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“The sector bias of skill-biased technical change in recent decades”

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Oliver Reiter, Bakk.rer.soc.oec., Bakk.rer.soc.oec.

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Contents

1 Introduction

Atkinson (1975) notes that there are two question about inequality at the heart of the economic science: 1) Why are some countries wealthier than others and 2) why are some individuals richer more than others? This work researches an aspect of the answer to the second question.

In recent decades, the study of the reasons of inequality between individuals gained widespread attention as incomes begin to diverge steadily but without an apparent explanation at hand. Soon the fact that the rise in income inequality is especially pronounced between skill groups was established. The skill premium, the wage of skilled workers relative to the wage of low skilled workers, is used as an indicator of this disparity.

Economists found that demand for skilled workers soared even though the number of well educated labour market entrants increased throughout the second half of the 20$^{\text{th}}$ century. The reasons for this development are multifold. Some economists regard institutional changes and increasing international trade as the main reasons. However, the explanation favoured by the majority of economists (or, the explanation that explains the largest part of the rise in income inequality) is technological progress.

The term "skill-biased technical change" was introduced to describe the kind of technological innovation that "favours skilled over unskilled labour by increasing its relative productivity and, therefore, its relative demand"[1].

This thesis tries to shed some light on the nature of SBTC. More specifically, its behaviour in the industrial sectors of an economy. Haskel and Slaughter (2002) advance the idea that technological change is not only skill-biased, but also *sector-biased*: Sectors that use a relatively high amount of skilled workers also experience higher rates of SBTC. Thus, the sector bias might strengthen the impact of SBTC on the economy-wide skill premium.

So, the questions are: Is there evidence of sector bias and did it amplify the growing income inequality?

[1]See Violante (2008).

2 Literature Review

In the upcoming section will give an overview over the research that has been undertaken in the field of income inequality and skill biased technical change[1]. Furthermore, these papers form a basis on which my own research question is built on.

It is a well established fact, not only among economists, that income inequality had been rising in the preceding decades.[2][3] Unclear, however, were the reasons for this development.

I separate the literature that seeks to explain the reasons for the widening of the wage distribution into three sections: First, a review of theories that favour institutional changes as the main driving force behind the increase in inequality. Then, theories about globalization and international trade and finally a section about theories in which innovation and technological progress play a crucial role.

2.1 Institutional changes

2.1.1 Minimum wage

In the US, the nominal value of the minimum wage was not adjusted between 1979 until 1988. Thus, its real value eroded. Since the minimum wage acts as a lower bound of the earnings distribution, and it decreases the wage dispersion. In fact, the minimum wage was the *mode* of the female wage distribution in 1979! Therefore, it is plausible that the constant nominal minimum wage had an inequality-increasing effect.

[1] In the following chapters I will abbreviate "skill biased technical change" with "SBTC", "technical change" with "TC" and "information and communication technology" with "ICT".

[2] See Atkinson (2003) and Acemoglu (2002) for an evaluation of the development of inequality. For a newer report see OECD (2012).

[3] Most of the research in this chapter is focused on the USA. Where possible, I point to differences of the European experience.

To get an idea about the magnitude of its influence, Fortin and Lemieux replace the lower part of the wage distribution (that below the minimum wage) of the year 1989 with that of 1979. According to them, this simple method yields comparable results as more complex alternatives. Now, a comparison of the log variances of the two distributions produces a difference of 24% for men, 32% for women and 39% for the whole economy.

Acemoglu (2002, p. 49), among others[4], contradicts this view. According to him, the minimum wage fails at two points: *a*) While the minimum wage can have an inequality reducing effect on the lower tail of the wage distribution, it will hardly influence earnings above the median. But the inequality did not only increase below the median, also the ratio of 90^{th} to 50^{th} percentile did grow substantially and its behaviour over time resembles that of the difference of 50^{th} to the 10^{th} percentile. Thus, the factors increasing inequality are working above and below the median, something the minimum wage cannot explain. Furthermore, *b*) the timing of both event does not fit good enough. The widening of the wage distribution started already in the 1970s, while the erosion of the minimum wage did not begin until the 1980s.

2.1.2 Deunionization

That unions "compress" wages is a well known fact. But they also have a counteracting effect: Unions increase the inequality between members and non-members. Fortin and Lemieux argue that the former effect outweighs the latter. Then, dwindling membership numbers, i.e. weaker unions, are likely to increase wage inequality.

They use the same method as above to estimate the effect of deunionization on the wage distribution and come to the result that the log variance had been 21% less, if the unionization rate would have remained at its 1979 level. Interestingly, they found no effect of unions on the female wage distribution.

Bound and Johnson (1992) reject the conclusion that falling union membership had a large influence on income inequality. In their analysis (They regress the competitive wage on several covariates, including age, education, experience, race and so on, and see if the wages of union members include a premium.) they do not find much evidence of a "union premium" and conclude, therefore, that deunionization could have had only a small effect. Acemoglu (2002) points out that also occupations, in which there were no

[4] See e.g. Bound and Johnson (1992).

unions (such as lawyers and doctors), saw a rise in inequality. Additionally, inequality started to rise a decade before union membership began to fall[5].

Still, differing wage setting procedures (such as collective bargaining through unions in Europe as opposed to decentralized contracting in the US) may explain different *levels* of wage inequality.[6]

2.2 International Trade

Growing international trade is an often cited reason for the rising income inequality. The increasing integration of a country in the global market affects the domestic industry as the production of certain goods becomes too expensive. The typical scenario one thinks of is that of an developed country which engages in trade with a less developed or a developing country. Industries which have to compete with the imports from abroad are typically industries employing a large fraction of low skilled workers. Firms then tend to react by laying off and/or outsourcing parts of their production. Thus, growing trade integration can lead to a widening wage distribution by lowering the demand and the wages of low skilled workers. Feenstra and Hanson (1999) estimate the contribution of outsourcing on the change of the wage gap between production and nonproduction workers.

To do this, they use a modified version of a "price regression". A price regression has usually the form (in first differences) $\Delta \log p_{it}^{VA} = -TFP_{it} + (s_{t-1} + s_t)/2 \times \Delta \log \omega_{it}$. However, since a price regression is, when fully identified, an *identity*, it cannot be used to predict changes[7]. To circumvent this problem, Feenstra and Hanson propose a two-stage estimation to determine of the effect of some structural variables (computer capital and outsourcing) on the wage of nonproduction workers: First, a regression of the change of value-added prices plus effective total factor productivity on the structural variables (computer capital and outsourcing) decomposes the dependent variable into components attributable to each structural variable:

[5] See Acemoglu (2002, p. 50).

[6] See e.g. Acemoglu (2003) and Kahn (2000) for an evaluation of explanations for cross-country differences in wage inequality.

[7] A price regression of $\Delta \log(p) = -TFP + (s_{t-1} + s_t)/2 \times \Delta \log(\omega) + \epsilon$ becomes fully identified, because total factor productivity is sometimes measured as the difference of log prices (p_t) and cost-share (ω_t) weighted factor prices (s_t), i.e., as $\Delta \log(p_t) - \log(\omega_t)s_t$.

$$\Delta \log p_{it}^{VA} + EFTP_{it} = \gamma \Delta z_{it} + \epsilon_{it} \tag{2.1}$$

These components $\gamma \Delta z_{it}$ are then used (separately) as dependent variables in the second-stage regression. The factor shares production and nonproduction wage and capital are the independent variables.

$$\widehat{\gamma \Delta z_{itk}} = \delta(s_{it-1} + s_{it})/2 + \eta_{itk} \tag{2.2}$$

The coefficients in equation (2.2) can be seen as the changes in primary factor prices that would have happened if the structural variable was the sole influence on prices and productivity.

Structural variables are outsourcing and computer capital, each measured in two different ways: Outsourcing is measured as a *narrow* and as a *broad* variant. The latter comprises the sum of all imported intermediate inputs in each industry, whereas the narrow alternative only counts the value of imported intermediate inputs that are produced in the same industry group. Computer capital is once measured as the share of office, computing and accounting machinery in total capital and once as the share of high-technology capital (which includes besides computer capital also communication, photocopy and engineering equipment).

The result of the first-stage regression finds a positive and significant influence of narrow outsourcing and computer capital. Broad outsourcing and high-tech capital seem to have no impact on industry prices and productivity. In the second-stage regression, where these four components (two for each structural variable) are then regressed on the shares of the production factors, narrow outsourcing and computer capital yield again the better results. Since these coefficients measure the increase of the nonproduction wage that is attributable to outsourcing and, respectively, computers, they can readily be compared to the annual percentage increase: A coefficient of 0.10 for outsourcing means that it accounts for 15% of the 0.72% annual increase in nonproduction wages. Computers, on the other hand, explain about 35% of the increase. The results for broad outsourcing and high-tech capital small and not significant. That means, although the effect of outsourcing is not the major force behind the rising wage inequality, it is still a big contributor and should not be ignored.

In his 2008 paper, Krugman admits that estimates in 1990s find little effect of trade on wages movements[8]. However, he argues that there is a substantial impact of trade which is hidden in the data. "Vertical specialization" means that imports from low skilled abundant countries are not competing with whole industry sectors in the US, but taking over low skill-intensive production steps *within* a sector.

Krugman (2008) mentions the case of computers and semiconductors, where the US (and Japan) fabricate the (rather sophisticated) parts and Chinese plants assemble the final product. But because this specialization happens within a sector, this development is not clearly traceable and estimates of the effect of trade and outsourcing are (especially when measured on industry sector level) might underestimate the effect of trade on the wages of low skilled worker within the developed country.

A piece of counter evidence comes from Autor et al. (1998): In a cross-sectional regression on industry level, they find little evidence of an influence of growing imports and exports or outsourcing on the change of the wage bill of nonproduction workers. What they do find, however, is a large and robust impact of the change of computer investment, thus favouring an explanation involving technology.

2.3 Technological changes

A paper by Berman et al. (1994) concentrates on the question how labour demand moved from low to high skilled workers in the USA. They try to determine whether this shift in demand occurred rather *between* or *within* industries. Changing product demand because of greater trade integration and rising public expenditures on defense from 1959 onwards would support the "between-industry" hypothesis, whereas labour-saving TC fits together with "within-industry" labour demand shifts.

To investigate this development, i.e., to track the changes in the composition of aggregate demand they perform a standard between/within analyis. This means splitting up the overall change of the share of high skilled workers (they use nonproduction workers as a proxy) into a term of employment shifts between industries and a term of proportion shifts within industries. Such an decomposition formula looks like this (where P_H is the proportion of high skilled workers, S_i the relative employment in sector i):

$$\Delta P_H = \sum_i \Delta S_i \bar{P}_{H_i} + \sum_i \Delta P_{H_i} \bar{S}_i \tag{2.3}$$

[8]See Krugman (2008, p. 104, table 1).

The first term captures changes in the relative employment *between* sectors and the second term changes in the fraction of skilled workers *within* sectors. The data comes from a survey of manufacturing establishments from the Census of Manufactures and spans from 1959 to 1987.

Berman et al. come to the conclusion that "the within-industry component dominate[d] the between in each period".[9] The within component explained more than 60% of the rise in nonproduction labour demand in all three periods, thus, SBTC is the better fitting explanation.

They also undertake a cross-sectional regression on industry level: The nonproduction workers wage bill share is used as a dependent variable and is regressed on log changes of capital and equipment and on the level of investment in computers as well as the level of expenditures in R&D. Berman et al. (1994) find a positive and significant coefficient for all these variables, indicating that there is a "capital-skill complementarity in general, and [an] equipment skill complementarity in particular"[10]. Additionally, the wage share of nonproduction workers increased the most in industries with large investments in computers.

Further evidence on the connection of technology and income inequality is provided by Autor et al. (1998). They first study the quantities of college graduates supplied to the labour market and the rise of the college/high school relative wage[11] from 1940 on. A large increase in the supply of workers with a college degree and the simultaneously increasing relative wage imply that there has also been a "strong secular relative demand growth for college workers since 1950"[12].

Then, Autor et al. use a shift-share analysis, similar to Berman et al. (1994), to assess whether this growth in demand for college graduates occurred mostly *between* or *within* industries. If the skill upgrading is due to growing international integration and subsequently a rise in the demand for some (skill intensive) products, then we would expect to see a dominant between industries component. On the other hand, a bigger within industries component points to increases in the skill demand in all industries, thus is associated with SBTC: the adoption of computing technology and changes in the production process, organizational structure and workplace characteristics. The result is in line with the findings of Berman et al. (1994): The by far greater part of the skill upgrading took place *within* sectors, thus favouring the explanation of SBTC.

[9] See Berman et al. (1994, p. 377).
[10] See Berman et al. (1994, p. 385).
[11] The college/high school relative wage acts as a proxy for the relative price of (better) skilled labour.
[12] See Autor et al. (1998, p. 1180).

To further explore this relationship, they look at the computer use at the workplace across sectors. Since it might be not equally possible for every sector to introduce and use computing machinery at a large scale, one would expect that sectors which are more amenable to new technology also experienced the bigger growth in demand for skilled workers. Using a simple regression analysis (with the change in employment of college/high school graduates as the dependent, and the change in the use of a computer keyboard as the independent variable), they find that the results support this hypothesis: Sectors, in which computer use grew the most where also the sectors in which demand for college workers increased and demand for high school workers decreased. As a robustness check, they replace the change in employment of the skill group by the change in the employment of workers in a *major occupational category.* The results show that in sectors with larger increases in computer use occupations with higher educational requirements and higher salaries gained in employment.

