{Y_s} + \frac{w_u L_u}{Y_u} - \frac{r_s K_s}{Y_s} - \frac{r_u K_u}{Y_u} = 0$, which is the case if $\frac{w_s L_s}{Y_s} = \frac{r_u K_u}{Y_u}$, $z \neq 0$ leads to a contradiction and the equation above must hold.

Next, I calculate skilled and unskilled labor shares for each period as $1-\beta = \frac{w_s L_s}{Y_s}$ and $1-\gamma = \frac{w_u L_u}{Y_u}$. These shares are not constant over time, as the model requires, so I take the average of the first and last period values, and subtract these results from one to obtain the capital shares for each industry.[7] These capital shares are given in table 2.1.

I prefer the average of the first and last period to the overall average, as the former better reflects large changes in the shares over time. The average over all periods cannot distinguish between a series of shares that has been fairly constant over time from one that has, for example, tripled over time at a decreasing rate of change. The average over all periods thus disguises large differences between the series and ignores valuable information that is better captured by using the average of first and last period only.

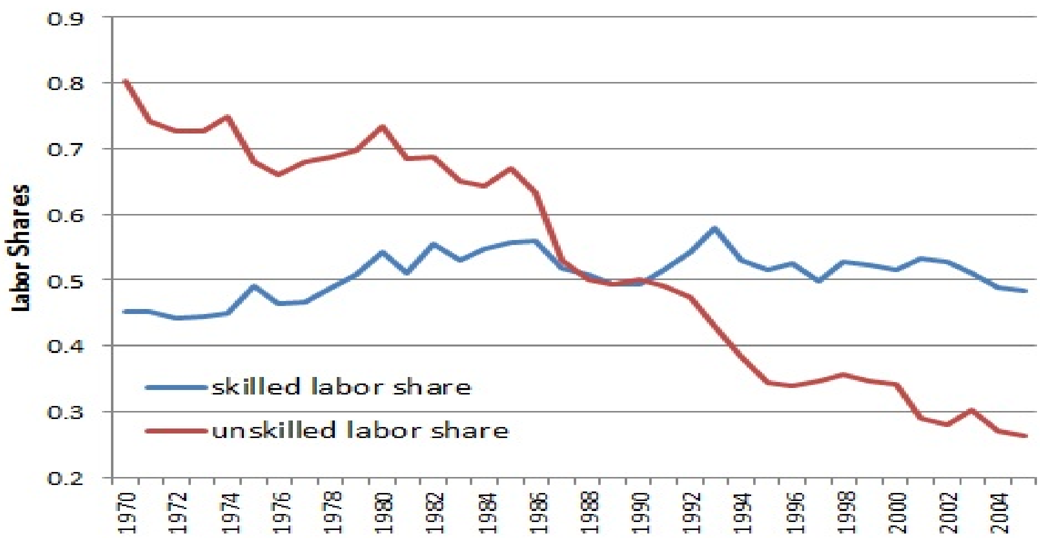
As an example, consider figure 2.3, which shows skilled and unskilled labor shares for *Chemicals* over time. The average labor share over all periods is 0.53 for skilled labor and 0.51 for unskilled labor. Clearly, the series are not as similar as the simple averages suggest.[8]

The capital shares derived in this manner are biased if the industry's true production function is represented by 2.2.2, as part of the labor share is captured in the capital share for one type of production and part of the capital share is captured in the labor share for the other type of production. The bias on β and γ individually is less important than effect of the bias on the difference between the two, though, as we know from chapter one that $g_s - g_u$ is decreasing in $\beta - \gamma$ and hence that the larger the difference between β and γ, the less likely is the existence of SBTC. The size and direction of the bias depends on $L_{s,uit}$ and $L_{u,sit}$, the hours of skilled labor worked in unskilled production and the hours of unskilled labor worked in skilled production. More precisely, the bias in the skilled capital

[7]In principle, this method is also valid for deriving capital shares in chapter one. This would yield $\beta = 0.39$ and $\gamma = 0.33$, resulting in a growth rate differential of 0.0025.

[8]Note that even though in the average of first and last period the condition that $\frac{w_s L_s}{Y_s} \neq \frac{r_u K_u}{Y_u}$ is violated, the method for finding x is still valid, as the condition is not violated in any period in the calculation.

Figure 2.3 Labor Share in Chemical Industry Over Time



share is

$$b_1 - \beta = \frac{w_s L_{s,uit} - w_u L_{u,sit}}{Y_s} \tag{2.3.3}$$

and in the unskilled capital share

$$c_1 - \gamma = \frac{w_u L_{u,sit} - w_s L_{s,uit}}{Y_u}, \tag{2.3.4}$$

where b_1 and c_1 are the capital shares in 2.2.2. Note that the biases of β and γ, when they exist, always are of opposite signs. The bias in the difference between the capital shares can then be expressed as

$$b_1 - c_1 = \beta - \gamma + \frac{1}{x(1-x)Y_{it}}(w_s L_{s,uit} - w_u L_{u,sit}) \tag{2.3.5}$$

with $Y_{i,t}$ total value added of industry i at time t and x still the share of skilled production value added in total value added.

There are three possible scenarios:

- $w_u L_{u,sit} = w_s L_{s,uit}$: In this case the bias is zero, and the observed capital shares are the same as the true capital shares.
- $w_u L_{u,sit} > w_s L_{s,uit}$: In this case, $c_1 > \gamma$ and $b_1 < \beta$ and thus $b_1 - c_1 <$

$\beta - \gamma$. As the observed difference in capital shares is larger than the true difference, the observed results on the difference in growth rates between skilled and unskilled production efficiency understate the true results and SBTC is more likely than the results suggest.

- $w_u L_{u,sit} < w_s L_{s,uit}$: In this case, $c_1 < \gamma$ and $b_1 > \beta$ and thus $b_1 - c_1 > \beta - \gamma$. The observed difference is smaller than the true difference and the observed results overstate the existence of SBTC.

As I do not know $L_{s,uit}$ and $L_{u,sit}$, I cannot determine with any certainty which of the three scenarios holds. One could argue that it is likely that more unskilled labor is needed in skilled production than vice versa and conclude that SBTC is understated. However, the higher skilled wage may outweigh the possibly greater numbers of $L_{u,sit}$ and thus SBTC may be overstated instead.

2.4 Results

2.4.1 Main Results

In this section I present the results of the simulation for all industries except two: for *Electricity and Gas* and *Real Estate Activities* the algorithm does not converge. I discuss possible reasons for non-convergence at the end of the section.

For four more industries (*Food and Tobacco*, *Machinery nec*, *Post and Telecommunications*, *Mining and Quarrying*) I stop the simulation at a higher value for the convergence criterion as it enters an infinite loop at very small values of the error criterion. This can in principle be remedied by further tightening the grid over which the code is run, but at a very large time cost. Testing the impact of different convergence criteria in other industries, I find that for any criterion smaller than 0.1 the results are identical to those using the standard criterion of $1e^{-5}$, and for 0.1 differences are only observed at the sixth decimal. The criterion used for these four industries should therefore not affect the results.

2.4.1.1 Converging Industries

Table 2.2 shows the difference in the average growth rates of skilled and unskilled production efficiencies. A positive value for the difference suggests that there has been SBTC in this industry, as the wage premium in these cases increases with an increase in the ratio of $\frac{A_s}{A_u}$.

Of the 22 industries for which I have results, the difference in the average growth rate is positive for ten. There has been SBTC in *Textiles and Leather*, *Rubber and Plastics*, *Machinery nec*, *Electrical and Optical Equipment*, *Transport Equipment*, *Manufacture nec*, *Construction*, *Trade*, and *Other Business Activities*. The difference in average growth rates is largest for *Health and Social Work*, which is a particularly interesting case: the growth rates of production efficiencies affect the skill premium positively, yet the skill premium actually declined over the period studied. This is due to much higher growth in unskilled than in skilled capital, in addition to the increase in skilled hours worked relative to unskilled hours worked.

All other industries exhibit a negative average difference between skilled and unskilled production efficiency, indicating that technological change was unskill-biased there. The difference in growth rates is less than one percentage point for all UBTC-industries and all but two SBTC industries (the difference is 1.7 percentage points for *Machinery nec*, 1.0 percentage points for *Other Business Activities*), and *Health and Social Work* (2.1 percentage points).

The irreversibility constraint is binding for at least one period and at least one type of capital for all but five industries. These five industries (*Agriculture and Fishing*, *Mining and Quarrying*, *Chemicals*, *Post and Telecommunications*, and *Hotels and Restaurants*) all show unskill bias. For four industries, the irreversibility constraint is only binding for unskilled capital, for two only on skilled capital. For the remaining eleven industries, the constraint is binding on both types of capital at some point, though not necessarily at the same time. Although one would expect that a binding irreversibility constraint on unskilled capital makes skill bias of technology more likely, three of the four industries exhibit unskill bias nonetheless. The constraint is only binding for five periods or less, though. For the one industry exhibiting skill bias, *Textiles and Leather*, the constraint is binding for fifteen periods. The irreversibility constraint is binding on skilled capital for one period in *Wood and Cork* (slight unskill bias) and for four periods in *Health and Social Work* (strong skill bias). Of the remaining industries, three show unskill bias and eight skill bias, though no clear pattern emerges that would allow conclusions if and how the binding constraint might affect the results on skill bias.

Aggregating these industry results to the level of the three main sectors of the economy (using unweighted averages) reveals that there has been UBTC in the primary sector (unweighted average of the differences between growth rates -0.007), and indicates SBTC for the secondary (0.002) and tertiary (0.004) sectors. Taking the weighted averages instead, with the average value added in each industry as the weights, yields a growth rate differential of -0.007 in the primary sector, 0.002 in the secondary sector, and 0.006 in services[9]. The average for the economy as a whole is 0.004, which would suggest SBTC in the economy as a whole.

2.4.1.2 Discussing Non-Convergence

For two industries, *Electricity and Gas* and *Real Estate Activities*, the algorithm does not converge. This is due to problems with the interval for the grid values for K_u and the fact that capital shares are very high for these industries. Although this is a purely technical problem, explaining why some results are not available merits this brief discussion.

High capital shares lead to high initial values for unskilled capital K_{u0}. The grid values for K_u, i.e. the interval of values over which the value function iteration is run, is determined by the initial value of unskilled capital. The smallest

[9]This much larger weighted average is entirely due to the large growth differential of *Health and Social Work*. The weighted average for the services sector excluding *Health* is 0.004, for the whole economy it is 0.003

Table 2.2: Growth Rate Differentials

Industry	Difference in average growth rates		
	full sample	1980-2005	1990-2005
Agriculture and Fishing	-0.008	-0.007	-0.006
Mining and Quarrying	-0.006	-0.001	0.004
Food and Tobacco	-0.004	-0.002	0.001
Textiles and Leather	0.005	0.008	0.007
Wood and Cork	-0.002	0.0002	0.001
Paper and Publishing	-0.009	-0.008	-0.004
Chemicals	-0.003	-0.001	0.002
Rubber and Plastics	0.007	0.002	0.003
Non-Metallic Minerals	-0.001	-0.005	-0.0002
Metal Products	-0.004	-0.002	0.001
Machinery nec	0.017	0.011	0.012
Electrical & Optical Eq.	0.008	0.013	0.013
Transport Equipment	0.006	0.005	0.008
Manufacture nec	0.002	0.003	0.001
Electricity and Gas	nc	nc	nc
Construction	0.005	0.004	0.007
Trade	0.006	0.006	0.004
Hotels and Restaurants	-0.001	-0.0004	0.003
Transport and Storage	-0.002	-0.003	-0.001
Post and Telecommunications	-0.002	-0.001	0.001
Financial Intermediation	-0.004	-0.006	0.0001
Real Estate Activities	nc	nc	nc
Other Business Activities	0.010	0.006	0.005
Health and Social Work	0.021	0.013	0.011

The numbers are the difference of the average skilled and unskilled production efficiency growth rates.
n.c. denotes non-convergence in that industry.

value of the interval is a fraction a of K_{u0}, the largest value is a multiple b.

If b is too small, the path of capital reaches the upper bound of the interval. If a is too large or the step size in the interval is not small enough, even the smallest possible choice of capital will lead to a negative level of consumption. In that case, the negative consumption value is replaced with a marginally positive one. But if all consumption values are the same marginally positive value, the level of capital that maximizes the value function is always the upper end point of the interval. In neither case will the path of capital be the optimal path.

In principle, this problem can be solved by increasing b, decreasing a and decreasing the step size of the interval. In practice, increasing the number of grid points enough to solve this problem makes the algorithm too time-consuming.