There is, however, the question of causality: Did the adoption of computer equipment really trigger the increase in skill demand or was it rather the other way around: Did computers follow well educated workers into the firms? The following regression design is able to provide an (at least partial) answer: If the change of the fraction of workers using a computer in the period from 1984 to 1993 in a sector is regressed on the change of the wage bill share of college graduates in the 1960s, 1970s, 1980s and 1990s, then a varying coefficient is evidence for the first line of causation (computers causing the demand for high skilled), and a stable coefficient for the second possible causation (high skilled workers causing the adoption of computers). Autor et al. record an increasing coefficient: 0.071, 0.127, 0.147 and 0.289 for the 1960s to the 1990s, respectively. Thus, they conclude, “the pace of skill upgrading”[13] rose after the 1960s in industries which experienced larger increases in the adoption of computing machinery in 1984 - 1993.

Autor et al. also try to distinguish whether the impact of computers on the labour market are due to computers themselves or to general capital-skill complementarities. To test this, they use a cross-industry regression with a measure of office equipment and accounting machinery (OCAM) per worker as well as capital per worker as independent variables. The change in the wage bill share of college graduates is again the dependent variable. In several different specifications of the regression model, they always find a strong impact of OCAM and a small and insignificant coefficient for capital intensity. When only manufacturing sectors are considered, OCAM is still highly significant, however, overall capital intensity become suddenly very crucial. This means

[13] See Autor et al. (1998, p. 1194).

that there might be a connection between capital and skilled personnel that should be further researched.

2.3.1 Capital-skill complementarity

Krusell et al. (2000) provide an explanation for the growing demand of high skilled labour using a simple feature of a production function: They introduce a *complementarity* between skilled labour and a special kind of capital, which they call equipment capital. Equipment capital, contrary to capital structures, can be thought of as being "new" capital, like electronical machinery, computers and also software. As the price for this sort of capital fell rapidly (even more when correcting for improvements in the quality of the products) in the second half of the previous century, adoption of and demand for equipment capital rose, such as standard theory would predict. Because of the complementarity between equipment and skilled workers, demand for the latter increased too.

In this specification, skilled workers did not get *more productive* because of technical innovations, instead, they "followed" the ever cheapening equipment capital into the firms.

Krusell et al. use a production function that contains a Cobb-Douglas production function for the capital structures k_{st} and a nested CES function for the three input factor that are left: skilled labour s_t, unskilled labour u_t and equipment capital k_{et}:

$$G(k_{st}, k_{et}, u_t, s_t) = k_{st}^{\alpha} \left[\mu u_t^{\sigma} + (1-\mu)(\lambda k_{et}^{\rho} + (1-\lambda)s_t^{\rho})^{\sigma/\rho}\right]^{(1-\alpha)/\sigma} \tag{2.4}$$

μ and λ are the income shares of the production factors, and ρ and σ the elasticities of substitution. From this equation, they derive an expression for the skill premium π. With US time series data on the skill premium, the quantity of hours supplied and the prices of the two types of capital, they are able to estimate the two elasticities of substitution.

As expected, there is significant evidence to conclude $\sigma > \rho$, which is the main requirement of capital-skill complementarity: Skilled workers are less substitutable (thus more complementary) with capital than unskilled workers. Only during the 1970s, when the skill premium fell, the fast growing supply of skilled workers seems to have outweighed the complementarity effect. Further calculations show that the capital-skill complementarity effect contributed around 60% of the rise in the skill premium.

A simpler approach that yields different results is given again in Acemoglu (2002): He uses data on the skill premium, the relative supply of skilled and unskilled workers, a time trend and the log of the relative price of equipment capital. The skill premium is the variable to be explained. Acemoglu finds that the time trend yields better results when included with the relative supply than the log relative price of equipment. However, the differences in the R^2 are not big. When both terms are included simultaneously, the log relative price is not significant, but the time trend is. This may be a consequence of the high correlation between the two variables: The log relative price is a (nearly linear) falling curve.[14]

Still, this finding casts some doubt on the linkage of equipment capital and high skilled labour and on the explaining power of "capital-skill complementarity".

2.3.2 Organizational changes

Some economists, among them Bresnahan (1999) and Greenwood and Yorukoglu (1997), focus on a very different idea: That the demand for skilled workers did not soar because of changes in the productivity, but because the production process *itself* did change!

The idea of Greenwood and Yorukoglu in their 1997 paper is the following: In their opinion, recent decades saw a technological revolution during which the organization of production changed. Since the transition from the "old" technology to the "new" technology is difficult and sophisticated, well educated workers are needed to *implement* the new machines. This is why wages for those workers increased. Furthermore, the usage of the new technology has to be learned and improved: TFP (total factor productivity) growth is low during that period. According to them, this three developments (technological innovation, rising skill premium and productivity increases are depressed) all occurred around 1974, a time in which the semiconductor and the *microchip* where adopted for commercial purposes and applications.

They go on to predict that "as IT matures, the skill premium should decline"[15]. However, this prediction has failed to come true until now as, e.g., OECD (2012) document.

Bresnahan (1999) provides an qualitative evaluation of the impact of ICT on the labour market. His three main ideas are the following: 1) Computer use was influential in white-collar bureaucracies, 2) there was *limited substitution* of machine decision making

[14] See Figure 6 in Acemoglu (2002, p. 29).
[15] See Greenwood and Yorukoglu (1997, p. 59).

for human decision making and 3) that "organizational complementarity" between ICT[16] and skilled workers in bureaucratic production was the force behind the rising skill premium.

As this ideas are important for the sections to come, I will elaborate them more thoroughly here. First, his observation that computers changed white-collar work is due to "organizational computing". According to Bresnahan, computers influenced mainly the bureaucratic production process (such as the accounting department), rather than the individual working place: In individual wage regressions, a *pencil* at the workplace predicts high wages as well as a computer. He argues that the causality goes the other way: PCs came to high-wage jobs, but they *did not cause* them. Additionally, most of the early computer users were mid-skilled employees, such as secretaries and accountants. Thus, the large wage gains of high skilled professionals during this period cannot be explained by a "direct" complementarity of PCs and (high) skills.

Limited substitution of machine for human decision making, Bresnahan's second idea, is based on an elementary insight: Computers are most effective at carrying out simple, repetitive tasks. In (the organization of) a firm there are a lot of repetitive tasks to be done, such as billing, auditing, accounting and so on. Routines, that were formerly done by middle skilled human clerks are partly "outsourced" to a computer. Thus, there is a "limited substitution" of capital for labour and a lower demand for *middle skilled* workers!

In his theory, high skilled workers profited from the adoption of computers in firms through "organizational complementarity". This complementarity arises in firms that use ICT in their bureaucracy and need managers, professionals and technical workers to make use of the new technology by improving customer services, processes and even products. Bresnahan calls this "daily co-invention"[17]. So, he concludes that the demand for modestly skilled clerks should have diminished, whereas the demand for high skilled professionals should have increased. His theory is largely based on observations from firms in the service industry, but it should also be valid for industrial firms, although to a smaller degree.

Furthermore, Bresnahan makes an important point for the upcoming section: Until now, education was a proxy for skills and economists interpreted the rising demand for better educated employees as a rise in the demand for skills, not exactly defining what those skills are. There is research that uses the dictionary of occupational titles to get an idea

[16] Bresnahan uses "Computers" and "ICT" interchangeably.
[17] See Bresnahan (1999, p. 409).

of the "skill content" of a job. The changes therein shed light on which skills rise and which fall in demand. The result is that the demand for *cognitive skills* and *people skills* rose[18]. This implies, that we should "shift way from a view of the individual job as the conceptual labour-demand unit"[19] and start looking at a job as a bundle of tasks to be done and the worker as a bundle of skills. Clearly, as job tasks change (as through the introduction of ICT in firms) so do the skills required by the worker in this job. This idea is presented in the upcoming section.

2.3.3 Routinization and Polarization Hypothesis

Autor et al. (2003) continue on the ideas of Bresnahan: They too look at what computers do best and derive empirical testable hypothesis for it. The use of the *dictionary of occupational titles* allows them to quantify the changes in the task content of occupations.

The starting point for their investigation is the following observation: Computers are good at carrying out simple, repetitive tasks. Tasks, which can be done by following a (programmable) set of rules or instructions. Autor et al. call them "routine" tasks as opposed to "nonroutine" tasks, for which there are no programmable instructions possible or available.

Economic reasoning implies that since the price of computers (and of computer capital) fell dramatically in the last decades, computers should have substituted labour input in executing these routine tasks. This means, furthermore, that computers are relative complements for workers carrying out nonroutine tasks.

This idea is not entirely new: Since the Industrial Revolution machines replaced (and are replacing) workers in conducting routine tasks. Up till now, however, these tasks were routine *manual* tasks. Computers, on the other hand, are used to perform routine *cognitive* tasks.

The dictionary of occupational titles (DOT, the editions of 1977 and 1991) contains descriptions of more than 12.000 jobs in 44 criteria. Autor et al. (2003) extract five variables from it, which correspond to 1) nonroutine cognitive tasks, 2) nonroutine interactive tasks, 3) routine cognitive tasks, 4) routine manual tasks and 5) nonroutine manual tasks. This allows them to measure the task input of all occupations. Since

[18]See Bresnahan (1999, p. 394) as well as Autor et al. (2003) in the next section.
[19]See Bresnahan (1999, p. 412).

there was a revision of the DOT in 1991, they can measure the "intensive" margin of task changes, which are changes in the task inputs within each occupation (by matching the occupations from the 1977 edition and the 1991 revision of the DOT), as well as the "extensive" margin, changes in the task inputs which are solemnly due to changes in the distribution of occupations (holding task inputs fixed at the 1977 level).

Aggregating the changes in employment of the five task inputs immediately confirms the predictions from above: Nonroutine task inputs, cognitive or interactive, rose in demand over the observed period 1960 - 1998. Nonroutine manual inputs fell over the whole period, whereas routine cognitive and routine manual inputs grew in the 1960s, fell thereafter and were 1998 below their 1960 level. Thus, these task shifts seem to provide quantitative evidence for the observations of Bresnahan (1999).

Then, using industry-level data on task inputs, Autor et al. test whether the prevalence of routine task inputs in an industry sector in 1960 predicts subsequent adoption of computers. Not surprisingly, they find that the greatest increases in computer use where in formerly routine task intensive industries.

They also conduct a between-within analysis on the task changes, since the changes in task input could also be the result of aggregate product demand shifts. In this case, the between component would be greater than the within component. The results, however, do not confirm this hypothesis: In all five task measures, only in the 1960s the task changes were dominated by between industry shifts. Since 1970 (1970 also marks the advent of the computer era), the within component was always greater than the between component. For the nonroutine manual task, the components were similar in all four decades.

Autor et al. then turn to industry-level relationships between computer use and task measures. Again, a simple regression framework is used: The change of computer use is regressed on the change of the task input, for each task measure and decade separately. The coefficients all inhibit the expected sign and rise in value and statistical significance over the decades. Even though the resulting R^2 are very low, several robustness checks of the outcomes (including additional controls for capital investment, capital intensity, and import/export penetration of a sector) let Autor et al. conclude that this evidence points to a "secularly rising relationship between computerization and task change"[20].

A further research objective is to look how these task changes work *within* each educational group: To this end, Autor et al. regress again the changes in the task input on

[20]See Autor et al. (2003, p. 1305).

the changes of computer use. They do this, however, for four educational groups (high school dropouts, high school graduates, some college and college graduates) separately. So it is possible to ascertain how the educational groups reacted to the introduction of computers and how the task input changed for each: Nonroutine cognitive and interactive tasks increased and routine cognitive and manual tasks fell in all educational groups. These developments are especially pronounced for high school graduates and workers with some college and less significant for dropouts and college graduates. So, this phenomenon affected all educational groups the same way. This means further, that changes in the demand for low and high skilled do not fully reflect the underlying changes in task input. The educational background of workers can only inadequately track changes in the task content.

Since the same might be true for occupations, Autor et al. look at the task changes within occupations too. The relationship between the task measures and computer use is the same as before: Positive changes in computer use are associated with increases in nonroutine task and with decreases in routine cognitive tasks. Routine manual tasks, in contrast, show no relationship with computer use. The inclusion of educational dummies does not substantially alter the outcomes.

Autor et al. provide evidence that the development underlying the demand growth of skilled workers is growth in demand of *nonroutine cognitive* and *interactive tasks* and a simultaneous fall of *routine cognitive tasks*.

Germany, according to Spitz-Oener (2006), experienced largely the same development. She uses the German equivalent to the DOT and tests whether 1) ICT substitutes human labour in routine tasks and 2) ICT complements nonroutine tasks.

In a cross-occupational regression, Spitz-Oener finds that occupations with greater computer use were also the ones which increased their input of analytical and interactive tasks and decreased routine manual and cognitive tasks. This relation also holds within educational groups.

As a check for causality, she repeats the regressions above with lagged computer use. Since the coefficient stays significant in all studied periods, computers seem to cause the growth in nonroutine skills, rather than the other way round.

Manning and Goos (2003) develop the idea of Autor et al. a bit further. They argue pervasively that nonroutine cognitive and interactive tasks are primarily done by workers in the upper end of the wage distribution, while nonroutine manual tasks are the main content of a job at the lower end. Between them, in the middle of the wage distribution, are the people carrying out routine manual and routine cognitive tasks. Thus, as demand shifted the nonroutine tasks low and high paying jobs must have gained in employment and the jobs paying average salaries must have declined in number. Manning and Goos term this development “job polarization”[21].

Using data from the UK, they rank all occupations by their median wage and look then at the change in employment over the period 1975 - 1999. According to their hypothesis, this curve should have a U-shape. An alternative way to measure the polarization is to look at the change in employment in each percentile of the wage distribution. Again, a U-shaped curve is expected. Manning and Goos (2003) find that both methods yield results that are in line with the hypothesis.