2.4.2 Robustness Checks

In theory, equation 2.2.8 provides an ideal check for whether the simulation results are credible or not. If the rates of return on capital are equal across industries, the results are consistent with the model and the code can be expected to deliver useful results. Rates of return on capital would only be exactly equal, however, if the simulated model were continuous in capital. I necessarily work with a discrete approximation, which means that the rates of return in two different industries can be different to some degree. How much difference still is consistent with equation 2.2.8 depends on the values for production efficiency, capital shares, and on φ, but also on the step size for the nodes of capital in the two industries. As step size is determined by the initial level of capital, the difference may become quite large and still not contradict equation 2.2.8.[10] Equation 2.2.8 holds between skilled and unskilled capital within the same industry by construction, as long as the irreversibility constraint is not binding.

[10]For example, for *Paper and Publishing* the step size is 0.266, while for *Wood and Cork* it is 0.057. The maximum difference consistent with equal rates of return is difficult to determine, but assuming all other variables are equal, a difference in the rates of return of these two industries of 0.16 would still be consistent with equation 2.2.8. Differences in production efficiency or capital shares could either increase or decrease this maximum consistent difference, depending on actual values.

2.4.2.1 Different Time Periods

The skill premium fell in the 1970s for most industries, and only started rising from 1980 onwards. This behavior in the skill premium suggests a negative difference between skilled and unskilled production efficiency growth for the first decade of the period under study. To check whether the results are driven by the behavior of the wage premium in the 1970s, I also compute the differentials starting from 1980. The results are also presented in table 2.2.

Comparing results for the full sample with those starting in 1980, the sign changes for one industry only: *Wood and Cork* exhibits UBTC when looking at the full sample, but seems to have experienced SBTC after 1980. For all other industries the direction of the bias remains the same, only the magnitudes differ. The results therefore are not driven by the behavior of the skill premium in the early years.

Finally, I also look at the production efficiency growth rates starting from 1990. Computers and the internet only started to be widely used in the 1990s, and they are thought to favor skilled labor. If the difference in growth rates turns positive for that period, this could be seen as an indication that information and communication technology (ICT) indeed had a positive effect on skilled production efficiency in these industries.

For the period 1990-2005, the difference between skilled and unskilled production efficiency is negative for only four industries: *Agriculture*, *Paper and Publishing*, *Non-Metallic Mineral Products*, and *Transport and Storage*. For all others, the difference is now positive. This may be an indication of the ICT revolution affecting skilled labor more than unskilled labor. Chapter three will explore the link between the skill premium and ICT capital in different industries in more detail.

2.4.2.2 CES Aggregator for Consumption

As the assumption of perfect substitutability of consumption goods produced in different industries is rather strong, I repeat the exercise for *Paper and Publishing* and *Transport Equipment* using a CES aggregator for consumption. To give an idea of the effect on the results it is not necessary to repeat the exercise for all industries, instead I choose two industries for which results are very different in the main version of the model.

Consumption goods produced in each industry are aggregated via $C = (\sum_{i=1}^{n} c_i^{\alpha})^{\frac{1}{\alpha}}$, where α is the elasticity of substitution between two goods. The same aggregator is used for capital goods (as in Arkolakis, Costinot, and Rodriguez-Clare (2012), among others). With this consumption aggregator, output prices are no longer equal to one for all industries at all points in time and need to be taken into account in the simulation.

Households now solve

$$\begin{aligned}
& max_{k_s,k_u} \quad U = \sum_{t=0}^{\infty} \rho^t ln(C_t) \qquad (2.4.1) \\
& s.t. \quad C_t = (\sum_{i=1}^{n} c_{it}^{\alpha})^{\frac{1}{\alpha}} = \sum_{i=1}^{n} C_{it} \\
& \sum_{i=1}^{n} C_{it} + \sum_{i=1}^{n} k_{sit+1} + \sum_{i=1}^{n} k_{uit+1} \leq \\
& \sum_{i=1}^{n} \frac{p_{it}}{P} y_{it}(k_{sit}, k_{uit}) + \sum_{i=1}^{n} (1-\delta_{si}) k_{sit} + \sum_{i=1}^{n} (1-\delta_{ui}) k_{uit} \quad \forall t \geq 0 \\
& k_{jit+1} \geq (1-\delta_{ji}) k_{jit} \qquad \forall t \geq 0, \quad j \in (s,u), \quad i \in (1,n) \\
& k_{si0}, k_{ui0} \quad \text{given} \quad \forall i
\end{aligned}$$

where P is the aggregate price level and p_{it} is the price of output in industry i at time t. Whenever the irreversibility constraint is not binding,

$$\rho(\frac{p_{it+1}}{P} r_{sit+1} + 1 - \delta_{si}) = \rho(\frac{p_{it+1}}{P} r_{uit+1} + 1 - \delta_{ui}) \qquad (2.4.2)$$

must hold. As the depreciation rates for skilled and unskilled capital are equal for each industry, the condition simplifies further to

$$r_{sit+1} = r_{uit+1} \qquad (2.4.3)$$

I do not need α at any point in the simulation, so the question of finding an appropriate value does not arise. The price level data are taken from EUKLEMS (2008), using value added prices of the economy as a whole for P and of the relevant industries for p_i. For the post-sample period I assume that the price ratio stays constant at the level of 2005. Some assumption on the evolution of relative prices after the end of the sample data is necessary, even though finding reasonable predictions for relative prices over many periods is impossible. This is one of the reasons why I prefer the assumption of perfect substitutability of consumption for the main specification.

The results are virtually identical to my baseline case: for *Paper and Publishing* the growth rate differential between skilled and unskilled production efficiency is -0.010 with the CES aggregator, compared to -0.009 with the baseline. For *Transport Equipment* the values are 0.006 for CES and 0.006 for the baseline. Assuming that consumption goods produced in different industries are perfect substitutes therefore seems to not be an overly restrictive assumption.

2.5 Conclusions

The purpose of this chapter is to investigate what lies beneath the results of the previous chapter, especially as there has been some variability in the evolution of wages and the skill composition of the labor force in different industries from 1970 to 2005.

The results suggest that technological progress has varied across industries, and that the result in chapter one is the result of averaging different developments in each industry. There are results for 22 industries, and less than half of these show skill biased technological change (SBTC). For the rest, unskilled production efficiency growth exceeded that of skilled production efficiency.

Differentiating by sector reveals that industries in the tertiary sector, services, are more likely to exhibit SBTC than the other sectors of the economy. There are, however, several industries in the services sector that do not exhibit SBTC (among them, somewhat against expectations, *Financial Intermediation* and *Post and Telecommunications*), and several manufacturing industries that do, so that the sector by itself is not a useful characteristic in determining the underlying causes of SBTC. Finding the common elements in the SBTC industries remains a question for future research.

Looking at the growth rates of production efficiency at shorter time horizons indicates that SBTC might have played a larger role after 1990. This may help in explaining the intuitive appeal of the SBTC hypothesis - it cannot explain the whole of the rise in the skill premium, but it might explain part of it in more recent years, which are fresher in people's memory. As the rise of information and communications technology also falls in the period after 1990, there might be some connection between ICT and SBTC.

Chapter 3

Information and Communication Technology and the Skill Premium in Different US Industries

3.1 Introduction

3.1.1 Motivation

One area where technological change has been very visible over the past forty years, and especially since the 1990s, is information and communication technology (ICT). Computers in particular have changed the way people work and the way firms organize their workforce (see Autor, Levy, and Murnane (2000)). In this chapter, I investigate the role of ICT capital in the production function and in the evolution of the skill premium in different US industries.

Following Jorgenson (1986) and Ruiz-Arranz (2003), I estimate a translog price function with four factors of production and a technology parameter for each industry. There are two ways in which ICT capital is of interest: one is the pattern of substitutability and complementarity of ICT capital with other factors of production. The first question therefore is which industries exhibit ICT capital-skill complementarity as defined by Griliches (1969). Autor, Katz, and Krueger (1997) find that more computer-intensive industries increase the use of skilled labor faster, indicating the presence of ICT capital-skill complementarity. My estimation results confirm this for most industries. Not all industries exhibit ICT capital-skill complementarity, however. There are skilled jobs that become unnecessary with increased use of ICT in some industries, so some variation is to be expected.

To illustrate the two possible effects of an increase in ICT capital, look at graphic designers in *Paper and Publishing* and at stock brokers in *Financial Intermediation*. The work of graphic designers, though requiring higher education, can largely be done by personal computers, reducing the number of graphic designers needed. In this case, ICT capital and skilled labor are substitutes. Stock brokers on the other hand use computers to make more trades, and the decision on each of these trades must be made by a broker (high frequency trading algorithms notwithstanding). Here it is more likely that more brokers are hired to be able to carry out even more transactions, making skilled labor and ICT capital complements.

The second matter of interest is the "ICT effect" on the skill premium, i.e. the question whether ICT capital has contributed to the increase in the skill premium in the period studied. The use of ICT capital requires a certain level of education, especially in the early stages of the technology. Krueger (1993) finds that workers using computers earn higher wages, and that skilled workers are more likely to use ICT. In that case an increase in the use of ICT should lead to an increase in the skill premium. DiNardo and Pischke (1997) dispute this connection, however. They find that other office items not particularly associated with highly skilled labor (e.g. pencils) correlate with wages similarly to computers, suggesting that there is no causal relationship between computers and higher wages. This is an argument against any effect of ICT on the skill premium. I find that for most industries increasing ICT capital depresses the skill premium. This is a somewhat unexpected result, for which I offer a possible explanation related to the complementarity between ICT capital and skilled labor and the substitutability of ICT capital and unskilled labor.

Apart from looking at ICT, I also investigate the patterns of factor use and factor saving in the biases of technology, concepts introduced by Binswanger (1974) and Jorgenson and Fraumeni (1983). Finally, I look at the overall effect of technology on the skill premium as implied by this model as a crude robustness check of the results from chapter two.

3.1.2 Discussion of Relevant Literature

There is a vast literature on estimating production functions, the elasticities of substitution between factors, and factor biases of technological change. An overview of the foundations and a large number of studies is given in Jorgenson (1986). There are a number of studies looking at data at the industry level, but to the best of my knowledge none that separate labor into skilled and unskilled labor. Authors looking at different types of labor separately tend to consider the economy as a whole, or several countries together.

One well known example of the second group of authors is Krusell, Ohanian, Rios-Rull, and Violante (2000), who estimate a CES production function with skilled and unskilled labor and two types of capital (equipment and structures) as inputs. They assume that the elasticities of substitution between skilled and unskilled labor and between equipment capital and unskilled labor are equal, and that the elasticity of substitution between equipment capital and skilled labor is different. If the latter elasticity is larger than the former ones, the production function exhibits capital-skill complementarity. Their main finding is that the changes in the skill premium for their period of study (1963 - 1992) can be explained by changes in factor inputs alone, without needing to resort to skill-biased technological change as an explanation. From their estimation they find evidence of equipment capital-skill complementarity. Separating the change in the skill premium into three distinct effects, they find that the "complementarity effect" has raised the skill premium by 60% over the time horizon studied, while the “quantity effect” of labor supply has decreased the skill premium by 40%. The “technology effect” is essentially zero.

Technological progress enters the Krusell, Ohanian, Rios-Rull, and Violante (2000) model in three ways. The first effect is via a TFP parameter that affects all factor prices equally and thus does not affect the skill premium. Second, technological progress affects the production of equipment capital and leads to declining relative prices of equipment capital relative to structures. This price decline affects the growth rate of equipment capital, and this growth rate in turn determines the “complementarity effect”. Thus, there is some effect of technology on the skill premium even in their results. This effect of technological progress in their model via relative prices cannot be quantified separately in their results. Third, technological progress determines skilled and unskilled labor efficiencies in their model. As these efficiencies are unknown, they are modeled as stochastic processes. The assumption is that each type of labor efficiency follows a random walk with a constant and without a time trend. Skill-biased technological change would be present if there were a time trend in these processes and the coefficient on a time trend component for skilled labor efficiency were larger than the coefficient on the time trend for unskilled labor efficiency. By assuming ex ante that both of these coefficients are zero, they assume away the possibility of skill-biased technological change in their results. [1]

Ruiz-Arranz (2003) disputes the findings in Krusell, Ohanian, Rios-Rull, and Violante (2000). She extends a model developed by Christensen, Jorgenson, and Lau (1973) (and described in detail in Jorgenson (1986)) to investigate the relative contributions of technological bias and ICT capital-skill complementarity to the evolution of the skill premium of the overall US economy. She estimates two versions of a translog production function [2]: one version with skilled and unskilled labor and IT and non-IT capital as inputs, the other splits capital further

[1] They analyze a different set of assumptions, too, where they allow for different time trends. However, in that version, they assume all elasticities of substitution are equal and thus rule out the entire “complementarity effect” ex-ante.