Of course, this result is at odds with the SBTC hypothesis (SBTC would *not* predict an increase in jobs with low skill requirements). To investigate this discrepancy, they do a shift-share analysis like Berman et al. (1994). However, instead of just production and nonproduction workers, they consider ten job categories (which are again ranked by their median wage). Their findings support the polarization hypothesis: Employment gains of well-paid occupations (like professional occupations, managers and administrators) were largely *within* industries. Craft workers and machine operators saw their employment share decline *both* between and within industries, whereas the employment of bureau clerks (who perform mostly routine cognitive work) increased *between* industries (reflecting the shift towards services) and decreased *within* industries. Low-paid nonroutine jobs, like sales personnel and personal services, experienced job growth between and within industries.

To get an idea of the degree of influence of polarization on the wage inequality, Manning and Goos assign weights to each individual according to the employment in an occupation in a given year relative to the base year 1979. The percentiles of the actual observed wage distribution are then compared to a “re-weighted” wage distribution. The conclusion is that job polarization can explain 33% of the rise in the log(50/10) differential and 54% of the log(90/50) differential.

Michaels et al. (2010) use EU-KLEMS data on the changes in the wage shares of high, middle and low skilled workers and changes in ICT investments in eleven OECD countries[22] to test the polarization hypothesis of the labour market.

In a cross-sectional regression on industry-level, they find support for the polarization hypothesis: The high skilled wage share increased the most in sectors with high growth

[21] See Manning and Goos (2003, p. 2).

[22] Besides the UK, the US and Japan, Michaels et al. (2010) consider eight European countries: Austria, Denmark, Finland, France, Germany, Italy, the Netherlands and Spain.

of ICT investment, whereas the opposite result is found for middle skilled workers. Their wage share decreased in sectors investing heavily in ICT. Low skilled workers were largely unaffected by this development.

For high skilled workers, this result becomes even more pronounced when only tradable sectors are considered. However, the negative impact on middle skilled workers weakens with this modification.

Comparing the ICT coefficient times its mean of ICT investments with the actual change in the wage share, Michaels et al. (2010) estimate that ICT growth can explain from 8 to 30% of the increase in the high skilled wage share.

Acemoglu and Autor (2011) and Goos et al. (2010) also find that employment changes in several countries in Europe resemble the Anglo-American experience: A growth in jobs for high-paid professionals, technicians, managers and low-paid service and elementary occupations, and a decline in middle skilled occupations, such as clerks, craft, trade and operative personnel.

2.3.4 Sector vs. Factor biased technical change

Haskel and Slaughter (2002) ask the question if TC (or SBTC) is *sector biased*. That would mean that not all industrial sectors of an economy are affected the same way by the introduction of innovations. Consequently, the rising skill premium (the main factor of the rising income inequality) is then not only influenced by the changing demand for high skilled workers but also by the magnitude of the sector bias.

They provide a theoretical explanation as well as an empirical analysis on the factor vs. sector question.

Theoretical framework The framework they develop consists of a Heckscher-Ohlin two-factor, two-sector open economy with exogenous prices for the products produced. The two sectors are machines M and apparel A. Product prices (which are exogenously determined) and the share of skilled labor in the sector's wage bill are denoted by P_k and ω_k, respectively, for both sectors $k = M, A$.

In the machines sector high skilled workers S are relatively more employed than unskilled workers U, whereas it is the other way round in the apparel sector. Y_k, the production output of sector k is then modelled with a CES function:

$$Y_k = A_k \left(\delta_k S_k^{1-1/\sigma} + (1-\delta_k) U_k^{1-1/\sigma} \right)^{\sigma/\sigma-1} \tag{2.5}$$

σ denotes the substitution of elasticity and is assumed, as most commonly in the SBTC literature, as being greater than 1. That means that the two factors of production are substitutes rather than complements. They assume further that the two production inputs are remunerated according to their marginal product and that there is enough mobility between sectors so that wages (w_U and w_S) for each skill group are the same in each sector. The relative wage $\frac{w_S}{w_U}$, or the skill premium, will be the main indicator of interest.

In this production function, TC in sector k is captured as an increase in A_k. In the notation of Haskel and Slaughter (2002) this TC is *factor-neutral* and can either be *sector-specific* (if it occurs in only one sector), or *sector-pervasive* (if it occurs all sectors). On the other hand, SBTC is embodied in an increase in δ_k and, of course, not factor-neutral. Again, SBTC can be either *sector-specific* or *sector-pervasive*.

With this assumptions made, the optimal relative labour demand can be derived ,

$$\left(\frac{S}{U} \right)_k = \left(\frac{\delta_k}{1-\delta_k} \right)^{\sigma} \left(\frac{w_S}{w_U} \right)^{-\sigma} \tag{2.6}$$

as well as the equilibrium skill premium ("hats" mark percentage changes):

$$\begin{aligned} \widehat{\left(\frac{w_S}{w_U} \right)}_k = \frac{1}{\omega_M - \omega_A} \Bigg(\widehat{\left(\frac{P_M}{P_A} \right)} + \widehat{\left(\frac{A_M}{A_A} \right)} \\ + \hat{\delta}_M \left(\frac{\sigma}{\sigma-1} \right) \left(\frac{\omega_M - \delta_M}{1-\delta_M} \right) - \hat{\delta}_A \left(\frac{\sigma}{\sigma-1} \right) \left(\frac{\omega_A - \delta_A}{1-\delta_A} \right) \Bigg) \end{aligned} \tag{2.7}$$

From equation 2.7 we can see that it not clear how $\frac{w_S}{w_U}$ reacts to TC. Only sector-specific changes (a rise in solely A_M or δ_M for example) result in a rise of the skill premium. If TC occurs only in one sector, it increases the profitability of that sector, and producers react to this by demanding more labourers. With fixed labour supply, this rises the wages of the kind of labour relatively more employed in this sector. So, if TC would occur in the relatively unskilled intensive apparel sector, then we would expect a fall in the skill premium. This holds also for a sector-specific SBTC.

On the other hand, if the sector-pervasive SBTC is the case, then the conclusions are not that straightforward. If δ_M and δ_A rise at the same time with the same amount, we cannot infer as to whether a rise or fall in the skill premium will take place. Even if we see different increases of the two δ_k, the induced changes on $\frac{w_S}{w_U}$ are unclear. This is because the skill premium depends on the relative costs and thus also on the exact magnitudes of the share of the skilled workers wage bill ω_k, as well as the SBTC in the two industries, δ_k.

So far, prices were assumed to be exogenous, i.e. the country is small enough so that TC does not influence the world market product prices. This assumption will now be relaxed.

The country is now sufficiently large. Considering endogenous prices, there may also be indirect effects (besides the direct effects from the paragraphs above) that influence the skill premium. For example, if TC occurs in the machines sector M, then the world relative supply $\frac{Y_M}{Y_A}$ increases, which leads to a fall in relative prices. This in turn has an effect on the wage premium. If relative prices decrease, so does $\frac{w_M}{w_A}$. The Stolper-Samuelson theorem is the argument for that kind of effect.[23] This is of course only true if the country is big enough so that changes in the output produced lead to changes in the world market product prices.

A rise/acceleration of TC in the apparel sector, where unskilled workers are employed more intensively, will be followed by a fall in relative supply, a rise in relative prices and, subsequently, a rise in the skill premium. So, the indirect effect, which is propagated through changes in world market prices, can offset the direct effect of TC on wages.

However, as the direct effect on wages is difficult to determine, so is the sum of direct and indirect effect.

In summary, even if it is difficult to pin down the effects of TC, we can see that sector biases might play a considerable role in determining the direction and magnitude of the change of the skill premium.

Empirical analysis Haskel and Slaughter (2002) supplement their theoretical conclusion with an econometric analysis.

[23] The Stolper-Samuelson theorem states that a rise in the price of a product will result in a rise of the price of the factor which is most intensively used in the production process.

Based on a translog cost function, they can derive an equation for the change of the share of high skilled labourers in the total wage bill in a sector k:

$$\Delta\omega_k = \beta_0 + \beta_1 \Delta \log \left(\frac{w_S}{w_U}\right)_k + \beta_2 \Delta \log \left(\frac{K}{Y}\right)_k + \epsilon_k \tag{2.8}$$

Δ indicates changes over time, K is the capital, Y the real value added output and ϵ_k is an error term. Everything that is not explained by the independent variables $\frac{w_S}{w_U}$ and $\frac{K}{Y}$ can be labelled SBTC. So the intercept captures "sector-pervasiveness" of SBTC across all sectors, whereas the error term is the sector bias of SBTC in sector k.

That measure of SBTC (the sum of intercept and error term), is then regressed on the skill intensity at the start of the period. If the estimated coefficient is *positive*, then SBTC was concentrated in sectors that were skill-intensive to begin with. A negative coefficient indicates that SBTC was prevalent in unskilled-intensive sectors. That means, the equation they estimate looks like this:

$$\text{SBTC}_k = \alpha + \beta_{bias} \left(\frac{S}{U}\right)_k + u_k \tag{2.9}$$

Haskel and Slaughter (2002) analyze ten countries over two periods, from 1970 to 1980 and from 1980 to 1990.

Their results are broadly consistent with the theoretical expectations. For the 1970s, the US and the UK experienced a drop in the skill premium and, according to their estimates, *unskill-biased* SBTC. This is exactly what they expected, since unskill-biased SBTC should lead to a fall in the skill premium. At the same time, Australia had unskill-biased TC as well, whereas Austria and Sweden experienced the opposite.

In the 1980s, seven countries had a positive coefficient (indicating a sector-biased SBTC towards skill-intensive industries) versus only three with a negative coefficient (SBTC in unskilled-intensive sectors). However, those countries with sector-biased SBTC were, more or less, those with a rising skill premium, and vice versa[24]. That means, also for the period from 1980 to 1990, the sector-bias hypothesis of Haskel & Slaughter is consistent with the data. Thus, the sector bias of SBTC seems to play an important part in explaining the rising and falling skill premium in recent decades.

[24] See figures 4 and 5 in Haskel and Slaughter (2002, p. 1776f).

Esposito and Stehrer (2009) apply the methodology of Haskel and Slaughter to data of three European transition economies: Czech Republic, Hungary and Poland. They also find that technical change was concentrated in skill-intensive sectors, thus their results confirm that a sector bias of SBTC cannot only be found in industrialized countries.

2.4 Hypotheses

Based on the findings of Haskel and Slaughter (2002), I want to test the following hypotheses:

First hypothesis
There exists a sector bias of SBTC in developed countries.

Second hypothesis
The sector bias of SBTC influences the skill premium. In periods, which saw SBTC biased towards skill-intensive sectors the skill premium increased. Vice versa, in periods with an unskill-intensive biased SBTC the skill premium fell.

3 Data

3.1 Data Construction

I use industry-level data from the EU-KLEMS database. It includes data on real value added, investment in Information and Communication technologies capital, as well as hours worked and compensation for three skill groups, and many variables more[1].

I use the 2008 release, as this release includes detailed labour input data and contains data on a further disaggregated industry level than the 2009 release. It covers the years 1970 to 2005.

As I need data on labour and capital input as well as output for a time period as long as possible, I consider eleven countries for my analysis. These are: Austria, Belgium, Denmark, Finland, France, Germany[2], Japan, the Netherlands, Spain, the UK and the USA[3]. Finland, Germany, the UK and the US have labour input data starting in 1970, the seven other countries in 1980. For all those countries, I construct the needed variables (e.g. wage premium, skill intensity, etc.). The time periods I study are the three decades from 1970 to 2000 and the five year period from 2000 to 2005, the end of of the data.

I use the data at the lowest level of industry disaggregation possible, which can vary from country to country[4]. As Haskel and Slaughter (2002) and others before, I restrict the sample to manufacturing industries, which leaves five industries in Austria up to 16

[1]See Timmer et al. (2007) and O'Mahony and Timmer (2009) for the 2008 and 2009 release, respectively.

[2]Germany refers to "West Germany" until 1990 and to "Germany" from 1991 onwards.

[3]Italy would have been a further candidate for inclusion into the analysis. However, some variables, e.g. the wage premium, contained very unplausible values and thus Italy was excluded as a whole.

[4]The exact aggregation on country level is given in appendix 6.1.

in Japan or 17 in Denmark for each period. Table 3.1[5] gives an overview of the number of industries in each country-period cell.

This subset of industries now constitutes the “whole” economy, thus, “total” industries or countrywide developments refer to the weighted average(s) over all manufacturing industries. Total hours worked by persons engaged are used as weights.

Country	Alternatives one to three	Alternative four
Austria	5	5
Belgium	5	5
Denmark	17	17
Finland	5	5
France	5	5
Germany	5	5
Japan	16	52
Netherlands	5	5
Spain	10	10
UK	5	5
USA	15	57

Table 3.1: Number of industries in the country-period cells

The EU-KLEMS database splits labour data into three skill groups, which is actually more than I need. To circumvent this problem, I keep the high skilled group as it is, but create a new group for the middle and low skilled. Grouping the middle and high skilled together would also have been a possible alternative, but since the middle skilled group contains sometimes as much as 60% of the employed persons this would have resulted in a very large “high” skilled group and (very likely) distorted the analysis heavily.

It is not necessary to convert the variables into a common currency, since the variables needed in the estimation are all growth rates, shares or ratios.

[5] As I will use different methods of calculating the SBTC in a sector, the number of industries varies also with the alternative used. Alternative four does not require data on capital stocks, which allows me to use much more data, but unfortunately only for Japan and the US.