[2] Strictly speaking, the dual of a translog production function.

into IT capital, non-IT equipment capital and structures. Using the translog production function imposes no ex-ante restrictions on the elasticities of substitution. Krusell, Ohanian, Rios-Rull, and Violante (2000) discuss the translog function, but decide against it because it comes at a high cost in terms of degrees of freedom in the estimation when the sample is small. This is a valid point, as the procedure in Krusell et al involves estimating 7 parameters on 29 observations, leaving 22 degrees of freedom, while the smaller Ruiz-Arranz (2003) model requires the estimation of 15 parameters on 35 observations for 19 degrees of freedom. Thus, using the translog production function limits the power of statistical tests that go beyond simple significance tests, while not using the translog function limits the information to be gained from estimation as the ex-ante restrictions on the elasticities of substitution between the factor inputs may hide information on the actual shape of these elasticities if they were unrestricted. Ruiz-Arranz also explicitly allows for different effects of technology on the production functions by introducing interaction terms between technology and the factors of production (as developed by Binswanger (1974)) and develops a framework to separate the effects on the growth of the skill premium from technological progress from the effects of capital-skill complementarity.

She finds that there is IT capital-skill complementarity both in the four- and the five-input model, but that non-IT equipment is a substitute for skilled labor, a result confirmed by Michaels, Natraj, and Van Reenen (2013) for a sample of 25 countries. IT capital-skill complementarity is stronger during the early part of the sample, during which there was only little increase in the skill premium. In both models there is a large negative effect of the relative increase of skilled labor supply (80% and 73% respectively) on the skill premium, a smaller positive "complementarity effect" from the changes in capital inputs (41% and 31%) and a large positive effect from technological progress and its effect on all four inputs to production (58% and 61%). This contrasts with the conclusion of Krusell, Ohanian, Rios-Rull, and Violante (2000) that all of the change in the skill premium can be explained by observable factors.

The results of chapter one of this thesis are very different compared to both Krusell and Ruiz Arranz at first sight, but this does not invalidate the motivation and results of Ruiz-Arranz (2003). The production function in chapter one is more restrictive and the capital inputs into production are separated along different lines, namely simply by which type of labor uses this capital - skilled or unskilled labor. This production function is the most general production function possible that allows me to tractably derive the paths of skilled and unskilled labor within the model. It is also in keeping with the theoretical model which motivates chapter one. The central result is that on average, unskilled factor productivity has increased slightly faster than skilled factor productivity, suggesting that there has not been skill-biased technological change. Skilled (unskilled) factor production in the model of chapter one combines the effects of technological progress on skilled (unskilled) labor and skilled (unskilled) capital. There is no direct capital equivalent in Ruiz-Arranz (2003) work, but if one uses IT capital as a crude proxy for skilled capital and non-IT capital as a very crude proxy for unskilled capital, the effects of "skilled factor productivity" in Ruiz-Arranz (2003) are smaller (13%) than the effects of "unskilled factor productivity" (45%), leading to a similar conclusion as in chapter one.

The innovation of this present chapter is to apply the more flexible methodology developed in Ruiz-Arranz (2003) for the first time to industry level data in the US. The application to industry data requires a different sample period, as the data are only available from 1970 onwards. Thus, I look at industry level data from 1970 to 2005, while Ruiz-Arranz (2003) studies the US economy as a whole from 1965 to 1999. The instruments used to mitigate the endogeneity bias in the estimation are also different. Finally, the focus in Ruiz-Arranz (2003) and in this chapter is distinct: the primary focus in Ruiz-Arranz (2003) is specifically on the effect of ICT capital-skill complementarity on the skill premium, whereas I am interested in the role of ICT capital in all aspects of the production function of different industries.

Two more examples of studies also estimating production functions for countries as a whole are Duffy, Papageorgiou, and Perez-Sebastian (2004) and Berndt and Morrison (1979). The former estimate CES production functions for a panel of countries and find capital-skill complementarity only when defining a very low threshold for skilled labor. They suggest that technology bias is likely a more important factor. The second study looks at the effect of an increase in energy prices on the wages of white and blue collar workers. Estimating a translog cost function for the manufacturing sector for 1947-1971, they find that blue collar workers' wage share would increase with energy prices, while the wages of white collar workers decrease. They do not consider technology at all, however.

Binswanger (1974) also employs the translog cost function in his estimations, looking at pooled data from 39 US states at different time periods, only considering labor as a whole. This study is the first to explicitly look at the biases of technological change and shows that, at least for short enough time periods, a linear trend is a good approximation to technological change. Jorgenson and Fraumeni (1983) use a translog price function with a linear trend for technology to look at the biases of technology and find distinct patterns of factor using and factor saving biases of technology across industries. They look at different industries, but do not differentiate labor by skill level. The linear approximation of technology still is commonly used, with the exception of Jin and Jorgenson (2010), who consider technological change a latent variable in the estimation process and use Kalman filter techniques to back it out. They look at US industries, but do not divide labor into several types.

The rest of this chapter is organized as follows: section 3.2 describes the production function to be estimated, including its properties, and the metrics of interest to determine technological bias and ICT capital-skill complementarity. Section 3.3 then explains the estimation strategy and section 3.4 the data used. The results are presented in section 3.5, section 3.6 concludes.

3.2 The Translog Price Function

This section closely follows Jorgenson (1986) and Ruiz-Arranz (2003).

3.2.1 Translog Function and Value Shares

There is perfect competition in factor markets, so that factors are paid their marginal products, and also in the goods market, so that producers set their profit-maximizing price. The production function is a translog function, which is also the second order Taylor approximation to any neoclassical production function and hence nests many possible production functions. Rather than looking at the production function and marginal products directly, I use its dual, the price function[3]:

$$ln(P) = \alpha_0 + \alpha_p' ln(p) + \alpha_t t + \frac{1}{2} ln(p)' A_{pp} ln(p) + ln(p)' a_{pt} t + \frac{1}{2} t^2 \qquad (3.2.1)$$

where P is the output price, p an $(n \times 1)$ vector of input prices and t the level of technology, modeled as a linear time trend.

A_{pp} is an $(n \times n)$ matrix describing substitution patterns between inputs and a_{pt} is an $(n \times 1)$ vector measuring factor bias in technological change. Finally, α_p is an $(n \times 1)$ vector of each factor's value share of the output price in the base year, and n is the number of factors used in production.

As the price function is homogeneous of degree one, the values in the $(n \times 1)$ vector of value shares of each factor in the output price, v, are simply the partial derivatives of the price function with respect to input prices:

$$v = \frac{\partial ln(P)}{\partial ln(p)} = \alpha_p + A_{pp} ln(p) + a_{pt} t. \qquad (3.2.2)$$

All price series are normalized to be one in the base year (so their log is equal to zero), and technology is normalized to zero in the same year, hence $v = \alpha_p$ in the

[3]Samuelson (1953-1954) is responsible for pointing out duality and Christensen, Jorgenson, and Lau (1973) are the first to apply it to the translog production and price function.

base year.

3.2.2 Restrictions from Producer Theory

To ensure that the estimated price functions represent neoclassical production functions, the following five restrictions on the coefficients must hold. The implementation of these restrictions in the estimation will be explained in section 3.3.

Product exhaustion

Under perfect competition, all value created in production is given as payment to the factors of production. If this is the case, the value shares must sum to one. This implies $\alpha_p' i = 1$ (as they also have to sum to one in the base year, when $v = \alpha_p$), $A_{pp}' i = 0$ (i.e. each column in A_{pp} must sum to zero) and $a_{pt}' i = 0$ (the technological biases must sum to zero).

Symmetry

The matrix of substitution patterns must be symmetric, i.e. $A_{pp} = A_{pp}'$. The elements a_{ij} of the matrix are the share elasticities between i and j. These elasticities are defined as $a_{ij} = \frac{\partial^2 P}{\partial p_i \partial p_j} = \frac{\partial^2 P}{\partial p_j \partial p_i} = a_{ji}$. This restriction therefore requires that the share elasticity between i and j is the same as the share elasticity between j and i.

Homogeneity

Taken together, product exhaustion and symmetry imply homogeneity: As the price function is homogeneous of degree one in input prices, by the Euler Theorem its first partial derivatives - the value shares- must be homogeneous of degree zero in input prices. This implies that $A_{pp} i = 0$, i.e. that each row in A_{pp} must sum to zero.

Nonnegativity

The value shares must always be nonnegative: $v = \alpha_p + A_{pp} ln(p) + a_{pt}t \geq 0$.

Concavity

The price function is concave. This requires that the Hessian matrix H, i.e. the matrix of second partial derivatives of the price function with respect to the factor prices is negative semi-definite ($u'Hu \leq 0$ for any vector u).

3.2.3 Elasticities of Substitution, ICT Effect and Technological Bias

3.2.3.1 Complementarity of Skilled Labor and ICT Capital

The matrix A_{pp} contains the so-called *share elasticities*. They describe how the value share of input p changes when the price of input q changes. A positive matrix element a_{pq} suggests an increase in p's value share, a negative a_{pq} means p's value share decreases with an increase in the price of q. Complementarity or substitutability of factors is commonly determined using the *Allen-Uzawa partial elasticities of substitution* (see, e.g. Griliches (1969), Ruiz-Arranz (2003) also uses these):

$$\sigma_{jk} = \frac{a_{jk} + v_j v_k}{v_j v_k} \qquad j \neq k \tag{3.2.3}$$

and

$$\sigma_{jj} = \frac{a_{jj} + v_j^2 - v_j}{v_j^2} \qquad \forall j. \tag{3.2.4}$$

If σ_{jk} is greater than zero, j and k are substitutes, if it is negative they are complements. The *Allen-Uzawa partial elasticities of substitution* have the double advantage over other elasticities of substitution that they are symmetric (see Blackorby and Russell (1989)) and make determining the existence of ICT capital-skill complementarity easier (see again Griliches (1969)): relative ICT capital-skill complementarity is observed if $\sigma_{si} < \sigma_{ui}$.

3.2.3.2 Technological Bias and ICT Effect

There are two aspects of technology that are of interest in this model. The first one is whether technology is *input saving* or *input using*. This is determined by the vector a_{pt}. As can be seen from $\frac{\partial v}{\partial t} = a_{pt}$, a_{jt} determines how the value share of factor j changes with an increase in the level of technology t. A positive value of a_{jt} leads to an increase in the value share, so technology is *using* input j. A negative value leads to a decreasing value share with an increase in t, hence technology is *saving* input j.

Even though the a_{jt} are referred to as the biases of technological change, just looking at their sign is not enough to determine if there has indeed been skill biased technological change. SBTC requires that $\frac{w_s}{w_u}$ increases as technology increases. In the previous two chapters this is the case when the average growth rate of skilled labor efficiency is greater than the average growth rate of unskilled labor efficiency. In this chapter, stating the same condition is slightly more involved.

The starting point for deriving the relationship is $v_j = \frac{p_j q_j}{Y}$, where q_j is the quantity employed of factor j and Y is nominal output of the industry. Taking the derivative with respect to technology (which is equivalent to taking the derivative with respect to time) and manipulating equations yields:

$$\begin{aligned} g_{p1} - g_{p2} = {} & g_{q1}(B_{11} - B_{21}) + g_{q2}(B_{12} - B_{22}) + g_{q3}(B_{13} - B_{23}) \\ & + g_{q4}(B_{14} - B_{24}) + \frac{1}{v_1}(B_{21} - B_{11})a_{1t} \\ & + \frac{1}{v_2}(B_{22} - B_{12})a_{2t} + \frac{1}{v_3}(B_{23} - B_{13})a_{3t} + \frac{1}{v_4}(B_{24} - B_{14})a_{4t}, \end{aligned} \tag{3.2.5}$$

where g_{pj} is the rate of change of the price of factor j and g_{qj} is the rate of change of the quantity of factor j. B_{jk} is the j,k-th element of the matrix B, defined by $B = (\Lambda A_{pp} - I)^{-1}$, where Λ is a diagonal matrix of the inverse of the value shares. The derivation of 3.2.5 is relegated to the appendix.

The last four elements of 3.2.5 determine the overall effect of technology on the difference in factor prices. Substitute w_s for $p1$ and w_u for $p2$, and these last four terms determine the existence of SBTC: if the sum of these four terms is greater than zero, the industry exhibits SBTC, if the sum is less than zero, it does not.

Equation 3.2.5 is also the basis for determining the overall effect of ICT capital on the skill premium. Replacing $p3$ with the rate of return on ICT capital, r_i, and $q3$ with ICT capital, K_i, the ICT effect is determined by $g_{K_i}(B_{13} - B_{23}) + \frac{1}{v_i}(B_{23} - B_{13})a_{it}$. It is the combination of the effect of ICT capital growth and of the technology bias of ICT capital. If it is larger than zero, the ICT effect has contributed to the rise in the skill premium; if it is negative, it has depressed the skill premium.

3.3 Estimation Procedure

This section again closely follows Jorgenson (1986) and Ruiz-Arranz (2003), as I use the same estimation procedure. I use Three Stage Least Squares estimation on systems of equations, taking into account the coefficient restrictions implied by producer theory. The procedure is described in detail to allow for the easier replication of results, as Ruiz-Arranz (2003) is unpublished.

3.3.1 Equations Estimated and Strategy

Each industry uses four factors in the production of its output: skilled and unskilled labor, ICT capital and non-ICT capital. For each industry, there is the price function and three value share equations: the shares of skilled and unskilled wages and of the return to ICT capital (though it does not matter which share equation is dropped). Including the fourth value share, of the return to non-ICT capital in this case, would lead to overidentification.

I estimate systems of four equations separately for each industry. This is preferable to estimating a large system including all industries, despite the loss of information in the errors, for two reasons: firstly, if the model is misspecified for one industry, the results for all other industries would be biased as well. Estimating a small system of four equations separately for each industry loses some information contained in the variance-covariance matrix of the large system's error, but there is no contagion to other industries if one industry is misspecified. Secondly, the variance-covariance matrix of the large system is near singular and hence not properly invertible.

Of the restrictions imposed by producer theory discussed in section 3.2.2, three can be implemented directly in the estimation as simple coefficient restrictions: product exhaustion, homogeneity, and symmetry.

The system of equations estimated for each industry j then is:

$$
\begin{aligned}
ln(P_j) = {} & \alpha_0 + \alpha_s\, ln(w_{sj}) + \alpha_u\, ln(w_{uj}) + \alpha_i\, ln(r_{ij}) \\
& + (1 - \alpha_s - \alpha_u - \alpha_i)\, ln(r_{nj}) + \alpha_t\, t \\
& + \frac{1}{2} a_{ss}\, (ln(w_{sj}))^2 + \frac{1}{2} a_{uu}\, (ln(w_{uj}))^2 + \frac{1}{2} a_{ii}\, (ln(r_{ij}))^2 \\
& + \frac{1}{2} (a_{ss} + a_{uu} + a_{ii} + 2a_{su} + 2a_{si} + 2a_{ui})\, (ln(r_{sj}))^2 \\
& + a_{su}\, ln(w_{sj})\, ln(w_{uj}) + (-a_{ss} - a_{su} - a_{si})\, ln(w_{sj})\, ln(r_{nj}) \\
& + a_{si}\, ln(w_{sj})\, ln(r_{ij}) + (-a_{su} - a_{uu} - a_{ui})\, ln(w_{uj})\, ln(r_{nj}) \\
& + a_{ui}\, ln(w_{uj})\, ln(r_{ij}) + (-a_{si} - a_{ui} - a_{ii})\, ln(r_{ij})\, ln(r_{nj}) \\
& + a_{st}\, ln(w_{si})\, t + a_{ut}\, ln(w_{uj})\, t + a_{it}\, ln(r_{ij})\, t \\
& + (-a_{st} - a_{ut} - a_{it})\, ln(r_{nj})\, t + a_{tt}\, t^2 + \epsilon_{1j} \\
v_{sj} = {} & \alpha_s + a_{ss}\, ln(w_{sj}) + a_{su}\, ln(w_{uj}) + a_{si}\, ln(r_{ij}) \\
& + (-a_{ss} - a_{su} - a_{si})\, ln(r_{nj}) + a_{st}\, t + \epsilon_{2j} \\
v_{uj} = {} & \alpha_u + a_{su}\, ln(w_{sj}) + a_{uu}\, ln(w_{uj}) + a_{ui}\, ln(r_{ij}) \\
& + (-a_{su} - a_{uu} - a_{ui})\, ln(r_{nj}) + a_{ut}\, t + \epsilon_{3j} \\
v_{ij} = {} & \alpha_i + a_{si}\, ln(w_{s,j}) + a_{ui}\, ln(w_{u,j}) + a_{ii}\, ln(r_{i,j}) \\
& + (-a_{si} - a_{ui} - a_{ii})\, ln(r_{n,j}) + a_{it}\, t + \epsilon_{4,j}
\end{aligned}
\tag{3.3.1}
$$

The output price in each industry is determined by the prices paid to factors, but the reverse is also true: the output price level in each industry influences the prices paid to factors. Hence there is an endogeneity problem, which I solve by instrumenting the factor prices of the industry I am interested in with the factor prices of other industries. As I estimate 15 independent coefficients in the first equation of the system, I need at least 15 instruments for the estimator to be identified. The choice of industries used as instruments is explained in section 3.4.2, where I also discuss the industries I study.

In order to estimate a system of equations with instruments, I use the Three

Stage Least Squares (3SLS) estimation originally developed by Zellner and Theil (1962). The first stage in this procedure is to regress the endogenous explanatory variables on the instruments and calculate the fitted values from this regression for each equation in the system. Next, the dependent variables are regressed on these fitted values. The residuals from this second regression are used to obtain an estimate of the variance-covariance matrix that is needed as a weighting matrix in the final stage. This yields a consistent variance-covariance matrix estimate and consistent and asymptotically efficient coefficient estimates.

The estimator is:

$$\hat{A}_{3SLS} = (Z(\hat{\Sigma}^{-1} \otimes X(X'X)^{-1}X')Z)^{-1}Z(\hat{\Sigma}^{-1} \otimes X(X'X)^{-1}X')y \tag{3.3.2}$$

where Z is the matrix of explanatory variables, X is the matrix of instruments, y is the vector of dependent variables and $\hat{\Sigma}$ is the estimated variance covariance matrix. A typical element $\hat{\sigma}_{jk}$ of the variance-covariance matrix $\hat{\Sigma}$ is determined by:

$$\hat{\sigma}_{jk} = ((y_j - Z_i\hat{\gamma}_{j,2SLS})'(y_k - Z_k\hat{\gamma}_{k,2SLS}))/N \tag{3.3.3}$$

where N is the number of observations, which is equal for all series in my estimation, and $\hat{\gamma}_{2SLS}$ is the estimated coefficient from the regression of the dependent variable on the fitted values obtained in the first step of the estimation procedure.

3.3.2 Imposing Concavity

Concavity of the production function requires that the Hessian H (with $H_{jk} = \frac{\partial P^2}{\partial p_j \partial p_k} \forall j \neq k$ and $H_{jj} = \frac{\partial P^2}{\partial^2 p_j}$) of the price function is negative semi-definite (i.e. that $u'Hu \leq 0$ for all vectors u). This cannot be imposed as a linear restriction in the estimation procedure, but must be tested and if necessary imposed afterwards. This may be done using the Cholesky decomposition due to Lau (1978) and also presented in Jorgenson (1986).

H is not observed directly, however, as I am not estimating the price function directly. Instead, I estimate the log of the price function, which yields a different Hessian $\tilde{H}$ (with $\tilde{H}_{jk} = \frac{\partial(lnP)^2}{\partial lnp_j \partial lnp_k} \forall j \neq k$ and $\tilde{H}_{jj} = \frac{\partial(lnP)^2}{\partial^2 lnp_j}$, where $j, k = s, u, i, n$). The two Hessians are related, however: $\frac{\partial(lnP)^2}{\partial lnp_j \partial lnp_k} = a_{jk} = -v_j v_k + \frac{p_j p_k}{P} \frac{\partial P^2}{\partial p_j \partial p_k}$ and $\frac{\partial(lnP)^2}{\partial^2 lnp_j} = a_{jj} = v_j - v_j^2 + \frac{p_j^2}{P} \frac{\partial P^2}{\partial^2 p_j}$. This yields $\frac{1}{P}\pi H \pi = A_{pp} + vv' - V$, where v is a (4×1) vector of value shares and V a (4×4) diagonal matrix that has the value shares on the diagonal, $\frac{1}{P}$ is a scalar representing the inverse of the output price and π is a (4×4) diagonal matrix of input prices. If H is to be negative semi-definite, $A_{pp} + vv' - V$ must be negative semi-definite, too.

This expression can be decomposed via $A_{pp} + vv' - V = TDT'$, where[4]

$$D = \begin{bmatrix} \delta_1 & 0 & 0 & 0 \\ 0 & \delta_2 & 0 & 0 \\ 0 & 0 & \delta_3 & 0 \\ 0 & 0 & 0 & \delta_4 \end{bmatrix}, T = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \lambda_{21} & 1 & 0 & 0 \\ \lambda_{31} & \lambda_{32} & 1 & 0 \\ \lambda_{41} & \lambda_{42} & \lambda_{43} & 1 \end{bmatrix}.$$

The individual elements of D and T can then be represented as follows:

$$\begin{aligned}
\delta_1 &= a_{ss} + v_s^2 - v_s \\
\lambda_{21} &= (a_{su} + v_s v_u)/\delta_1 \\
\delta_2 &= a_{uu} + v_u^2 - v_u - \delta_1 \lambda_{21}^2 \\
\lambda_{31} &= (a_{si} + v_s v_i)/\delta_1 \\
\lambda_{32} &= (a_{ui} + v_u v_i - \delta_1 \lambda_{21} \lambda_{31})/\delta_2 \\
\delta_3 &= a_{ii} + v_i^2 - v_i - \delta_1 \lambda_{31}^2 - \delta_2 \lambda_{32}^2 \\
\lambda_{41} &= (a_{sn} + v_s v_n)/\delta_1 \\
\lambda_{42} &= (a_{un} + v_u v_n - \delta_1 \lambda_{21} \lambda_{41})/\delta_2 \\
\lambda_{43} &= (a_{sn} + v_i v_n - \delta_1 \lambda_{31} \lambda_{41} - \delta_2 \lambda_{32} \lambda_{42})/\delta_3 \\
\delta_4 &= a_{nn} + v_n^2 - v_4 - \delta_1 \lambda_{41}^2 - \delta_2 \lambda_{42}^2 - \delta_3 \lambda_{43}^2
\end{aligned} \tag{3.3.4}$$

[4]This and the following discussion generalize to n factors, but since I am only interested in $n = 4$, I limit the discussion to this case.

$A_{pp} + vv' - V$ is negative semi-definite if $\delta_j \leq 0 \quad \forall j$. The other constraints must still hold (product exhaustion, symmetry, and homogeneity), which implies the following restrictions:

$$\begin{aligned} 1 + \lambda_{21} + \lambda_{31} + \lambda_{41} &= 0 \\ 1 + \lambda_{32} + \lambda_{42} &= 0 \\ 1 + \lambda_{43} &= 0 \\ \delta_4 &= 0. \end{aligned} \tag{3.3.5}$$

For each industry, concavity is tested by calculating δ_1 through δ_4 for each period. If they are all non-positive, the estimation results fulfill the concavity condition; if at least one of the δ_i is positive in at least one period they do not. In that case, the estimated parameters need to be adjusted accordingly. The restrictions in 3.3.5 serve as a useful additional check on the estimation results.

Using $A_{pp} + vv' - V$ to ensure concavity will only deliver local concavity, as $vv' - V$ is always negative semi-definite and thus "forgives" a matrix A that deviates somewhat from negative semi-definiteness. When concavity is imposed on $A_{pp} + vv' - V$, the Hessian is negative semi-definite for all observed values, and thus the production function is concave for all observed values. It does not mean, however, that the production function is concave at all possible values. To ensure this, concavity would need to be imposed on A.

The nonnegativity constraint is checked by calculating the fitted values of the estimation equations once concavity is ensured. As the α_j are determined by the value share of j in the base year, and the elements of A_{pp} need to fulfill the concavity restriction, nonnegativity needs to be imposed by restricting the values of a_{jt} if necessary. The a_{jt}, j being the factor whose nonnegativity constraint is violated, is raised until the value shares are all positive. Product exhaustion implies that the other a_{kt}, where $k \neq j$, are automatically affected, too, even if their value shares are always positive.

An exception to this procedure is when the only violation of nonnegativity occurs for the value shares of IT capital. As v_i is very close to zero in the data for some industry, it can show up negative in the fitted values without actually being significantly different from zero. If these are the only violations, I leave a_{it} as it is.