3.2 Descriptive Statistics

3.2.1 Country Trends

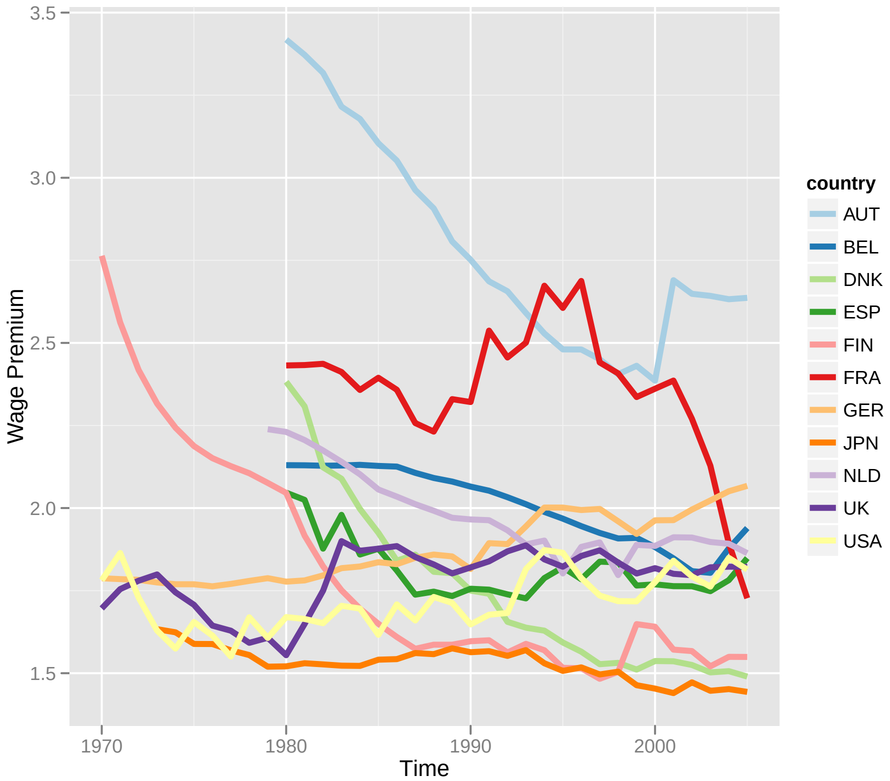

Figure 3.1: The development of the wage premium across countries

Figure 3.1 depicts the development of the skill (or wage) premium, calculated from the hourly wages, in all considered countries across the time for which data on wages and skill groups is available. Because hourly wages are not directly given in the dataset, I use total wages and total worked hours along with the shares of received wages and worked hours by the two skill groups to calculate a measure of the earnings per hour.

Generally, one sees that the skill premium decreased in most continental European countries. The only exception is Germany, where the skill premium increased over the years. In all other countries, the skill premium fell from 1970 onwards, with a short uplift (or stabilization) at the end of the observed time span. In the anglo-saxon World, comprising of the UK and the USA, the wage premium shows the typical (and in the economical literature well-established) behaviour: A fall in the 70s and a steady rise after that. Japan, the third large economic region in my sample, experienced a slow but steady fall in the skill premium from 1.6 at the beginning of the time span to 1.45 in 2005. Acemoglu (2003) finds similar developments in continental Europe using data from the Luxembourg Income Survey (LIS).

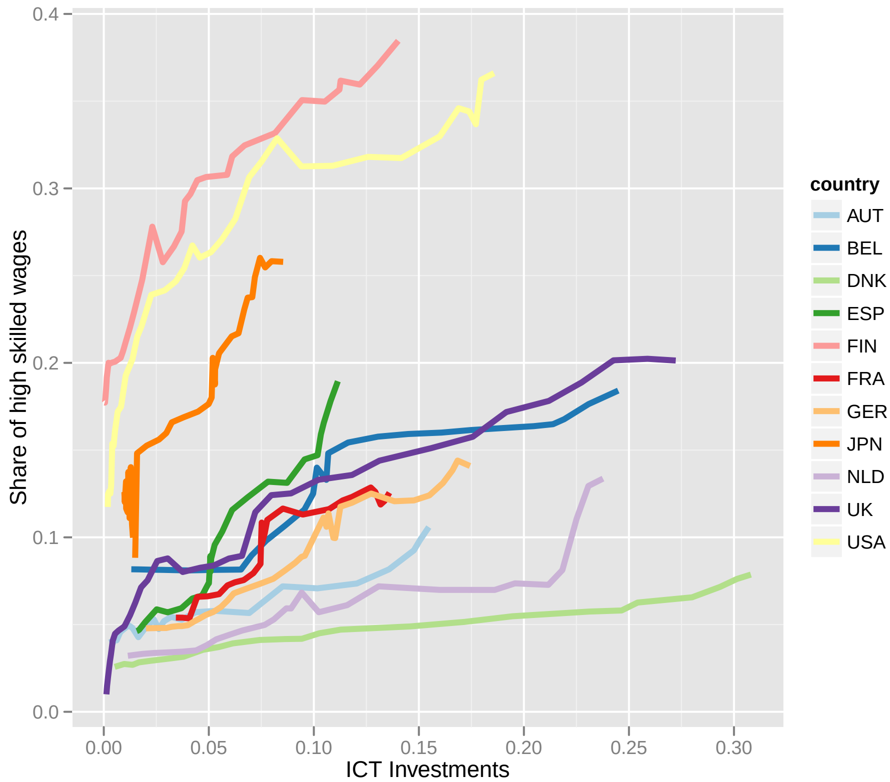

Figure 3.2: Changes in ICT investments and demand for high skilled workers over time

An interesting development is illustrated by figure 3.2, where the movement over time of ICT investment in the economy and the demand for high skilled workers are plotted together. The essential idea is that the lines tend to point to the upper-right corner, i.e., the two variables seem to be positively correlated over time. Finland and the USA show the most pronounced reaction of demand for high skilled workers to increasing investments in ICT. However, some curves seem to follow a concave parable.

3.2.2 Industry Trends

It is also interesting to look at the developments at the industrial level. In figure 3.3 changes in ICT investments are plotted against changes in the hours worked by high skilled. This figure considers only data from the US. The size of the circle indicates the amount of hours worked of all workers, averaged over the period at question.

In each panel, the vast majority of points lie in the upper-right quadrant, which means positive changes in the investments in computers and other electronical machinery are associated with positive changes in the demand for skilled working hours. In the three periods after 1980, the correlation across the industries was also positive, meaning that greater changes in investments (seem to) induce greater changes in the working time by skilled workers.

The interpretation is largely the same when all countries are pooled together, as figure 3.4 shows. Only several industries do not lie in the upper-right part of the plots. The inner-country trends are, as in the US case above, pointing up rather than down. So, the stylized fact that increases in the demand for skilled labour are positively related to changes in the investment for ICT goods is backed by the EU-KLEMS data.

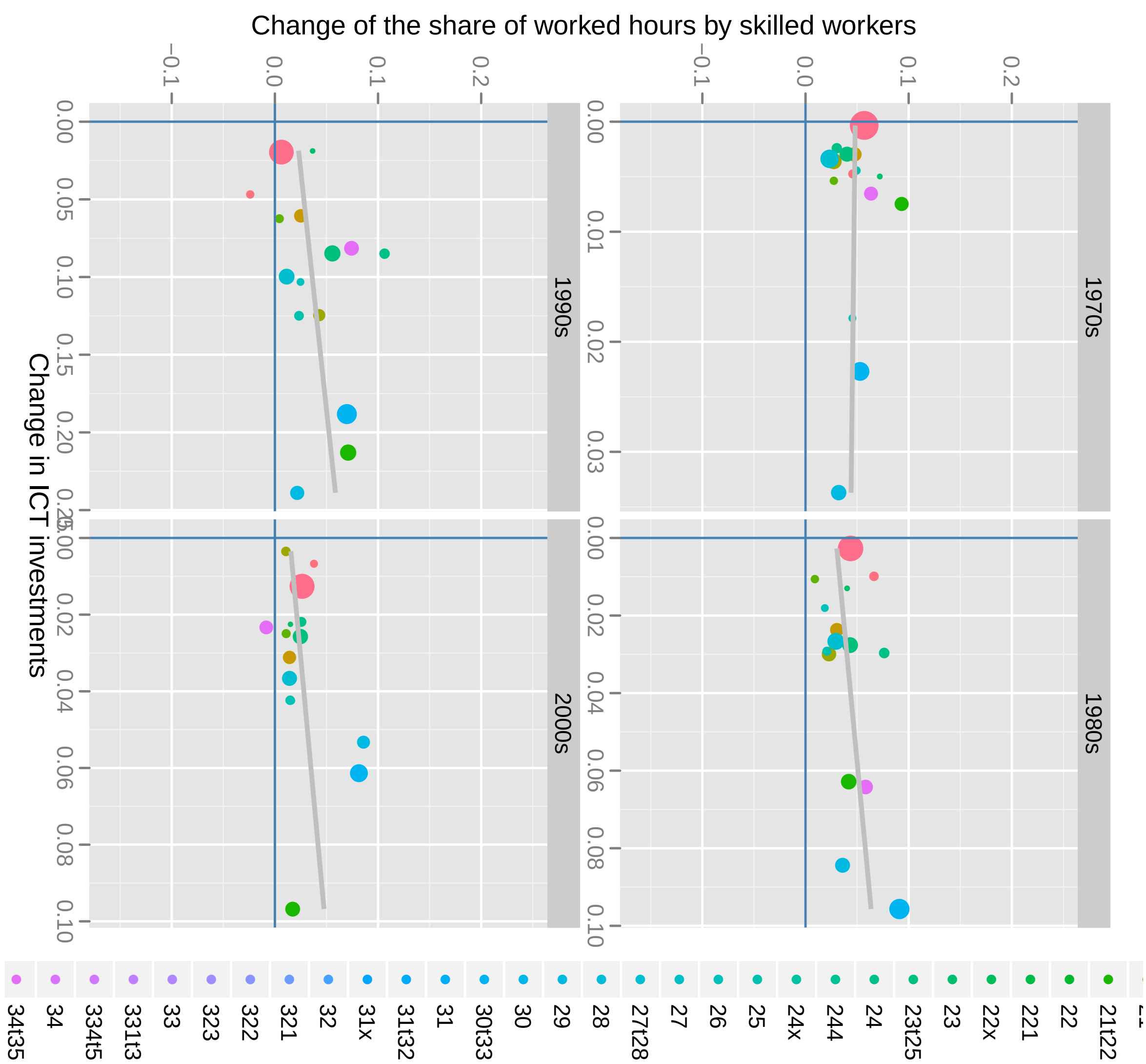

Figure 3.3: Changes in hours worked by skilled workers and ICT investments in the US

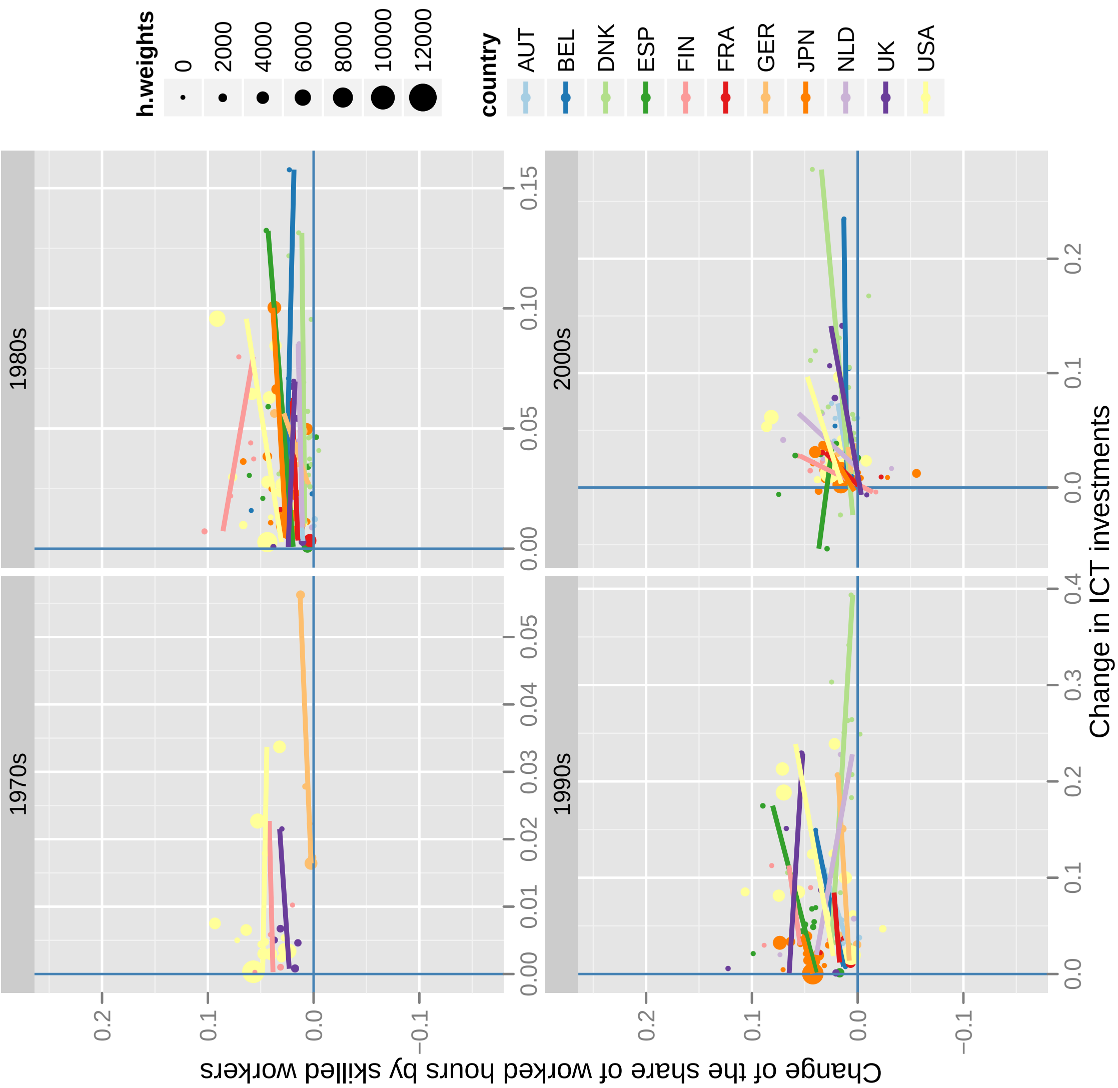

Figure 3.4: Changes in hours worked by skilled workers and ICT investments, all countries pooled

4 Empirical results

4.1 Regression design

In the following chapter I will estimate the sector bias of skill biased technical change and its effect on the skill premium following the methodology of Haskel and Slaughter (2002).

As a first step, I estimate the equation

$$\Delta \omega_k = \beta_0 + \beta_1 \Delta \log \left(\frac{w_S}{w_U} \right)_k + \beta_2 \Delta \log \left(\frac{K}{Y} \right)_k + \epsilon_k \tag{4.1}$$

as stated in chapter 2 to get a measure for SBTC.

$\Delta \omega_j$, the change of the share of high skilled workers in the total wage bill, is the independent variable. This variable is readily available from the dataset. The first independent term, $\frac{w_S}{w_U}$, the skill or wage premium, is computed as the total wages times the share of the respective skill group, divided by the hours worked by each skill group. Thus, it is a rough measure for the hourly wages. Then, the capital intensity $\frac{K}{Y}$, is measured as the real fixed capital stock divided by the real value added.

Changes in the high skilled wage share that cannot be explained by either changes in the log wage premium or by changes in the log capital intensity are naturally attributed to SBTC. Thus, the sum of the intercept (which captures the skill bias common to all sectors) plus ϵ_j (the sector-specific bias) is a valid measure for the SBTC in each sector.

The second step (4.2) is then to take the SBTC measure derived from the first estimation and to regress it on start-of-decade skill intensity, calculated as the relation of hours worked by the two skill groups. A significantly positive coefficient provides evidence that SBTC was concentrated in skill-intensive sectors whereas a negative coefficient means that it unskill-intensive sectors experienced more SBTC. This is was Haskel and

Slaughter (2002) term the "sector bias of SBTC". According to their theory, in periods where the skill premium rose we expect to see a positive coefficient and in periods where the skill premium fell a negative one. Thus, when plotted against each other, we would expect to see the periods in the upper right or lower left corner of the plot.

$$\mathrm{SBTC}_k = \alpha + \beta_{bias}\left(\frac{S}{U}\right)_k + u_k \tag{4.2}$$

All theses calculations were carried for each country-period, where data is available. I use the hours worked[1] in each industry averaged over the corresponding period as weights for the estimations below. The robust standard errors reported in the following tables are all White's heteroskedasticity robust errors.

As a robustness check, I will also use three other methods of calculating the SBTC beside the method given above.

In the second specification, I drop the wage premium term of equation (4.1), since it could also capture differences in the skill composition in a sector rather than wage changes. Thus, the intercept captures the wage effects across all industries, and what is left in the error term will be the SBTC measure for the second step estimation.

My third measure includes a computer regressor to the equation (4.1) above. I use the share of ICT capital services per hours worked for this variable. This variable will capture the SBTC induced changes in the industries. In step 2, I will use the computer coefficient of the first step regression times the value of computer regressor itself as the dependent variable.

The last measure of SBTC is ω_j, the share of high skilled in the total wage bill itself. So, I do not need to run the first regression, but just insert the dependent variable into the second estimation.

The first-stage regressions of the first method are given in the appendix 6.

[1] Another possibility would have been to use average employment of the sector as weights for the estimation. However, these two measures correlate heavily with a correlation coefficient of 0.99.

4.2 Regression analysis

4.2.1 Alternative one

Here, the constant a_0 (SBTC across all industries) plus the error term ϵ_j (industry-specific SBTC) will act as the measure for SBTC.

	1970s	1980s	1990s	2000s
AUT		0.549	-0.034	-0.008
BEL		-0.075	-0.035	0.106*
DNK		0.808***	0.267*	0.354***
ESP		0.541*	0.351**	0.049
FIN	0.172	-0.02	0.035	0.009
FRA		0.322	0.502	-0.139
GER	0.002	0.311	0.008	0.009
JPN		0.151*	0.027	-0.019
NLD		0.315	0.188	-0.533
UK	0.542	0.326	1.496*	0.151
USA	-0.065	0.203*	0.241**	0.009

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4.1: Estimates of the sector bias, alternative 1

Table 4.1 contains the results of the second-stage regressions of each of the 37 country-period cells. It contains the coefficients of the regression (skill intensity regressed on the SBTC measure) plus their significancy. Ten of them are significant at a level of at least 5%. Especially Denmark shows strong support of a sector bias, whereas the other European countries seem to have missed that development. More importantly, the coefficients of the USA exhibit the same pattern that also Haskel and Slaughter (2002) find: A negative coefficient in the 1970s (i.e. SBTC was concentrated in unskill-intensive sectors) and positive coefficients afterwards (i.e. skill intensive sectors experienced more SBTC). However, no general pattern can be spotted.

A graphical inspection of the connection of the sector bias and the wage premium in figure 4.1[2] shows no positive correlation (Corr(ΔSector Bias, ΔWage Premium) = -0.2752) between the two variables. Thus, there is evidence of sector bias, but a link to the growing skill premium is missing.

[2] Figure 4.1 contains only periods which are significant at 5% level.

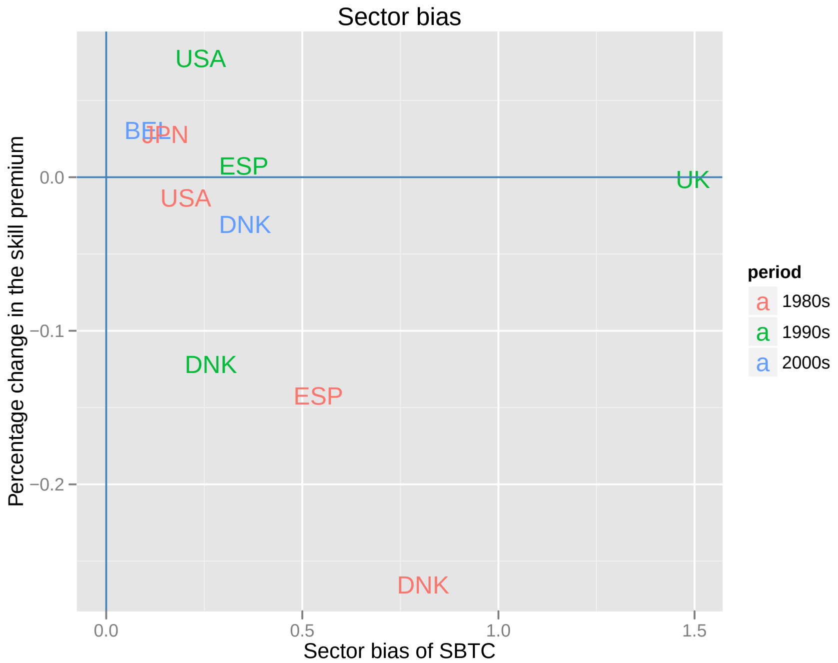

Figure 4.1: Sector bias and the change in skill premium, alternative 1

	1970s	1980s	1990s	2000s
constant	0.058***	0.005	0.029***	0.022†
	(0.012)	(0.011)	(0.008)	(0.011)
skill intensity	−0.054	0.234**	0.222***	0.003
	(0.148)	(0.082)	(0.054)	(0.052)
N	30	93	93	93
R^2	0.014	0.419	0.362	0.000
adj. R^2	−0.144	0.340	0.275	−0.136
Resid. sd	1.197	0.563	0.873	0.952

Country effects included
Robust standard errors in parentheses
† significant at $p < .10$; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4.2: Estimates of the sector bias (all countries pooled), alternative 1

As a further check on the existence of a sector bias, I pool all countries in my sample and run the same regressions as above, but with country effects included. The results are presented in table 4.2. Now, with much more observations per period, there is strong evidence that SBTC during the 1980s and 1990s was concentrated in skill-intensive sectors[3]. Around 30% of the variation of SBTC in all sectors can be attributed to the sector bias.

4.2.2 Alternative two

	1970s	1980s	1990s	2000s
AUT		2.005	0.387	-0.026
BEL		0.095	0.118	0.095
DNK		1.236***	0.246*	0.351***
ESP		0.653**	0.332*	0.042
FIN	-0.025	-0.106	0.299	0.007
FRA		0.885*	0.589*	-0.035
GER	0.189*	0.439*	0.235**	0.242*
JPN		0.149*	0.026	-0.113
NLD		0.364	0.969	-1.443
UK	0.666	0.436	1.765*	0.074
USA	-0.045	0.198*	0.332*	0.004

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4.3: Estimates of the sector bias, alternative 2

The log wage premium term is removed from the equation (4.1) in this specification. Wage effects across all factors now go into the constant and all that cannot be explained is the SBTC in a sector. Thus, the error term is the chosen measure of SBTC.

The results of this variant are presented in table 4.3. One can readily see that there are more significant periods, nearly half of all country-period cells exhibit a p-value smaller than 5%. Very remarkably, all significant coefficients are positive.

[3] As the weights are again the hours worked in each sector averaged over the period, the US should have a big influence on this results. However, if the US is excluded only the coefficient in the 1990s turns insignificant, the other coefficients stay largely the same.

Generally, the pattern of coefficients and significancies is comparable to the first alternative: This is especially true for Denmark, Japan, Spain, the UK and the USA.

Interesting are the cases of Germany and (to a lesser extent) France, which show now a strong and significant sector bias. Also remarkably are the very high coefficients of Austria, Denmark and the UK.

Still, there seems to be no connection between the sector bias and the wage premium, as Figure 4.2 shows. Germany partly exhibits the expected behaviour, with three of the four periods in the upper right corner of the plot.

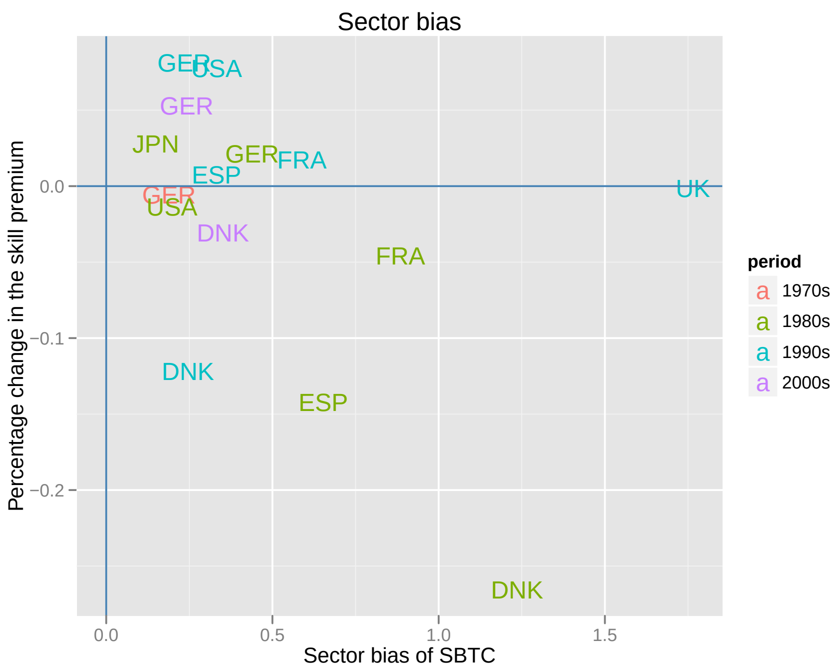

Figure 4.2: Sector bias and the change in skill premium, alternative 2

In a pooled-country estimation (with results given in table 4.4), I again find a clear indication of a sector bias. The coefficients strongly resemble their counterparts in the first variant.

	1970s	1980s	1990s	2000s
constant	0.003	−0.003	−0.005	0.000
	(0.013)	(0.021)	(0.021)	(0.006)
skill intensity	−0.040	0.233**	0.282**	−0.016
	(0.157)	(0.088)	(0.091)	(0.049)
N	30	93	93	93
R^2	0.006	0.388	0.333	0.005
adj. R^2	−0.153	0.305	0.242	−0.131
Resid. sd	1.326	0.595	1.184	0.998

Country effects included

Robust standard errors in parentheses

† significant at $p < .10$; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4.4: Estimates of the sector bias (all countries pooled), alternative 2

	1970s	1980s	1990s	2000s
AUT		-0.643	0.06	-0.007
BEL		-0.014	0.076	0.111*
DNK		0.066	0.017	0.021
ESP		0.373*	0.03	-0.002**
FIN	-0.024	-0.116	-0.041	-0.027
FRA		0.637	0.382	0.037
GER	-0.071*	0.724	0.004	0.175*
JPN		0.007	-0.005	0.025
NLD		0.191	2.311	-0.095
UK	2.608	0.455	1.039	0.344
USA	-0.01	0.046*	0.12*	-0.003

$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4.5: Estimates of the sector bias, alternative 3

4.2.3 Alternative three

Variant three is very different from the former two methods: I include a computer regressor to (4.1) and use the computer regressor coefficient of the first regression times the computer regressor as SBTC.

Table 4.5 contains again the results of the second-stage regression. Using this method, only seven out of 37 country-periods show a significant coefficient. Whereas for the most countries the results are different compared to the two methods before, the US American outcomes here are quite similar to previous ones.

However, when looking at the plot, there is now a slight indication that sector bias and skill premium are positively associated. Five of the seven periods are in the correct quadrant, with the US in the 1980s only little, but 1980s' Spain far off the hypothesized relationship.