3.4 Data

3.4.1 Deriving Variables for Estimation

As in the previous chapters, I use the EUKLEMS (2008) dataset as it provides internally consistent labor and capital data as well as data on value added and prices by industry. The limiting factor in the level of disaggregation I use is the capital data, which is available for most industries at the one or two digit level in the EU KLEMS industry classification.

For each industry, I need a number of variables to estimate the system: output prices, skilled and unskilled wages (w_s and w_u), the returns to ICT and non-ICT capital (r_i and r_n), and the value shares of the factors. For the prices I use the price index for value added for each industry. The index's base year is 1995, which I also choose as base year of the estimation (i.e. 1995 is the year when technology equals zero). Both wage series and both capital returns series are normalized to be one in 1995 as well. Descriptive statistics of these variables across all industries are given in table 3.1.

Skilled and unskilled wages are derived from the shares of labor compensation paid to skilled and unskilled labor, divided by the number of hours worked. As in chapters one and two, to reduce the three skill levels in the dataset to the two skill levels I need, I add one third of the medium skilled hours worked and labor compensation to the high skilled, and the rest to low skilled.

Deriving the returns to ICT and non-ICT capital, I divide capital compensation paid to ICT and non-ICT capital by the units of ICT and non-ICT capital service respectively. The capital services series in turn are the volume indices for ICT and non-ICT capital, with base year 1995, multiplied by the real stock of capital

Table 3.1: Descriptive Statistics of Variables, Across all Industries Studied

	mean	median	std. dev.
v_s	0.2864	0.2920	0.1048
v_u	0.3737	0.4018	0.1486
v_i	0.0210	0.0152	0.0186
v_n	0.3169	0.2482	0.1884
w_s	0.7683	0.7437	0.3890
w_u	0.7993	0.8093	0.3605
r_i	2.0109	1.2556	1.7921
r_n	0.7925	0.7631	0.3816

v_s: value share of skilled labor
v_u: value share of unskilled labor
v_i: value share of ICT capital
v_n: value share of non-ICT capital
w_s: skilled wage
w_u: unskilled wage
r_i: return to ICT capital
r_n: return to non-ICT capital

in 1995.[5]

To find the value shares, I divide total payment to skilled labor (i.e. hourly wage times hours worked, or simply labor compensation paid to skilled labor), unskilled labor, ICT capital, and non-ICT capital by the value added of the industry. The four value shares need to sum to one in each industry and for each period, and, with the exception of five industries, they do in my data. The exceptions are *Metal Products*, *Machinery nec*, *Electrical & Optical Equipment*, *Trade*, and *Other Business Activities*. For these five industries, the labor and capital compensation data in the dataset do not sum to value added in the industry, so their value shares cannot sum to one. As I estimate industries separately, I leave these five industries in the sample, though their results should be treated with caution.

[5]An assumption implicit in the dataset's construction of the capital services series is that services are proportional to the capital stock with the factor of proportionality equal to one (See Timmer, O'Mahony, and van Ark (2007), Jorgenson, Ho, and Stiroh (2003)). Hence, the services series can be multiplied with capital stock series without further adjustment.

3.4.2 Industry Wage and Rate of Return on Capital Differences

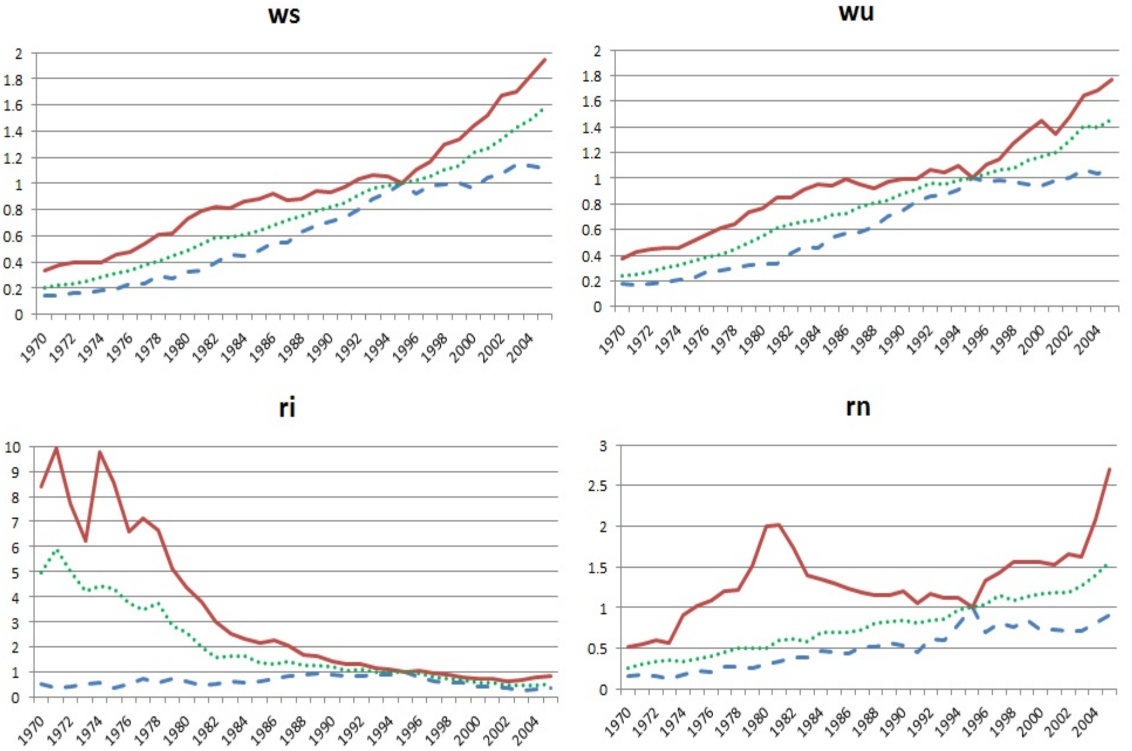
It is not usually discussed in the literature on production function estimation by industry, but where the differences in wages across industries come from and how this affects estimation results are pertinent questions for this analysis, too. As one key assumption of the estimation procedure is that there is perfect competition in both the goods and the factor markets, the effects of a deviation from this assumption on the results merit some thought. The extent of the differences in the data can be seen in figure 3.1, which shows the minimum, median and maximum value of the return of each factor across industries each period.

In chapter two, various reasons for industry wage differentials have been discussed. The most likely reason, at least according to Krueger and Summers (1986), is rent sharing between firms and workers, due to considerations of fairness: a "fair wage" above the marginal product of labor is negotiated between firm and workers, that also redistributes some of the rent accruing to the owners of capital towards labor. The rent of capital is thus shared between labor and the owners of capital. Rent sharing affects both types of labor in one industry in the same direction, which can also be seen from the very similar patterns in the panels on w_s and w_u of figure 3.1.

For the estimation this would mean that the regressors w_s and w_u are larger than they would be if wages were perfectly competitive, at least for the higher wage industries where rent sharing is more likely to have occurred. As all factor prices are normalized to be one in the base year, and their logarithms used, the differences across industries are compressed somewhat. This should help in attenuating any bias in the results that would arise from the "overstated" wage series.

This rent sharing across workers would also directly affect the return to capital, as a larger share of the pie given to labor leaves a smaller share than expected under perfectly competitive factor markets for capital. This in itself, however, does not explain the difference in the rates of return of the two types of capital

Figure 3.1 Maximum (solid red), Median (dotted green) and Minimum (dashed blue) Value of Each Factor in Each Period (normalized to one in 1995).



within one industry. A couple of potential reasons exist: Firstly, it is possible that investment in capital is lower than it would optimally be due to a lack of qualified workers who can use the new capital (along the lines of the model developed in Greenwood and Yorukoglu (1997)). Secondly, there could be some form of irreversibility constraint, like the one used in chapter two, that prevents capital from reallocating and equalizing returns. Independent of the cause of the differences, the same reasoning applies for the effect of these differences as for wages: the normalization of returns and the utilization of their logarithms should help in limiting the biases introduced by the violation of the assumption of perfect competition.

If any of the other reasons discussed in chapter two (e.g. barriers to entry, unobserved skill differences, compensating differentials) are true, their effects would be captured in the constant or the coefficient on technology, t. Neither of these is relevant for my results.

3.4.3 Choice of Industries and Instruments

The first limiting factor in choosing the industries to study is the availability of data on capital. This data is available for 32 industries at the one- and two-digit level. If more disaggregated industry data is available, but very similar among the subgroups, I choose the more aggregated industry. This is the case for *Trade*, which encompasses *Sale, Maintenance and Repair of Motor Vehicles*, *Wholesale and Commission Trade*, and *Retail Trade*.

The components of the category *Community, Social and Personal Services*[6] are excluded altogether, as their primary motive is not (or at least not for a sizable share of them) profit maximization, but the public provision of services. *Coke, Refined Petroleum Products and Nuclear Fuel* is excluded due to its extreme variation in output price, which suggests other factors besides input prices may be important in the determination of this industry's output prices.

As the estimation tries to explain the evolution of an industry's output prices as a function of the industry's input prices, industries in which prices are regulated are excluded as well. The standard model does not apply to them (see Jorgenson (1986)). This involves three industries: *Electricity and Gas*, *Transport and Storage*, and *Post and Telecommunications*. In all three industries, prices were regulated at least in the first part of the sample, and though deregulation started in the 1980s (and even 1970s in case of *Air Transport*, a subcategory of *Transport and Storage*) it was a drawn out process lasting until the mid 1990s (see Winston (1998)). The sample for these industries would therefore be less than ten periods long, too little to estimate 15 parameters.

These industries' input prices are, however, highly correlated with the input prices of all other industries: for normalized skilled wages, the correlation is between 0.91 and 0.99, for normalized unskilled wages between 0.87 and 0.99. The interval of correlations for returns to non-ICT capital is 0.64 to 0.98. For returns to ICT capital, correlations are high and positive for *Electricity* and *Transport and*

[6]These components are *Public Administration and Defense*, *Education*, *Health and Social Work*, and *Other Community, Social, and Personal Services*.

Storage, and negative with large absolute values for *Post and Telecommunications*.[7] Given these strong correlations with other industries' input prices, I use them as instruments to solve the endogeneity problem.[8]

The exclusion restriction requires that instruments do not explain the dependent variable beyond their effect through the independent variables. The wages and rates of return to capital paid in the instrument industry B thus should not directly affect output prices in the industry I estimate, A. The only way industry B's input prices can affect industry A's output price, is if industry B's output is used in the production process of industry A. If this is the case, the factor prices of industry A reflect the output price of industry B, but there should not be a separate effect of industry B's input prices on industry A's output price.

A more indirect effect of industry B's input prices on industry A's output price could work via demand for industry A's output: if, for some reason intrinsic to that industry, wages in industry B increase, this might lead to an increase in demand for industry A's output (as an example: an increase in wages in *Electricity and Gas* could lead to increase in demand for clothing, i.e. the output of *Textiles and Leather*) and thus to a new, higher, equilibrium price for that output. However, there is only a small fraction of workers employed in the instrument industries (on average 13% of hours worked and 14% of labor compensation is due to these industries), and demand for any industry's output comes from individuals working in all industries, so an increase in demand by this fraction should have a marginal effect on equilibrium prices at best.

In principle, the exogeneity of instruments could be tested via the Hausman test, provided there are more instruments than are strictly necessary for identification. The test compares the results of two estimations: one using all instruments

[7]The latter industry has, almost by definition, always been a large user of ICT capital, as this category also includes communication technology. While virtually all other industries have seen their rates of return to ICT capital fall over time, the opposite has happened for telecommunications. One outlier in the strongly negative correlations is with *Real Estate Activities*, where it is -0.14 only.

[8]To have a large enough number of instruments for the price equation, I also use the factor prices for *Health and Social Work* there.

that delivers $\hat{A}$, and the other exluding a subset of instruments yielding $\tilde{A}$. Under the null hypothesis, the estimation results are equal (i.e. $\hat{A} = \tilde{A}$), which is taken to mean that the instruments that have been excluded in the estimation of˜are exogenous. This requires that the instruments that are not excluded are exogenous. The test statistic is a Wald-type statistic with a χ^2-distribution asymptotically:

$$W = (\hat{A} - \tilde{A})'[cov(\hat{A}) - cov(\tilde{A})]^{-1}(\hat{A} - \tilde{A}) \tag{3.4.1}$$

where $cov(\bullet)$ is the variance-covariance matrix of the respective coefficent estimations.

While I have enough instruments to perform the test, the number of observations in my estimation is very small. The Hausman test distribution, and that of Wald-type tests more generally, is known asymptotically only, so the results obtained in very small samples can be poor. This has been shown by e.g. Burnside and Eichenbaum (1994), who generate data from two models, then estimate these models using GMM and perform Wald-type tests on their results. They find that in small samples of 100 observations , the null hypothesis is rejected when the results were, in fact, correct up to 80% of the time.