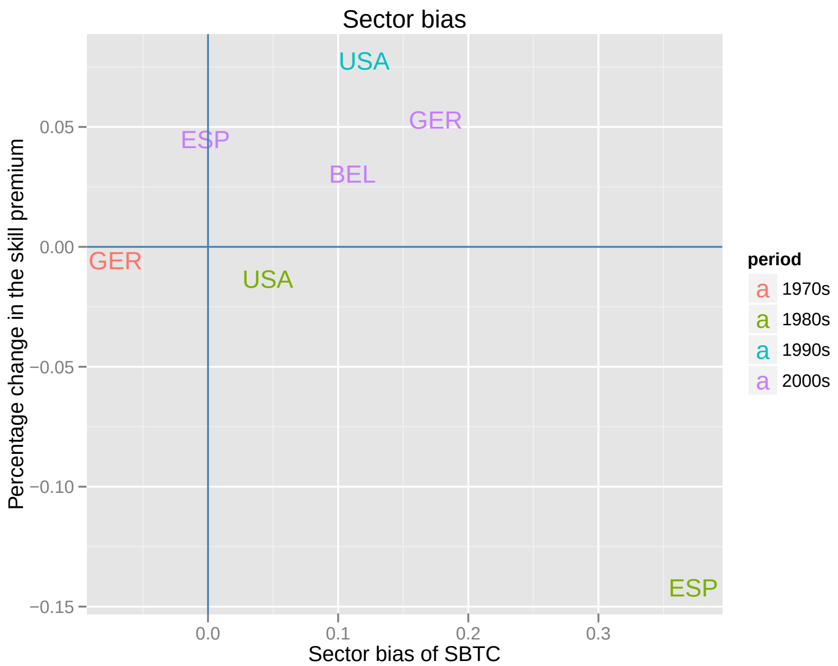

Figure 4.3: Sector bias and the change in skill premium, alternative 3

Also the pooled-country variation shows that the use of the computer regressor yields very different results. Here, only the 1980s coefficient is positive and significant such as

	1970s	1980s	1990s	2000s
constant	−0.006	0.010***	−0.050***	−0.000***
	(0.004)	(0.000)	(0.009)	(0.000)
skill intensity	−0.007	0.013*	0.030	0.000
	(0.023)	(0.005)	(0.021)	(0.000)
N	30	93	93	93
R^2	0.411	0.266	0.783	0.269
adj. R^2	0.317	0.166	0.754	0.169
Resid. sd	0.229	0.076	0.338	0.005

Country effects included

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4.6: Estimates of the sector bias (all countries pooled), alternative 3

we would expect. Remarkable is the very high R^2 in the third period, which is solely attributable to the negative coefficient.

4.2.4 Alternative four

Alternative four is a simplified method of measuring the sectoral SBTC: Instead of calculating it as a residual, the change of the high skilled wage share is used as an indicator for SBTC. This variable is then regressed on the skill intensity. Again, a positive coefficient provides evidence of sector bias.

The results in table 4.7 are generally comparable to the outcomes of variants one and two. There are 15 periods significant, all of which indicate a sector bias, i.e. more SBTC in skill intensive industries. Austria, Denmark, Japan, Spain and the USA show the same sector bias pattern as in alternative two.

Figure 4.4 shows again that an association of sector bias and skill premium cannot be found in the data. We observe more or less only positive sector biases, but the change of the skill premium is both positive and negative, without any observable connection to the sector bias.

Pooling all countries together, one gets the results presented in table 4.8. The 1980s are highly significant, as are the 1990s, which is a bit surprising. The significant constant

	1970s	1980s	1990s	2000s
AUT		3.332**	1.263*	-0.167
BEL		0.835	0.29	0.092
DNK		1.249***	0.248*	0.352***
ESP		0.697**	0.502*	0.045
FIN	-0.09	-0.113	0.422	0.004
FRA		0.853	0.555	0.194
GER	0.195**	0.475**	0.268	0.226
JPN		0.271***	0.091**	-0.196***
NLD		0.824**	0.873	-1.773*
UK	2.836*	0.965	1.764*	-0.056
USA	-0.029	0.17***	0.233**	-0.022

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4.7: Estimates of the sector bias, alternative 4

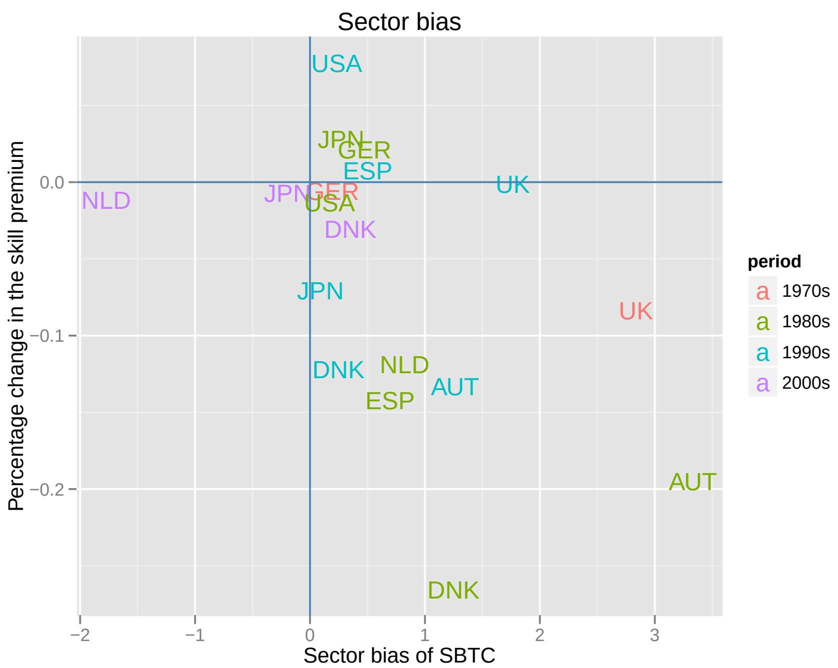

Figure 4.4: Sector bias and the change in skill premium, alternative 4

	1970s	1980s	1990s	2000s
constant	0.031*	−0.008	0.003	0.039***
	(0.014)	(0.020)	(0.022)	(0.006)
skill intensity	−0.026	0.199***	0.211**	−0.039
	(0.084)	(0.041)	(0.065)	(0.025)
N	72	171	171	171
R^2	0.168	0.518	0.211	0.134
adj. R^2	0.118	0.485	0.157	0.074
Resid. sd	1.515	0.813	1.784	1.287

Country effects included

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4.8: Estimates of the sector bias (all countries pooled), alternative 4

in the other two regressions shows that there was SBTC in all sectors, but it was not sector-biased in any kind.

4.3 Summary of the regression analysis

In each of the four variants of calculating the SBTC measure for each sector in a country-period cell, I find evidence *in favour* of sector-biased SBTC. The pattern of significancy and value of the coefficients varies with the method used, but alternatives one, two and four yield results which are similar. Alternative two exhibits with 16 of 37 the largest number of significant coefficients. In all four methods, the largest part of significant periods is concentrated in the 1980s, with the 1990s in the second place.

However, I find no clear evidence of the theorized relationship of a sector-biased SBTC and an increasing skill premium as Haskel and Slaughter (2002) do. Only alternative three shows a slight indication of a positive correlation between the sector bias and the wage premium. One simple explanation for this result is at hand: I observe, at least for the majority of Continental European countries, only falling skill premia. This may be the consequence of the social benefit systems, which counteracted the inequality-increasing forces of SBTC.

Another possibility would be that the skill groups as defined in the EU-KLEMS data inadequately reflect the skills whose demand rose: Since low and medium skilled groups are combined in this analysis, there might be hidden development in this two groups which causes this counterintuitive behaviour.

The results for the USA resemble the ones that Haskel and Slaughter (2002) compute, with a negative sector bias (though not significant) in the 1970s, and positive sector biases afterwards. As already mentioned, there is no evidence of a link between the sector bias and skill premium, also not if only the Anglo-Saxon countries are selected.

Therefore, I find that the EU KLEMS data does only partly support the hypothesis of Haskel and Slaughter (2002).

4.4 Panel estimation

I will now undertake a panel estimation. With this method, I hope to uncover the long-term trends in a country's industries. Of course, this contradicts the evidence from above: Some countries, especially the USA, experience negative as well as positive sector biases. Panel estimation imposes the assumption that the whole period experienced *one* trend over the whole period. This assumption fits for some countries, for others not.

4.4.1 Alternative four

In contrast to the regression design above, I will use changes in *five year intervals* instead of decades as above. This will add some data, but is still long-term enough to circumvent yearly fluctuations of the data. I will carry out the panel equivalent of variant four from above: It takes the changes in the high skilled wage share as indicators of SBTC. Thus, the first step regression is not needed and one can readily regress the high skilled wage share on the skill intensity. Industry fixed effects are used to account for differences in the wage setting process or the skill mix.

Table 4.6 contains the results of the panel regression. As in the simple OLS regressions before, Denmark, Germany and Spain show a sector-biased SBTC throughout the whole time period. USA, on the other hand, always showed a negative coefficient in the first period and positive coefficient thereafter. It is clear, that a panel regression does not fit well for this kind of behaviour. Counteracting forces cannot be found by the panel regression.

	Estimate
AUT	0.2797
BEL	-0.2118
DNK	0.2532**
ESP	0.1666*
FIN	0.0832*
FRA	-0.5624*
JPN	-0.0463
NLD	-0.2725
UK	-0.0206
USA	-0.0632
GER	0.218**

Table 4.9: Panel estimates, alternative 4

Interesting is also the case of Finland and France. The former never had, at least according to the results above, a sector bias. The results here indicate, however, a significant sector bias in Finland. The latter, France, had only significant coefficients in the second variant. There, they were positive. Here, France shows a significantly negative coefficient and, thus, unskill-biased SBTC.

The results of the remaining countries are statistically insignificant. Most of them had contradictory outcomes in the OLS regressions before.

5 Conclusion

Many economists have studied the developments of wage inequality. The three most important reasons for this development are found to be 1) growing international trade, 2) changes in labour market institutions and 3) technological innovations.

Rising international trade integration has certainly influenced the wage distribution in the industrial countries. It is, however, difficult to put a number on this effect. Estimates range from no effect to around 15%[1], depending on the method and data used. The pressure of international trade on firms to cut expenses may have strengthened the need of firms to increase the productivity of their low skilled workforce (especially in Europe, where labour markets are not that flexible, see Acemoglu (2003) for a similar argument). Thus, the effect of trade on income inequality could subtle.

The biggest influence on the distribution of wages certainly has been technological progress. The introduction of the computer and other electronical devices changed the working place profoundly. Technology seems to favour skilled workers, as the employment *and* wages of skilled workers rose throughout the second half of the previous century. That is why this development was termed “skill-biased technical change”.

However, simple models of SBTC cannot fully explain certain trends in the labour market. Here Autor et al. (2003) provide a modified view of how computers changed the working place: Computers did not only change *the way* we work, but also changed *what* we work: They are perfect for carrying out simple and repetitive tasks. Because the price of computers fell rapidly, they substituted human labour in routine tasks and complemented workers in nonroutine tasks.

Manning and Goos (2003) saw that not only high skilled workers carry out nonroutine tasks, but also low skilled workers. Employment fell in occupations requiring moderately skilled workers, like clerks and machine operators. They termed this development “job

[1]See Berman et al. (1994) and Feenstra and Hanson (1999).

polarization". This theory seems to go a long way in explaining recent changes in wages and employment in Europe and the US[2].

Though not the main reason behind the growing wage inequality, the weakening of labour market institutions helps to explain parts of the story: The diminishing power of unions to set wages for their member may account for the worsening position of low skilled males[3], especially in routine task occupations.

The purpose of this work was to test the hypotheses of Haskel and Slaughter (2002) with new data. Their hypotheses add an interesting aspect to the SBTC literature. Skill-biased technological change may also be sector-biased, meaning that sectors which are more skill-intensive (i.e. employing relatively more skilled workers) experienced bigger increases in SBTC.

First hypothesis
There exists a sector bias of SBTC in developed countries, i.e. sectors which employ a higher fraction of skilled workers also experienced higher rates of SBTC.

Second hypothesis
The sector bias of SBTC influences the skill premium. In periods which saw SBTC biased towards skill-intensive sectors the skill premium increased. Vice versa, the skill premium falls in periods with SBTC predominantly located in unskill-intensive sectors.

In my empirical analysis, I find evidence *in favour* of the first hypothesis. Especially the US, Denmark, Spain and Germany show significant signs of a sector-biased SBTC. Furthermore, when all countries in my sample are pooled together, the sector bias becomes a strong and significant feature of the data.

Less clear is the evidence on the second hypothesis. The skill premium *does not* depend on the direction of the sector bias. In only one of the four alternatives to measure SBTC, I am able to find a positive association of the skill premium and the sector bias.

Explanations for this result are likely to include labour market institutions: Because of the rather rigid European labour markets, wages cannot adjust as fast as they do in the USA and, subsequently, the skill premium remains stable. Thus, downward pressure on wages of some groups may instead be channelled into unemployment of these groups.[4]

[2]See e.g. Spitz-Oener (2006), Michaels et al. (2010) and Goos et al. (2010).
[3]Because unions are important for this group in the wage setting process, see e.g. and Kahn (2000).
[4]See Kahn (2000) for a discussion about how the centralized wage setting process generates higher wages, but also higher unemployment.

Additionally, Acemoglu (2003) argues that collective bargaining influences the technology adoption of European firms: Since unskilled workers are paid above their marginal productivity, firms are more eager to implement technology that favours less-skilled workers. So, SBTC might have a mitigated impact in Europe.

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List of Figures

List of Tables

6 Data Appendix

6.1 Industries in EU-KLEMS database

Country	NACE Codes
Austria, Belgium, France, UK	15t16 and 17t19 and 36t37; 20 and 21t22 and 24 and 25 and 26 and 27t28; 29 and 30t33 and 34t35; 50 and 51 and 52 and H; 60t63; 64; 70 and 71t74; AtB; C and E; F; J; L; M; N; O.
Denmark	15t16; 17t19; 20; 21t22; 23t25; 23; 24; 25; 26; 27t28; 29; 30t33; 34t35; 36t37; 50; 51; 52; 60t63; 64; 70; 71t74; AtB; C; E; F; J; H; I; L; M; N; O.
Finland, Netherlands	15t16 and 17t19; 20 and 21t22 and 24 and 25 and 26 and 27t28; 29 and 30t33 and 34t35 and 36t37; 50 and 51 and 52 and H; 60t63; 64; 70 and 71t74; AtB; C and E; F; J; L; M; N; O.
Germany	15t16 and 17t19; 20 and 21t22 and 24 and 25 and 26 and 27t28 and 29; 30t33 and 34t35; 50 and 51 and 52 and H; 60t63 and 64; 70 and 71t74; AtB; C and E and 36t37; F; J; L; M; N; O.
Spain	15t16; 17t19; 20 and 21t22 and 23t25 and 26 and 27t28; 29; 30t33; 34t35; 36t37; 50 and 51 and 52; 60t63; 64; 70 and 71t74 and K; AtB; C; E; F; H; I; J; L; M; N; O.
Japan, USA	In alternatives 1 to 3: 15t16; 17t19; 20; 21t22; 23t25; 23; 24; 25; 26; 27t28; 29; 30t33; 34t35; 36t37; 50; 51; 52; 60t63; 64; 70; 71t74; AtB; C; E; F; J; H; I; L; M; N; O. In alternative 4: no aggregation

Table 6.1: List of industries pooled by country

6.2 Tables from the first step regression

6.2.1 Alternative one

	AUT.1980s	AUT.1990s	AUT.2000s
constant	0.019	0.053^{*}	$0.046^{\dagger}$
	(0.032)	(0.008)	(0.012)
log(wage premium)	0.114	$0.247^{\dagger}$	0.012
	(0.476)	(0.066)	(0.186)
log(capital intensity)	0.053	0.113	0.140
	(0.131)	(0.039)	(0.144)
N	5	5	5
R^2	0.776	0.987	0.989
adj. R^2	0.551	0.975	0.979
Resid. sd	0.231	0.054	0.017

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.2: Estimates for Austria, first step regression, alternative 1

	BEL.1980s	BEL.1990s	BEL.2000s
constant	0.016	0.050	0.014
	(0.007)	(0.025)	(0.014)
log(wage premium)	−0.642	0.116	0.051
	(0.636)	(0.420)	(0.206)
log(capital intensity)	0.029	−0.004	−0.016
	(0.058)	(0.050)	(0.126)
N	5	5	5
R^2	0.872	0.903	0.187
adj. R^2	0.744	0.806	−0.627
Resid. sd	0.122	0.060	0.060

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.3: Estimates for Belgium, first step regression, alternative 1

	DNK.1980s	DNK.1990s	DNK.2000s
constant	0.025*	0.019*	0.018
	(0.011)	(0.007)	(0.013)
log(wage premium)	0.047	0.015	0.043
	(0.063)	(0.029)	(0.146)
log(capital intensity)	−0.009	−0.005	0.005
	(0.016)	(0.014)	(0.070)
N	17	17	17
R^2	0.423	0.027	0.016
adj. R^2	0.340	−0.113	−0.124
Resid. sd	0.114	0.091	0.136

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.4: Estimates for Denmark, first step regression, alternative 1

	ESP.1980s	ESP.1990s	ESP.2000s
constant	0.037	0.064*	0.040
	(0.032)	(0.026)	(0.021)
log(wage premium)	0.115	−0.204	0.011
	(0.300)	(0.284)	(0.246)
log(capital intensity)	−0.031	0.022	−0.009
	(0.090)	(0.067)	(0.162)
N	10	10	10
R^2	0.166	0.547	0.002
adj. R^2	−0.072	0.417	−0.283
Resid. sd	0.539	0.548	0.529

Robust standard errors in parentheses

† significant at $p < .10$; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.5: Estimates for Spain, first step regression, alternative 1

	FIN.1970s	FIN.1980s	FIN.1990s	FIN.2000s
constant	0.060	0.065	0.072*	0.032
	(0.076)	(0.029)	(0.012)	(0.016)
log(wage premium)	0.132	−0.046	0.179	0.013
	(0.271)	(0.231)	(0.133)	(0.112)
log(capital intensity)	0.000	0.005	0.128	0.017
	(0.005)	(0.035)	(0.090)	(0.065)
N	5	5	5	5
R^2	0.659	0.554	0.986	0.100
adj. R^2	0.318	0.107	0.973	−0.799
Resid. sd	0.120	0.122	0.080	0.097

Robust standard errors in parentheses

† significant at $p < .10$; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.6: Estimates for Finland, first step regression, alternative 1

	FRA.1980s	FRA.1990s	FRA.2000s
constant	0.026	0.024	0.035
	(0.024)	(0.021)	(0.060)
log(wage premium)	0.127	0.067	0.099
	(0.188)	(0.332)	(0.150)
log(capital intensity)	−0.035	0.027	−0.078
	(0.097)	(0.177)	(0.138)
N	5	5	5
R^2	0.812	0.150	0.575
adj. R^2	0.624	−0.700	0.149
Resid. sd	0.370	0.656	0.438

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.7: Estimates for France, first step regression, alternative 1

	GER.1970s	GER.1980s	GER.1990s	GER.2000s
constant	0.009	0.046	0.009	0.004
	(0.004)	(0.066)	(0.018)	(0.010)
log(wage premium)	−0.259	−0.501	0.271	0.317
	(0.152)	(1.473)	(0.273)	(0.144)
log(capital intensity)	0.002	−0.031	0.126	−0.004
	(0.024)	(0.349)	(0.082)	(0.080)
N	5	5	5	5
R^2	0.926	0.272	0.960	0.885
adj. R^2	0.851	−0.456	0.919	0.770
Resid. sd	0.084	0.715	0.159	0.247

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.8: Estimates for Germany, first step regression, alternative 1

	JPN.1980s	JPN.1990s	JPN.2000s
constant	0.034***	0.062*	0.024
	(0.004)	(0.021)	(0.015)
log(wage premium)	0.023	0.102	0.416
	(0.108)	(0.207)	(0.598)
log(capital intensity)	−0.025***	−0.018	−0.007
	(0.006)	(0.067)	(0.105)
N	16	16	16
R^2	0.435	0.144	0.288
adj. R^2	0.348	0.012	0.179
Resid. sd	0.617	0.686	1.288

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.9: Estimates for Japan, first step regression, alternative 1

	NLD.1980s	NLD.1990s	NLD.2000s
constant	0.020	0.054	0.081
	(0.020)	(0.115)	(1.287)
log(wage premium)	0.047	0.291	0.780
	(0.195)	(0.746)	(11.390)
log(capital intensity)	0.052	−0.137	0.129
	(0.063)	(0.713)	(70.480)
N	5	5	5
R^2	0.644	0.651	0.791
adj. R^2	0.288	0.303	0.582
Resid. sd	0.104	0.260	0.541

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.10: Estimates for the Netherlands, first step regression, alternative 1

	UK.1970s	UK.1980s	UK.1990s	UK.2000s
constant	0.033	0.024	0.101	0.017
	(0.019)	(0.032)	(0.075)	(0.018)
log(wage premium)	−0.077	0.096	−0.775	0.292
	(0.368)	(0.220)	(1.650)	(0.625)
log(capital intensity)	−0.003	0.039	−0.088	−0.097
	(0.129)	(0.048)	(0.324)	(0.227)
N	5	5	5	5
R^2	0.757	0.855	0.297	0.383
adj. R^2	0.514	0.710	−0.405	−0.234
Resid. sd	0.249	0.266	1.250	0.591

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.11: Estimates for the UK, first step regression, alternative 1

	USA.1970s	USA.1980s	USA.1990s	USA.2000s
constant	0.071^{***}	0.061^{***}	0.039^{*}	0.039^{*}
	(0.011)	(0.008)	(0.016)	(0.016)
log(wage premium)	$0.102^{\dagger}$	0.026	$0.316^{\dagger}$	$0.316^{\dagger}$
	(0.053)	(0.074)	(0.154)	(0.154)
log(capital intensity)	−0.020	0.004	−0.006	−0.006
	(0.026)	(0.016)	(0.158)	(0.158)
N	15	15	15	15
R^2	0.281	0.022	0.581	0.581
adj. R^2	0.161	−0.142	0.511	0.511
Resid. sd	1.632	1.587	2.289	2.289

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.12: Estimates for the USA, first step regression, alternative 1

6.2.2 Alternative two

	AUT.1980s	AUT.1990s	AUT.2000s
constant	−0.025	−0.007	0.001
	(0.033)	(0.032)	(0.000)
log(wage premium)	2.005	0.387	−0.026
	(2.121)	(0.985)	(0.023)
N	5	5	5
R^2	0.578	0.147	0.429
adj. R^2	0.437	−0.137	0.238
Resid. sd	0.202	0.255	0.015

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.13: Estimates for Austria, first step regression, alternative 2

	BEL.1980s	BEL.1990s	BEL.2000s
constant	−0.003	−0.005	−0.006
	(0.009)	(0.003)	(0.007)
log(wage premium)	0.095	0.118	0.095
	(0.527)	(0.111)	(0.068)
N	5	5	5
R^2	0.029	0.216	0.618
adj. R^2	−0.295	−0.045	0.491
Resid. sd	0.146	0.083	0.033

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.14: Estimates for Belgium, first step regression, alternative 2

	DNK.1980s	DNK.1990s	DNK.2000s
constant	-0.015^{***}	-0.006	-0.015^{*}
	(0.002)	(0.004)	(0.007)
log(wage premium)	1.236^{***}	0.246	0.351
	(0.175)	(0.159)	(0.206)
N	17	17	17
R^2	0.859	0.238	0.689
adj. R^2	0.850	0.187	0.668
Resid. sd	0.052	0.078	0.073

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.15: Estimates for Denmark, first step regression, alternative 2

	ESP.1980s	ESP.1990s	ESP.2000s
constant	-0.013^{*}	$-0.013^{\dagger}$	-0.004
	(0.004)	(0.007)	(0.016)
log(wage premium)	0.653^{***}	$0.332^{\dagger}$	0.042
	(0.108)	(0.146)	(0.104)
N	10	10	10
R^2	0.683	0.438	0.026
adj. R^2	0.643	0.368	-0.096
Resid. sd	0.301	0.432	0.488

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.16: Estimates for Spain, first step regression, alternative 2

	FIN.1970s	FIN.1980s	FIN.1990s	FIN.2000s
constant	0.002	0.012	−0.073	−0.002
	(0.032)	(0.020)	(0.062)	(0.012)
log(wage premium)	−0.025	−0.106	0.299	0.007
	(0.316)	(0.120)	(0.243)	(0.037)
N	5	5	5	5
R^2	0.004	0.161	0.705	0.007
adj. R^2	−0.329	−0.119	0.607	−0.325
Resid. sd	0.147	0.136	0.123	0.080

Robust standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.17: Estimates for Finland, first step regression, alternative 2

	FRA.1980s	FRA.1990s	FRA.2000s
constant	−0.013	−0.014	0.001
	(0.014)	(0.011)	(0.018)
log(wage premium)	0.885	$0.589^{\dagger}$	−0.035
	(0.388)	(0.202)	(0.495)
N	5	5	5
R^2	0.865	0.907	0.007
adj. R^2	0.820	0.877	−0.324
Resid. sd	0.243	0.170	0.447

Robust standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.18: Estimates for France, first step regression, alternative 2

	GER.1970s	GER.1980s	GER.1990s	GER.2000s
constant	−0.006	−0.017	−0.014	−0.017
	(0.003)	(0.009)	(0.006)	(0.011)
log(wage premium)	0.189	0.439†	0.235	0.242
	(0.154)	(0.152)	(0.201)	(0.285)
N	5	5	5	5
R^2	0.895	0.855	0.933	0.850
adj. R^2	0.860	0.807	0.910	0.800
Resid. sd	0.080	0.254	0.131	0.224

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.19: Estimates for Germany, first step regression, alternative 2

	JPN.1980s	JPN.1990s	JPN.2000s
constant	−0.016*	−0.004	0.025
	(0.007)	(0.013)	(0.036)
log(wage premium)	0.149*	0.026	−0.113
	(0.066)	(0.086)	(0.204)
N	16	16	16
R^2	0.356	0.015	0.084
adj. R^2	0.310	−0.055	0.018
Resid. sd	0.478	0.667	1.403

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.20: Estimates for Japan, first step regression, alternative 2

	NLD.1980s	NLD.1990s	NLD.2000s
constant	−0.003	−0.014	0.040
	(0.009)	(0.027)	(0.049)
log(wage premium)	0.364	0.969	−1.443
	(0.484)	(0.978)	(0.938)
N	5	5	5
R^2	0.475	0.578	0.614
adj. R^2	0.301	0.437	0.486
Resid. sd	0.065	0.231	0.550

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.21: Estimates for the Netherlands, first step regression, alternative 2

	UK.1970s	UK.1980s	UK.1990s	UK.2000s
constant	−0.003	−0.013	$-0.079^{\dagger}$	−0.007
	(0.008)	(0.008)	(0.029)	(0.031)
log(wage premium)	0.666	0.436	1.765^{*}	0.074
	(1.755)	(0.262)	(0.520)	(0.211)
N	5	5	5	5
R^2	0.124	0.355	0.890	0.047
adj. R^2	−0.169	0.140	0.854	−0.271
Resid. sd	0.239	0.279	0.403	0.510

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.22: Estimates for the UK, first step regression, alternative 2

	USA.1970s	USA.1980s	USA.1990s	USA.2000s
constant	0.004	-0.030^{*}	$-0.075^{\dagger}$	$-0.075^{\dagger}$
	(0.025)	(0.013)	(0.037)	(0.037)
log(wage premium)	-0.045	0.198	0.332^{*}	0.332^{*}
	(0.164)	(0.128)	(0.115)	(0.115)
N	15	15	15	15
R^2	0.008	0.314	0.400	0.400
adj. R^2	-0.068	0.261	0.354	0.354
Resid. sd	1.794	1.267	2.628	2.628