Dhrymes (1994) reaches a similar conclusion. He generates data from two separate four-equation models and performs 3SLS-estimation, very similar to the estimation problem in this chapter. With the results, he performs Hausman identification tests. At a sample size of 100 observations, the Hausman test accepts the null hypothesis wrongly 54% of the time for one model and 39% of the time for the other model. These percentages drop to 22% and 1.4% respectively when the sample size is increased to 500 observations.

The poor performance of the Wald-type tests discussed in Burnside and Eichenbaum (1994) and of the Hausman test discussed in Dhrymes (1994) suggest that the results I would obtain from my sample would be unreliable, as my sample is less than half as large at 36 observations. There is, however, a good theoretical argument for why the instruments I propose to use are exogenous, and given their high correlation with the regressors, the instruments are strong. Therefore, I use these instruments. Besides, there are no plausible alternatives.

All in all, I am left with 20 industries. These are listed in table 3.2.

3.5 Results

3.5.1 Main Results

The main results are derived from the estimation of systems of four equations, separately for each industry for the period 1970 - 2005. The estimation results of all industries are presented in tables 3.5 to 3.8 in the appendix.

The nonnegativity constraint is not violated for the fitted values of the value shares of skilled and unskilled wages and for non-ICT capital. The fitted value for the ICT capital value share is negative for at least some periods for most industries. This is due to the very low value shares for ICT capital in the data, and there is some correlation between the number of periods for which the estimated value share is negative and the value share in the data is less than 0.01. The number of periods for which the nonnegativity constraint on the ICT capital share is violated is also given in tables 3.5 to 3.8.

Concavity needs to be imposed for all industries except *Wood and Cork*, for which the estimates fulfill local concavity already. For nine industries the adjustments leave the share elasticities within the 95% confidence interval around the point estimates, suggesting that the concavity constraint is not binding for them. For the rest the adjustments need to be larger, the concavity constraint binds. These industries are marked with an asterisk in the results table in the appendix.

3.5.1.1 Elasticities of Substitution Between Two Factors

Table 3.2 shows the unweighted average across time of the elasticities of substitution between factors.

ICT capital-skill complementarity requires that σ_{si}, the *Allen elasticity of substitution* between skilled labor and ICT capital, is smaller than σ_{ui}, the *Allen elasticity of substitution* between unskilled labor and ICT capital. Technically, this condition means that skilled labor is relatively more complementary to ICT capital than unskilled labor, as both elasticities can be positive and thus substitutes.

The Allen elasticity between skilled labor and ICT capital is negative for most industries, indicating that these factors are indeed complements. There are seven exceptions: *Agriculture and Fishing*, *Textiles and Leather*, *Paper and Publishing*, *Rubber and Plastics*, *Non-metallic Minerals*, *Hotels and Restaurants*, and *Real Estate Activities*. These industries, apart from *Textiles and Leather*, are also the industries not exhibiting ICT capital-skill complementarity. For all other industries, $\sigma_{si} < \sigma_{ui}$ holds. Unskilled labor and ICT capital are substitutes for all but three industries: *Agriculture and Fishing*, *Non-metallic Minerals*, and *Hotels and Restaurants*.

The Allen elasticities between skilled and unskilled labor are usually positive, indicating the two types of labor are substitutes. *Non-metallic Minerals*, *Financial Intermediation*, and *Other Business Activities* are the exceptions, skilled and unskilled labor are complements there. Non-ICT capital and skilled labor generally are also substitutes, apart from *Agriculture and Fishing*, *Construction*, and *Hotels and Restaurants*, where they are complements. Non-ICT capital and unskilled labor are substitutes for all industries, without exception. For the elasticities of ICT and non-ICT capital results are mixed. They are complements in seven industries, all of them manufacturing or closely related industries: *Food and Tobacco*, *Textiles and Leather*, *Wood and Cork*, *Rubber and Plastics*, *Metal Products*, *Manufacture nec*, and *Construction*. The two types of capital are substitutes for the thirteen remaining industries.

The own-price elasticities are all negative, both on average and in each period. This provides a quick sanity check for the estimation results. *Agriculture and Fishing* exhibits very large absolute values of the elasticities whenever ICT capital is involved. This is due to the near-zero levels of ICT value shares in the early part of the sample, and very small levels later on. As the Allen elasticities require division by the value shares, their value blows up for very small value shares. This will be a problem for all other results on *Agriculture and Fishing*, so the interpretation of the technology effects later on should be treated with caution for this industry.

Summing up, there seems to be no obvious pattern to the substitutability and complementarity of factors. The Allen elasticities suggest varying degrees of differences across production functions for most industries and thus different usage of the factors of production. The pattern of substitutes and complements of *Agriculture and Fishing* and *Hotels and Restaurants* differ from the pattern of other industries along several dimensions. The other industries are somewhat more similar, with the following observations standing out: ICT and non-ICT capital can be complements in manufacturing industries, but apparently not in the services sector; most of the industries exhibit ICT capital-skill complementarity; in general, capital substitutes for labor.

3.5.1.2 Input Saving and Input Using Technology

The factor biases of technology indicate whether the use of an input factor increases (factor using) or decreases (factor saving) with technological progress. There are fourteen possible combinations of factor biases: 2^4 less the options "all factor using" and "all factor saving", as the four biases must sum to zero. Of the fourteen possible combinations of biases, eight occur among the industries studied. They are presented in table 3.3, along with the industries exhibiting these patterns of bias.

In six industries, technological change is skilled labor using (*Agriculture and Fishing*, *Textiles and Leather*, *Wood and Cork*, *Transport Equipment*, *Hotels and Restaurants*, and *Real Estate Activities*), in five industries it is unskilled labor using (*Mining and Quarrying*, *Food and Tobacco*, *Wood and Cork*, *Real Estate Activities*, and *Other Business Activities*). For capital, sixteen industries show a bias towards using ICT

Table 3.2: Average Elasticities of Substitution (excluding own elasticities)

Industry	σ_{si}	σ_{ui}	σ_{su}	σ_{in}	σ_{sn}	σ_{un}
Agriculture	692.16	−203.31	1.62	91.51	−0.01	0.19
Mining and Quarrying	−23.53	21.92	0.96	5.81	0.56	0.30
Food Products	−6.04	11.22	0.18	−2.67	0.72	0.42
Textiles	0.75	2.61	0.28	−4.67	0.69	0.58
Wood and Cork	−31.47	20.88	4.54	−4.95	0.86	0.10
Paper and Publishing	0.67	0.23	0.42	2.10	0.40	1.43
Chemical Products	−18.20	6.04	0.28	17.99	1.00	0.52
Rubber and Plastics	1.85	1.19	0.06	−1.79	1.15	0.26
Non-Metallic Minerals	2.30	−0.26	−0.16	4.02	1.31	1.94
Metal Products	−4.35	7.69	0.33	−4.77	0.13	0.88
Machinery nec	−0.75	1.12	0.11	2.29	1.01	0.06
Electrical & Optical Eq.	−1.97	3.07	1.11	2.20	1.54	0.73
Transport Equipment	−4.13	3.60	1.09	7.89	0.09	0.52
Manufacturing nec	−5.21	4.60	1.20	−0.22	0.38	0.03
Construction	−75.21	79.53	1.88	−102.35	−1.58	2.16
Trade	−0.10	1.51	1.00	0.53	2.10	2.51
Hotels and Restaurants	0.59	−4.81	0.56	22.72	−0.27	1.21
Financial Intermediation	−1.08	4.35	−0.45	0.76	1.06	2.49
Real Estate Activities	29.08	5.63	0.08	1.66	0.22	0.18
Other Business Activities	−0.46	0.39	−0.36	12.59	0.75	2.79

capital, and fifteen industries towards using non-ICT capital.

Three combinations of biases are observed in one industry each: for *Chemicals* technological progress uses non-ICT capital and saves all other factors; technology in *Other Business Activities* uses unskilled labor and ICT capital and saves skilled labor and non-ICT capital, while technology in *Hotels and Restaurants* has the exactly opposite effect. Seven industries (*Paper and Publishing*, *Rubber and Plastics*, *Metal Products*, *Electrical and Optical Equipment*, *Manufacture nec*, *Trade*, and *Financial Intermediation*) share the same combination of biases - saving both types of labor and using both types of capital.

Of the remaining industries, technology in *Wood and Cork* and *Real Estate Activities* is using both types of labor and saving both types of capital; technology in *Food and Tobacco* and *Mining and Quarrying* is saving skilled labor and using all other factors. In *Agriculture and Fishing*, *Textiles and Leather*, and *Transport Equipment* technology has been unskilled labor saving and using the other three factors. Finally, technology has been using ICT capital and saving all other factors for *Non-metallic Minerals*, *Machinery nec*, and *Construction*.

There are thus substantial differences in how technological progress affects the production process in different industries. Broadly speaking, technology has increased the use of capital and reduced the use of at least one type of labor in most industries.

3.5.1.3 ICT Effect

The ICT effect for each industry is shown in the second column of table 3.4. Note that the order of magnitude of the effects is not comparable to the results in chapters one and two, as the effects here are derived from an estimation of elasticities.

The growth of ICT capital and the technological bias associated with it affect the skill premium negatively in fourteen of the twenty industries studied. Only in six industries, namely *Agriculture and Fishing*, *Wood and Cork*, *Paper and Publishing*, *Chemicals*, *Non-metallic Minerals*, and *Hotels and Restaurants*, is the skill premium

Table 3.3: Effect of Technological Progress on Input Use and Saving across Industries

Effect of technological progress on inputs	Industries exhibiting this pattern
Skilled labor saving Unskilled labor saving ICT capital saving Non-ICT capital using	Chemicals
Skilled labor saving Unskilled labor saving ICT capital using Non-ICT capital saving	Non-metallic Minerals Machinery nec Construction
Skilled labor saving Unskilled labor saving ICT capital using Non-ICT capital using	Metal Products, Manufacture nec Paper and Publishing, Trade Rubber and Plastics, Financial Intermediation Electrical & Optical Equipment
Skilled labor saving Unskilled labor using ICT capital using Non-ICT capital saving	Other Business Activities
Skilled labor saving Unskilled labor using ICT capital using Non-ICT capital using	Food and Tobacco Mining and Quarrying
Skilled labor using Unskilled labor saving ICT capital saving Non-ICT capital using	Hotels and Restaurants
Skilled labor using Unskilled labor using ICT capital saving Non-ICT capital saving	Wood and Cork Real Estate Activities
Skilled labor using Unskilled labor saving ICT capital using Non-ICT capital using	Textiles and Leather Transport Equipment Agriculture and Fishing

pushed up by the ICT effect.

This result is somewhat unexpected. Looking for commonalities among the industries that exhibit the negative ICT effect and differences from those with a positive effect, it turns out that twelve of the fourteen industries with a negative ICT effect[9] (and none of those with a positive ICT effect) are ICT capital using and exhibit ICT capital-skill complementarity, both relative (i.e. $\sigma_{si} < \sigma_{ui}$) and apart from *Textiles and Leather* also absolute (i.e. $\sigma_{si} < 0$).

One possible explanation that then comes to mind is that the increase in ICT capital use as a result of technological progress has led to a decrease in the rate of return to ICT capital (which can be observed in the data). ICT capital-skill complementarity suggests this leads to an increase in the value share of skilled labor. If this increase in the value shares follows from a large increase in the amount of skilled labor used, this would reduce the wage paid to skilled labor. This explanation is supported by the fact that the share of hours worked by skilled labor has increased over time in all industries.

By a similar mechanism it is also possible that the increased use of ICT capital leads to a decrease in the skill premium via an increase in unskilled wages. As ICT capital and unskilled labor are substitutes, the decrease in the rate of return to ICT capital is associated with a decrease in the value share of unskilled labor. If this decrease is due to the fall in unskilled hours worked, it is possible that unskilled wages rise. This mechanism would suggest that in some industries some unskilled labor is replaced with ICT capital, presumably leaving ICT-savvy unskilled labor in place, who could then command a higher wage (consistent with Krueger (1993)'s findings).

3.5.1.4 Evidence on the Skill Bias of Technological Change

Finally, table 3.4 shows the results on the existence of skill bias of technological change (SBTC). SBTC is present when the technology effect is positive for an in-

[9] The exceptions are *Rubber and Plastics* and *Real Estate Activities*.

Table 3.4: ICT Effect and Technology Bias

Industry	ICT effect	Technology effect	Same sign as chapter 2
Agriculture and Fishing	0.6107	6.0678	no
Mining and Quarrying	-0.5994	-3.0517	yes
Food and Tobacco	-0.7943	-2.9852	yes
Textiles and Leather	-0.7052	1.2614	yes
Wood and Cork	0.3653	0.3112	no
Paper and Publishing	0.0355	-1.7554	yes
Chemicals	0.9499	-2.8592	yes
Rubber and Plastics	-0.1783	2.1229	yes
Non-metallic Minerals	0.4207	0.5569	no
Metal Products	-2.3764	-5.4247	yes
Machinery nec	-1.1265	-3.0823	no
Electrical & Optical Eq.	-0.3917	0.6176	yes
Transport Equipment	-0.0223	0.6117	yes
Manufacture nec	-0.8019	-0.5576	no
Construction	-0.5211	-0.6828	no
Trade	-0.0856	0.2794	yes
Hotels and Restaurants	0.0203	2.2838	no
Financial Intermediation	-1.4826	-2.4792	yes
Real Estate Activities	-0.3154	2.7857	NA
Other Business Activities	-0.4182	-8.5615	no

dustry, indicating that an increase in technology pushes up the skill premium.

Ten of the twenty industries studied exhibit SBTC, though the results on *Agriculture and Fishing* should again be treated with caution. The remaining nine are: *Textiles and Leather*, *Wood and Cork*, *Rubber and Plastics*, *Metal Products*, *Electrical and Optical Equipment*, *Transport Equipment*, *Trade*, *Hotels and Restaurants*, and *Real Estate Activities*. For the remaining industries, the effect of technology on the skill premium is negative.

This again confirms that the developments in the economy as a whole are the averaging out of very different effects across industries. The instruments I use in the 3SLS estimation are not suitable for estimating the model for the economy as a whole, as they do not solve the endogeneity problem for that case: input prices from the four sectors used as instruments likely have some impact on the output price of the economy as a whole. But at the same time, the economy wide price level has some bearing on the input prices as well, especially as I only have yearly data and no information on whether the different series were observed at the same time of the year. Therefore, I cannot directly compare results from chapter one and from estimating this model.

It is, however, possible to compare this chapter's results with those from chapter two, with one caveat. In chapter two, skilled and unskilled capital are derived from the simulation and the level of technology embodied in both types is constant over time. In this chapter, I use data for ICT and non-ICT capital, which is imperfectly adjusted (if at all) for embodied technological change. It is therefore possible that some effects of technology in chapter two are attributed to either type of capital here.

The last column in table 3.4 indicates whether the technology effect in this chapter and the difference in the skilled and unskilled labor efficiency growth rate of chapter two go in the same direction. A comparison is possible for nineteen of the twenty industries, as there is no result for *Real Estate Activities* in chapter two. Overall, the effect of technology on the skill premium goes in the same direction in the results from the two chapters in eleven industries. For eight industries, the results are opposite, one of them being *Agriculture and Fishing*. Of the other results that differ, *Wood and Cork*, *Metal Products*, and *Hotels and Restaurants* show SBTC in this chapter, but not in chapter two, while the reverse is true for *Machinery nec*, *Manufacture nec*, *Construction*, and *Other Business Activities*.

For four of these industries, the difference in skilled and unskilled labor efficiency growth rates in chapter two is very small, and the technology bias in this chapter is also relatively small for *Wood and Cork*, *Metal Products* and *Manufacture nec*. This suggests that technology in these industries is largely neutral and depending on the methodology used shows up as a small positive or a small negative bias. For *Construction* the bias in this chapter is also quite small. The results on *Machinery nec* and *Other Business Activities* are a bit puzzling: in chapter two, these two industries have some of the largest positive growth rate differentials; in chapter three they have the largest negative technology effect. However, these two are among the five industries mentioned above where the value shares of the input factors do not sum to one, so their results must be treated with some caution.

3.5.2 Accounting for Possible Measurement Error for ICT Capital

Capital is difficult to measure correctly, especially if it is new and subject to rapid changes in quality, as is the case with ICT capital. I therefore also consider dropping the returns to ICT capital from the list of instruments and replacing them with different ones to check whether measurement error of ICT capital is a problem for my results.

As instruments I use the previous year's year-on-year returns to the stocks of General Electric, Hewlett Packard and IBM. The data are taken from *Yahoo! Finance* and are adjusted for stock splits and dividend payments[10]. The choice of

[10]The series can be found via `http://finance.yahoo.com/q/hp?s=GE` for General Elec-

companies is driven by two criteria: they need to be involved in the production of ICT capital goods and they need to have been listed on the stock exchange since at least 1969. This leaves only a very limited number of stocks.

The exclusion restriction is the following: as there is perfect competition in all industries, output prices are fully determined by prices of inputs in production. As the shares are not used in production, they should not affect output prices directly. At the same time, the previous period's return to stocks depends on the companies' earnings, which in turn depends on how many ICT capital goods they sell. The amount of ICT capital goods bought in turn affects the return to ICT capital.

The correlation between these instruments and the return to ICT capital is low, indicating that the instruments' relevance is limited. Nonetheless, as there is some correlation and exogeneity is plausible, results should be affected if these instruments are used and measurement error of ICT capital is indeed a problem. As the estimation results do not change when using these instruments instead of the returns to ICT capital, I conclude that errors in measuring the return to ICT capital are not a concern for the results.

3.6 Conclusion

The intention of this paper is to investigate the role of ICT in the production technologies of different industries, as well as to estimate the effect of ICT capital on the skill premium. The elasticities of substitution suggest broadly similar production functions for most industries, with few differences between manufacturing and services industries. The conclusion on ICT capital-skill complementarity is mixed, with fourteen out of twenty industries showing signs of it. This suggests that ICT capital is not used uniformly across all industries.

The ICT effect on the skill premium is negative for fourteen of twenty indus-

tric, `http://finance.yahoo.com/q/hp?s=HPQ+Historical+Prices` for Hewlett Packard, and `http://finance.yahoo.com/q/hp?s=IBM` for IBM.

tries. This might be a consequence of complementarity between skilled labor and ICT capital and substitutability between unskilled labor and ICT capital. More work is needed to establish whether this is indeed the channel through which the ICT effect works.

The negative ICT effect is likely linked to the technology bias associated with ICT capital: technological progress turns out to increase the use of both types of capital for most industries. In contrast, it is mostly labor saving, though the differences in the patterns of bias across industries are substantial.

For half the industries studied, the results indicate the presence of SBTC, which further supports the conclusion from chapter two that the evolution of the whole economy is the average of very varied developments across industries. Comparing the results by industry with those of chapter two, the indication on the presence of SBTC coincides more often than not, and in the industries for which it is different, the results are close to zero in both chapters.

Two main avenues for further work come to mind. The first is to find different, and more precise, ways of specifying technological progress instead of using a linear time trend. A possible alternative is the Kalman filter procedure developed in Jin and Jorgenson (2010).

The second is to think about the wider implications of these results: Deriving the aggregate production function for the whole economy from the various industry production functions requires that the production functions are identical across industries. If they are not identical, there is no aggregate production function, which these results seem to suggest. Exploring this implication in more depth seems worthwhile, but would go too far in this chapter.

3.7 Appendix

3.7.1 Deriving the Relationship Between the Skill Premium and the Technology Biases

As explained in section 3.2, the starting point for the derivation, which is similar to that of equation (15) in Ruiz-Arranz (2003), is the definition of the value share that is used in its derivation from the data: $v_j = \frac{p_j q_j}{Y}$. Solving out for the price of factor j yields $p_j = \frac{v_j Y}{q_j}$. Taking logs and differentiating with respect to time leads to $g_{pj} = g_Y + g_{vj} - g_{qj}$. The growth rate of the value share is determined by

$$g_{vj} = \frac{\dot{v}_j}{v_j} = \frac{1}{v_j}(a_{1j}g_{p1} + a_{2j}g_{p2} + a_{3j}g_{p3} + a_{4j}g_{p4} + a_{jt}). \tag{3.7.1}$$

Taking all four sectors together, the growth rate of inputs can be rewritten in matrix form:

$$\begin{bmatrix} g_{p1} \\ g_{p2} \\ g_{p3} \\ g_{p4} \end{bmatrix} = \begin{bmatrix} \frac{1}{v_1} & 0 & 0 & 0 \\ 0 & \frac{1}{v_2} & 0 & 0 \\ 0 & 0 & \frac{1}{v_3} & 0 \\ 0 & 0 & 0 & \frac{1}{v_4} \end{bmatrix} (A_{pp} \begin{bmatrix} g_{p1} \\ g_{p2} \\ g_{p3} \\ g_{p4} \end{bmatrix} + \begin{bmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{bmatrix}) + \begin{bmatrix} g_Y \\ g_Y \\ g_Y \\ g_Y \end{bmatrix} - \begin{bmatrix} g_{q1} \\ g_{q2} \\ g_{q3} \\ g_{q4} \end{bmatrix}$$

or in more compact form,

$$g_p = V * (A_{pp}g_p + A_t) + g_Y - g_q. \tag{3.7.2}$$

Solving out for the g_p yields

$$(V * A_{pp} - I)g_p = g_q - V * A_t - g_Y \tag{3.7.3}$$

and then

$$g_p = (V * A_{pp} - I)^{-1}(g_q - V * A_t - g_Y). \tag{3.7.4}$$

Defining $B = (V * A_{pp} - I)^{-1}$ and subtracting the second row of g_p from the first row leads to

$$\begin{aligned} g_{p1} - g_{p2} = {} & g_{q1}(B_{11} - B_{21}) + g_{q2}(B_{12} - B_{22}) + g_{q3}(B_{13} - B_{23}) + g_{q4}(B_{14} - B_{24}) \\ & + \frac{1}{v_1}(B_{21} - B_{11})a_{1t} + \frac{1}{v_2}(B_{22} - B_{12})a_{2t} \\ & + \frac{1}{v_3}(B_{23} - B_{13})a_{3t} + \frac{1}{v_4}(B_{24} - B_{14})a_{4t}, \end{aligned} \tag{3.7.5}$$

3.7.2 Estimation Results After Imposing Concavity

Table 3.5: Estimation Results by Industry After Imposing Concavity Constraint, Standard Errors in Parentheses

	Agriculture and Fishing*	Mining and Quarrying	Food and Tobacco	Textiles and Leather*	Wood and Cork
a_0	0.0104	0.1725	0.0307	-0.0692	-0.1030
	(0.0260)	(0.0368)	(0.0113)	(0.0144)	(0.0287)
α_s	0.2242	0.1590	0.2318	0.3004	0.2336
	(0.0052)	(0.0070)	(0.0037)	(0.0031)	(0.0075)
α_u	0.2841	0.1789	0.2735	0.4516	0.4161
	(0.0055)	(0.0085)	(0.0041)	(0.0028)	(0.0088)
α_i	0.0079	0.0211	0.0108	0.0176	0.0041
	(0.0028)	(0.0082)	(0.0018)	(0.0014)	(0.0050)
α_n	0.4839	0.6410	0.4839	0.2304	0.3461
	(0.0101)	(0.0191)	(0.0041)	(0.0036)	(0.0125)
α_t	-1.4473	-0.8503	-0.5442	-1.1859	0.0696
	(0.1435)	(0.2060)	(0.0622)	(0.0795)	(0.1588)
a_{ss}	0.0271	0.0653	0.1093	0.1060	-0.2945
	(0.0341)	(0.0291)	(0.0635)	(0.0531)	(0.1165)
a_{uu}	0.1200	0.0507	0.1021	0.1279	-0.2772
	(0.0400)	(0.0342)	(0.0535)	(0.0523)	(0.1140)
a_{ii}	-0.0230	-0.0310	-0.0140	0.0029	-0.0150
	(0.0079)	(0.0184)	(0.0043)	(0.0050)	(0.0137)
a_{nn}	0.1885	0.0990	0.1131	0.0709	0.1475
	(0.0352)	(0.0582)	(0.0180)	(0.0240)	(0.0476)
a_{su}	0.0274	-0.0010	-0.0690	-0.0906	0.3409
	(0.0349)	(0.0305)	(0.0574)	(0.0516)	(0.1138)
a_{si}	0.0288	-0.0238	-0.0170	-0.0005	-0.0379
	(0.0096)	(0.0114)	(0.0079)	(0.0097)	(0.0158)
a_{sn}	-0.0833	-0.0405	-0.0233	-0.0148	-0.0085
	(0.0168)	(0.0213)	(0.0115)	(0.0169)	(0.0259)
a_{ui}	-0.0240	0.0318	0.0439	0.0082	0.0641
	(0.0112)	(0.0125)	(0.0076)	(0.0089)	(0.0169)
a_{un}	-0.1234	-0.0815	-0.0770	-0.0455	-0.1278
	(0.0176)	(0.0258)	(0.0124)	(0.0135)	(0.0296)
a_{in}	0.0182	0.0230	-0.0129	-0.0106	-0.0112
	(0.0087)	(0.0242)	(0.0077)	(0.0079)	(0.0196)
a_{st}	0.2438	-0.1098	-0.0731	0.0826	0.0682
	(0.0328)	(0.0544)	(0.0506)	(0.0622)	(0.0845)
a_{ut}	-0.3967	0.0224	0.0316	-0.2281	0.0289
	(0.0379)	(0.0587)	(0.0478)	(0.0578)	(0.0888)
a_{it}	0.0342	0.0342	0.0215	0.1156	-0.0471
	(0.0244)	(0.0836)	(0.0224)	(0.0251)	(0.0646)
a_{nt}	0.1187	0.0531	0.0200	0.0300	-0.0500
	(0.0388)	(0.1036)	(0.0415)	(0.0344)	(0.0933)
a_{tt}	0.9536	-2.8969	0.0992	0.1185	1.0586
	(0.3306)	(0.5196)	(0.1627)	(0.1977)	(0.4068)
$v_i < 0$	22	17	11	19	3