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.23: Estimates for the USA, first step regression, alternative 2

6.2.3 Alternative three

	BEL.1980s	BEL.1990s	BEL.2000s
constant	0.129	0.039	−0.006
	(0.262)	(0.061)	(0.006)
log(wage premium)	−0.771	0.114	0.051
	(0.582)	(0.611)	(0.032)
log(capital intensity)	0.005	−0.014	0.010
	(0.097)	(0.090)	(0.019)
log(ICT intensity)	−0.307	0.065	0.212
	(0.719)	(0.352)	(0.047)
N	5	5	5
R^2	0.982	0.941	0.997
adj. R^2	0.929	0.763	0.989
Resid. sd	0.064	0.067	0.005

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.24: Estimates for Belgium, first step regression, alternative 3

	DNK.1980s	DNK.1990s	DNK.2000s
constant	0.036	0.013	0.014
	(0.042)	(0.041)	(0.016)
log(wage premium)	0.042	0.017	0.146
	(0.094)	(0.048)	(0.262)
log(capital intensity)	−0.008	−0.008	0.002
	(0.019)	(0.012)	(0.091)
log(ICT intensity)	−0.038	0.018	0.102
	(0.130)	(0.100)	(0.260)
N	17	17	17
R^2	0.436	0.045	0.049
adj. R^2	0.306	−0.175	−0.171
Resid. sd	0.116	0.094	0.138

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.25: Estimates for Denmark, first step regression, alternative 3

	ESP.1980s	ESP.1990s	ESP.2000s
constant	−0.024	0.025	0.040
	(0.074)	(0.087)	(0.022)
log(wage premium)	−0.023	−0.190	0.010
	(0.214)	(0.297)	(0.265)
log(capital intensity)	−0.000	0.020	−0.011
	(0.055)	(0.069)	(0.180)
log(ICT intensity)	0.204	0.258	0.005
	(0.256)	(0.535)	(0.206)
N	10	10	10
R^2	0.373	0.600	0.003
adj. R^2	0.060	0.401	−0.496
Resid. sd	0.505	0.556	0.571

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.26: Estimates for Spain, first step regression, alternative 3

	FIN.1970s	FIN.1980s	FIN.1990s	FIN.2000s
constant	0.057	0.171	0.120	0.014
	(0.182)	(0.125)	(0.186)	(0.304)
log(wage premium)	0.094	0.001	0.250	0.066
	(0.543)	(0.064)	(0.204)	(0.414)
log(capital intensity)	−0.000	−0.043	0.049	−0.018
	(0.187)	(0.078)	(0.256)	(0.595)
log(ICT intensity)	−0.093	−0.326	−0.185	0.383
	(1.587)	(0.405)	(0.685)	(5.370)
N	5	5	5	5
R^2	0.688	0.996	0.998	0.366
adj. R^2	−0.249	0.983	0.994	−1.535
Resid. sd	0.162	0.017	0.039	0.115

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.27: Estimates for Finland, first step regression, alternative 3

	FRA.1980s	FRA.1990s	FRA.2000s
constant	0.076	0.058	0.028
	(0.157)	(0.060)	(1.076)
log(wage premium)	0.044	0.121	0.097
	(0.355)	(0.225)	(2.125)
log(capital intensity)	−0.036	0.018	−0.065
	(0.139)	(0.099)	(0.816)
log(ICT intensity)	−0.213	−0.128	0.195
	(0.923)	(0.399)	(18.280)
N	5	5	5
R^2	0.994	0.944	0.579
adj. R^2	0.978	0.775	−0.683
Resid. sd	0.090	0.239	0.616

Robust standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.28: Estimates for France, first step regression, alternative 3

	GER.1970s	GER.1980s	GER.1990s	GER.2000s
constant	0.038	0.139	0.014	0.041
	(0.141)	(0.360)	(0.054)	(0.250)
log(wage premium)	−0.347	−0.400	0.271	0.069
	(0.509)	(3.218)	(0.430)	(2.254)
log(capital intensity)	0.001	−0.167	0.112	0.021
	(0.024)	(0.493)	(0.154)	(0.418)
log(ICT intensity)	−0.162	−0.520	−0.058	−0.479
	(0.810)	(2.147)	(0.508)	(3.275)
N	5	5	5	5
R^2	0.954	0.981	0.969	0.909
adj. R^2	0.816	0.922	0.875	0.635
Resid. sd	0.093	0.165	0.198	0.311

Robust standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.29: Estimates for Germany, first step regression, alternative 3

	JPN.1980s	JPN.1990s	JPN.2000s
constant	0.029	0.063*	0.008
	(0.024)	(0.027)	(0.045)
log(wage premium)	0.014	0.093	0.462
	(0.124)	(0.234)	(0.739)
log(capital intensity)	−0.024**	−0.018	0.015
	(0.007)	(0.068)	(0.132)
log(ICT intensity)	0.020	−0.020	0.274
	(0.096)	(0.166)	(0.739)
N	16	16	16
R^2	0.440	0.150	0.331
adj. R^2	0.300	−0.062	0.164
Resid. sd	0.639	0.712	1.300

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.30: Estimates for Japan, first step regression, alternative 3

	NLD.1980s	NLD.1990s	NLD.2000s
constant	−0.017	0.181*	0.066
	(0.113)	(0.006)	(2.393)
log(wage premium)	0.043	−0.446*	0.744
	(0.285)	(0.031)	(12.536)
log(capital intensity)	0.058	0.077	0.170
	(0.054)	(0.020)	(70.845)
log(ICT intensity)	0.131	−0.534*	0.221
	(0.365)	(0.021)	(31.637)
N	5	5	5
R^2	0.982	1.000	0.791
adj. R^2	0.927	1.000	0.165
Resid. sd	0.033	0.004	0.764

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.31: Estimates for the Netherlands, first step regression, alternative 3

	UK.1970s	UK.1980s	UK.1990s	UK.2000s
constant	0.025	0.042	0.048	0.044
	(0.009)	(0.026)	(4.939)	(0.024)
log(wage premium)	−0.333	0.132	−0.511	0.660
	(0.235)	(0.177)	(77.014)	(0.444)
log(capital intensity)	−0.086	0.018	−0.245	−0.177
	(0.075)	(0.061)	(13.806)	(0.173)
log(ICT intensity)	0.183	−0.075	0.310	−0.203
	(0.141)	(0.097)	(27.704)	(0.267)
N	5	5	5	5
R^2	0.993	0.996	0.729	0.979
adj. R^2	0.971	0.985	−0.083	0.916
Resid. sd	0.061	0.060	1.097	0.154

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.32: Estimates for the UK, first step regression, alternative 3

	USA.1970s	USA.1980s	USA.1990s	USA.2000s
constant	0.082**	0.033	0.174	0.174
	(0.020)	(0.037)	(0.123)	(0.123)
log(wage premium)	0.109†	0.039	0.172	0.172
	(0.058)	(0.105)	(0.173)	(0.173)
log(capital intensity)	−0.016	−0.002	0.004	0.004
	(0.021)	(0.021)	(0.134)	(0.134)
log(ICT intensity)	−0.179	0.104	−0.346	−0.346
	(0.192)	(0.157)	(0.324)	(0.324)
N	15	15	15	15
R^2	0.341	0.074	0.657	0.657
adj. R^2	0.162	−0.178	0.564	0.564
Resid. sd	1.631	1.612	2.162	2.162

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.33: Estimates for the USA, first step regression, alternative 3

6.2.4 Pooled regressions

	1970s	1980s	1990s	2000s
constant	0.054^{**}	0.008	$0.033^{\dagger}$	0.022
	(0.016)	(0.015)	(0.018)	(0.018)
log(wage premium)	0.087	$0.065^{\dagger}$	0.269^{*}	0.143
	(0.052)	(0.036)	(0.124)	(0.136)
log(capital intensity)	−0.007	−0.008	−0.000	−0.003
	(0.009)	(0.009)	(0.044)	(0.062)
N	30	93	93	93
R^2	0.498	0.457	0.506	0.275
adj. R^2	0.394	0.376	0.432	0.167
Resid. sd	1.231	0.743	1.099	0.958

Country effects included

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.34: Estimates of the first stage regression (all countries pooled), alternative 1

	1970s	1980s	1990s	2000s
constant	0.037***	−0.005	0.008	0.039***
	(0.009)	(0.022)	(0.028)	(0.007)
log(capital intensity)	−0.010	−0.003	0.006	0.024
	(0.010)	(0.010)	(0.065)	(0.051)
N	30	93	93	93
R^2	0.390	0.423	0.130	0.199
adj. R^2	0.292	0.345	0.012	0.091
Resid. sd	1.330	0.761	1.450	1.001

Country effects included

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.35: Estimates of the first stage regression (all countries pooled), alternative 2

	1970s	1980s	1990s	2000s
constant	0.059**	−0.002	0.078†	0.023
	(0.020)	(0.019)	(0.043)	(0.024)
log(wage premium)	0.089	0.064†	0.219*	0.143
	(0.055)	(0.036)	(0.109)	(0.133)
log(capital intensity)	−0.034	0.022	−0.062	−0.012
	(0.024)	(0.021)	(0.039)	(0.017)
log(ICT intensity)	−0.002	0.023	0.014	−0.004
	(0.022)	(0.019)	(0.048)	(0.023)
N	30	93	93	93
R^2	0.515	0.463	0.544	0.275
adj. R^2	0.389	0.375	0.469	0.156
Resid. sd	1.235	0.743	1.063	0.964

Country effects included

Robust standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6.36: Estimates for the first stage regression (all countries pooled), alternative 3

7 Abstract

7.1 English abstract

The wage distribution has been widening in nearly all developed countries. Changes in labour market institutions, international trade and technological advances are normally seen as the main reasons for this development.

In this work I explore a part of the explanation favouring technological innovations. Skill-biased technical change is the term for innovations which favour skilled workers relatively more than unskilled workers. These innovations are thought to have changed the tasks carried out by workers and, subsequently, changed labour demand and wages. What is not yet fully clear is how SBTC works across sectors.

Haskel and Slaughter (2002) conjecture that skill-intensive sectors (which are employing relatively more skilled workers than other sectors) experience larger SBTC and that this "sector bias" influenced the movement of the skill premium.

I find that there *is* evidence of a sector bias in several countries. However, there is *no* evidence that this sector bias mainly influenced the skill premium. This may be a consequence of labour market institutions, especially in Europe.

7.2 Deutsche Zusammenfassung

Die Lohnungleichheit ist in den letzten Jahrzehnten in beinahe allen industrialisierten Ländern gestiegen. Als Hauptgründe für diese Entwicklung werden meist gestiegener internationaler Handel, geschwächte Arbeitsmarktinstitutionen und technologischen Wandel gesehen.

Technologischer Fortschritt wird als "skill-biased" beschrieben, das heißt, gut ausgebildete Personen profitierten mehr vom technologischen Fortschritt als eher schlecht ausgebildete Personen. Eine der aussagekräftigsten Theorien besagt, dass die Einführung von Computer (die als das Symbol der Fortschritts gesehen werden) die zu erledigenden Aufgaben in einem Beruf verändert hat. Computer scheinen menschliche Arbeit in Routineaufgaben ersetzt zu haben. Davon waren vor allem mäßig qualifizierte Arbeiter und Angestellte betroffen.

In dieser Arbeit untersuche ich einen Teilaspekt von jenen Erklärungen, die Technologie als die treibende Kraft hinter der steigenden Lohnungleichheit sehen. Haskel and Slaughter (2002) vermuten, das technologischer Fortschritt nicht nur "skill-biased", sondern auch "sector-biased" ist. Dies würde bedeuten, dass Industriesektoren, die relativ mehr ausgebildete Arbeiter verwenden auch mehr qualifikationsbevorzugenden technologischen Fortschritt verzeichnen. Sie vermuten weiters, dass diese Tendenz die Lohnungleichheit entscheidend beeinflusst hat.

Meine Resultate zeigen, dass es in einigen Ländern Beweise für diesen "sector bias" gibt. Dieser sektorale Bias scheint allerdings keinen großen Einfluss auf den relativen Lohn von gut und schlecht ausgebildeten Arbeitern gehabt zu haben. Arbeitsmarktinstitutionen könnten diesen Zustand erklären.

Oliver Reiter

CONTACT INFORMATION
Liechtensteinstraße 95/14
1090 Vienna
E-mail: a0603045@unet.univie.ac.at

PERSONAL INFORMATION

Birthday	3. October 1985
Place of birth	Linz
Citizenship	Austria
Marital status	Single

SECONDARY EDUCATION

Primary school in Waldhausen, 1992 - 1996, Upper Austria

Secondary school in Waldhausen, 1996 - 2000, Upper Austria

Academy of commerce in Perg, 2000 - 2005, Upper Austria

TERTIARY EDUCATION

University of Vienna, Vienna, Austria

Bakk.rer.soc.oec., Economics, November 2009

- Subject of first bachelor thesis: *Fertility Reduction in India*
- Subject of second bachelor thesis: *Wage Inequality and Technical Change*

Bakk.rer.soc.oec., Statistics, November 2012

- Subject of first bachelor thesis: *Linear Optimization in Microeconomics*
- Subject of second bachelor thesis: *Wage Inequality and Technical Change*

Master program in Economics Currently 6^{th} semester

WORK EXPERIENCE

R-Programming, joint with Prof. Schlag

Package "npExact" **Summer 2012 until now**

- Creation
- Writing of the functions
- Available on Github
- Still in development phase

LANGUAGE SKILLS

Excellent knowledge
- English

Advanced knowledge
- French
- Spanish