Table 3.6: Estimation Results (cont'd)

	Paper and Publishing*	Chemicals	Rubber and Plastics*	Non-Metallic Minerals*	Metal Products*
a_0	-0.1176	-0.0277	-0.0086	0.0139	-0.0079
	(0.0104)	(0.0154)	(0.0095)	(0.0110)	(0.0129)
α_s	0.4000	0.2945	0.3437	0.2836	0.2744
	(0.0052)	(0.0031)	(0.0033)	(0.0031)	(0.0024)
α_u	0.3015	0.1537	0.4157	0.4110	0.4039
	(0.0051)	(0.0028)	(0.0028)	(0.0028)	(0.0024)
α_i	0.0394	0.0308	0.0168	0.0203	0.0203
	(0.0013)	(0.0019)	(0.0008)	(0.0015)	(0.0011)
α_n	0.2591	0.5210	0.2239	0.2851	0.3014
	(0.0023)	(0.0037)	(0.0038)	(0.0032)	(0.0030)
α_t	-0.1501	-0.4002	-1.3909	-1.0024	-1.2382
	(0.0557)	(0.0857)	(0.0521)	(0.0585)	(0.0681)
a_{ss}	0.1231	0.1003	0.1162	0.1183	0.1501
	(0.0708)	(0.0418)	(0.0459)	(0.1294)	(0.0872)
a_{uu}	0.0357	0.0730	0.2011	0.0421	0.0629
	(0.0705)	(0.0357)	(0.0545)	(0.1365)	(0.0781)
a_{ii}	0.0021	-0.0343	0.0027	-0.0035	-0.0045
	(0.0052)	(0.0147)	(0.0028)	(0.0060)	(0.0048)
a_{nn}	0.0069	-0.0349	0.0703	-0.1298	0.0872
	(0.0177)	(0.0426)	(0.0210)	(0.0092)	(0.0210)
a_{su}	-0.0699	-0.0418	-0.1285	-0.1397	-0.0781
	(0.0676)	(0.0364)	(0.0493)	(0.1326)	(0.0819)
a_{si}	-0.0017	-0.0591	0.0027	0.0028	-0.0120
	(0.0110)	(0.0194)	(0.0055)	(0.0127)	(0.0091)
a_{sn}	-0.0516	0.0007	0.0096	0.0186	-0.0600
	(0.0228)	(0.0330)	(0.0154)	(0.0122)	(0.0179)
a_{ui}	-0.0055	0.0140	0.0010	-0.0065	0.0294
	(0.0095)	(0.0149)	(0.0057)	(0.0134)	(0.0089)
a_{un}	0.0396	-0.0452	-0.0736	0.1040	-0.0142
	(0.0214)	(0.0234)	(0.0119)	(0.0120)	(0.0178)
a_{in}	0.0051	0.0794	-0.0064	0.0073	-0.0130
	(0.0070)	(0.0239)	(0.0043)	(0.0057)	(0.0085)
a_{st}	-0.2788	-0.2689	-0.0633	-0.0344	-0.1563
	(0.0629)	(0.0938)	(0.0294)	(0.0563)	(0.0482)
a_{ut}	-0.0118	-0.1033	-0.1707	-0.0813	-0.0293
	(0.0530)	(0.0752)	(0.0289)	(0.0588)	(0.0471)
a_{it}	0.2817	-0.0378	0.0975	0.1223	0.1075
	(0.0263)	(0.0702)	(0.0149)	(0.0290)	(0.0243)
a_{nt}	0.0089	0.4100	0.1365	-0.0066	0.0781
	(0.0354)	(0.1141)	(0.0250)	(0.0285)	(0.0432)
a_{tt}	0.2552	-1.0744	-0.0772	-0.9213	-1.6757
	(0.1383)	(0.2742)	(0.1337)	(0.1499)	(0.1637)
$v_i < 0$	19	17	18	20	18

Table 3.7: Estimation Results (cont'd)

	Machinery nec*	Electrical & Optical Eq.	Transport Equipment	Manufacture nec*	Construction*
a_0	0.0617	-0.1070	-0.0697	-0.0301	-0.0171
	(0.0171)	(0.0182)	(0.0176)	(0.0116)	(0.0135)
α_s	0.3621	0.4100	0.4147	0.3238	0.3359
	(0.0039)	(0.0075)	(0.0032)	(0.0032)	(0.0041)
α_u	0.3945	0.2578	0.3625	0.4193	0.5338
	(0.0051)	(0.0068)	(0.0035)	(0.0029)	(0.0044)
α_i	0.0489	0.0594	0.0164	0.0175	0.0070
	(0.0020)	(0.0023)	(0.0017)	(0.0008)	(0.0021)
α_n	0.1945	0.2729	0.2064	0.2394	0.1233
	(0.0052)	(0.0069)	(0.0047)	(0.0025)	(0.0051)
α_t	-0.6439	-4.3966	-0.9696	-0.8906	0.7801
	(0.0932)	(0.1002)	(0.0962)	(0.0623)	(0.0748)
a_{ss}	0.1439	-0.0282	0.0683	0.0298	-0.0235
	(0.0580)	(0.0946)	(0.0467)	(0.0683)	(0.1592)
a_{uu}	0.1968	-0.0161	0.0139	0.0611	-0.2884
	(0.0598)	(0.0758)	(0.0372)	(0.0576)	(0.1536)
a_{ii}	0.0092	0.0026	-0.0085	0.0005	-0.0163
	(0.0048)	(0.0109)	(0.0062)	(0.0031)	(0.0075)
a_{nn}	0.0656	-0.0314	0.0888	0.1467	0.0270
	(0.0202)	(0.0259)	(0.0153)	(0.0172)	(0.0241)
a_{su}	-0.1224	0.0139	0.0130	0.0252	0.1445
	(0.0579)	(0.0836)	(0.0403)	(0.0617)	(0.1558)
a_{si}	-0.0220	-0.0294	-0.0163	-0.0158	-0.0279
	(0.0089)	(0.0230)	(0.0127)	(0.0092)	(0.0171)
a_{sn}	0.0004	0.0438	-0.0649	-0.0392	-0.0931
	(0.0149)	(0.0324)	(0.0103)	(0.0186)	(0.0214)
a_{ui}	0.0022	0.0207	0.0109	0.0182	0.0610
	(0.0098)	(0.0206)	(0.0115)	(0.0085)	(0.0170)
a_{un}	-0.0766	-0.0184	-0.0378	-0.1046	0.0829
	(0.0181)	(0.0272)	(0.0106)	(0.0164)	(0.0226)
a_{in}	0.0105	0.0061	0.0139	-0.0029	-0.0169
	(0.0074)	(0.0132)	(0.0058)	(0.0047)	(0.0103)
a_{st}	-0.1073	-0.0488	0.0957	-0.0372	-0.0511
	(0.0491)	(0.0933)	(0.0701)	(0.0469)	(0.1106)
a_{ut}	-0.0055	-0.3381	-0.1856	-0.0901	-0.0304
	(0.0556)	(0.0839)	(0.0613)	(0.0433)	(0.1100)
a_{it}	0.1232	0.1159	0.0069	0.0815	0.0873
	(0.0251)	(0.0417)	(0.0324)	(0.0145)	(0.0391)
a_{nt}	-0.0104	0.2710	0.0830	0.0458	-0.0057
	(0.0445)	(0.0516)	(0.0289)	(0.0227)	(0.0592)
a_t	-1.4644	-1.8580	-1.4134	-0.9609	0.2774
	(0.2345)	(0.2434)	(0.2383)	(0.1517)	(0.2143)
$v_i < 0$	0	1	8	16	22

Table 3.8: Estimation Results (cont'd)

	Trade	Hotels and Restaurants*	Financial Intermediation	Real Estate Activities	Other Business Activities*
a_0	-0.0300	0.0388	-0.0522	0.0006	0.0253
	(0.0075)	(0.0108)	(0.0071)	(0.0058)	(0.0068)
α_s	0.4056	0.2990	0.3657	0.0728	0.5405
	(0.0037)	(0.0025)	(0.0028)	(0.0015)	(0.0034)
α_u	0.3978	0.4688	0.1708	0.0381	0.1948
	(0.0037)	(0.0024)	(0.0033)	(0.0009)	(0.0035)
α_i	0.0610	0.0190	0.0537	0.0198	0.0599
	(0.0019)	(0.0011)	(0.0014)	(0.0016)	(0.0030)
α_n	0.1357	0.2133	0.4098	0.8692	0.2048
	(0.0036)	(0.0032)	(0.0021)	(0.0020)	(0.0049)
α_t	-0.6504	0.1547	-0.5855	-0.0900	0.1628
	(0.0420)	(0.0582)	(0.0391)	(0.0325)	(0.0358)
a_{ss}	-0.0823	0.1280	0.1179	0.0205	0.1775
	(0.1189)	(0.0682)	(0.0652)	(0.0115)	(0.0428)
a_{uu}	-0.1504	0.0596	-0.0317	0.0285	0.0993
	(0.0883)	(0.0575)	(0.0684)	(0.0101)	(0.0498)
a_{ii}	-0.0027	-0.0061	0.0019	-0.0312	-0.0292
	(0.0067)	(0.0066)	(0.0052)	(0.0078)	(0.0151)
a_{nn}	-0.2402	0.0196	-0.1165	0.0597	-0.0856
	(0.0230)	(0.0189)	(0.0229)	(0.0156)	(0.0351)
a_{su}	-0.0006	-0.0605	-0.1029	-0.0021	-0.1409
	(0.1015)	(0.0619)	(0.0649)	(0.0098)	(0.0428)
a_{si}	-0.0072	-0.0006	-0.0226	0.0204	-0.0210
	(0.0133)	(0.0134)	(0.0076)	(0.0058)	(0.0158)
a_{sn}	0.0901	-0.0669	0.0075	-0.0389	-0.0156
	(0.0251)	(0.0208)	(0.0203)	(0.0090)	(0.0214)
a_{ui}	0.0053	-0.0198	0.0232	0.0026	-0.0047
	(0.0123)	(0.0126)	(0.0091)	(0.0041)	(0.0168)
a_{un}	0.1456	0.0207	0.1114	-0.0290	0.0463
	(0.0225)	(0.0192)	(0.0223)	(0.0061)	(0.0195)
a_{in}	0.0045	0.0266	-0.0024	0.0082	0.0549
	(0.0108)	(0.0101)	(0.0074)	(0.0092)	(0.0165)
a_{st}	-0.0330	0.1687	-0.1767	0.1208	-0.0520
	(0.0898)	(0.0760)	(0.0558)	(0.0178)	(0.0807)
a_{ut}	-0.2658	-0.2407	-0.0989	0.0076	0.2383
	(0.0811)	(0.0724)	(0.0631)	(0.0116)	(0.0832)
a_{it}	0.1562	-0.0039	0.1414	-0.0328	0.0411
	(0.0310)	(0.0349)	(0.0265)	(0.0227)	(0.0714)
a_{nt}	0.1426	0.0759	0.1342	-0.0956	-0.2274
	(0.0464)	(0.0528)	(0.0435)	(0.0253)	(0.0715)
a_{tt}	0.5822	-1.3135	0.2289	0.1684	-0.5396
	(0.1242)	(0.1614)	(0.1165)	(0.0818)	(0.1792)
$v_i < 0$	7	0	8	11	8

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