Knowledge Spillovers and Wage Inequality: An Empirical Investigation of Knowledge-Skill Complementarity*

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Abstract

This paper examines the importance of knowledge-skill complementarity in the process of contemporary economic growth. By analyzing Dutch manufacturing and carrying out an extensive spillover and wage inequality analysis, it is shown that knowledge-intensive sectors pay their high-skilled workers a relatively higher wage in the form of a wage premium, which is defined as the sector bias of technical change.

Keywords: Knowledge; Spillovers; Wage inequality.

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1. Introduction

There is a growing recognition that knowledge, both as an input in the production process and as a final product, becomes central to the contemporary process of economic growth and wealth accumulation. Put differently, most industrialized economies have increasingly become, what some scholars in the field of economic growth call, knowledge-based.[1] This shift in perception brings in many ways to the forefront the importance of Joseph Schumpeter's work on technological regimes through which the innovative process, which enhances, induces and possibly accelerates economic growth, takes place.[2] Figure 1 gives a basic schematic presentation of economic activities in a Schumpeterian environment. This figure shows us that a firm possibly splits its labour force in a research department and a manufacturing division. In the research department, workers are supposed to invent new products and/or technology standards, while workers in the manufacturing division produce intermediate goods, that are used to create the final output of a particular firm.

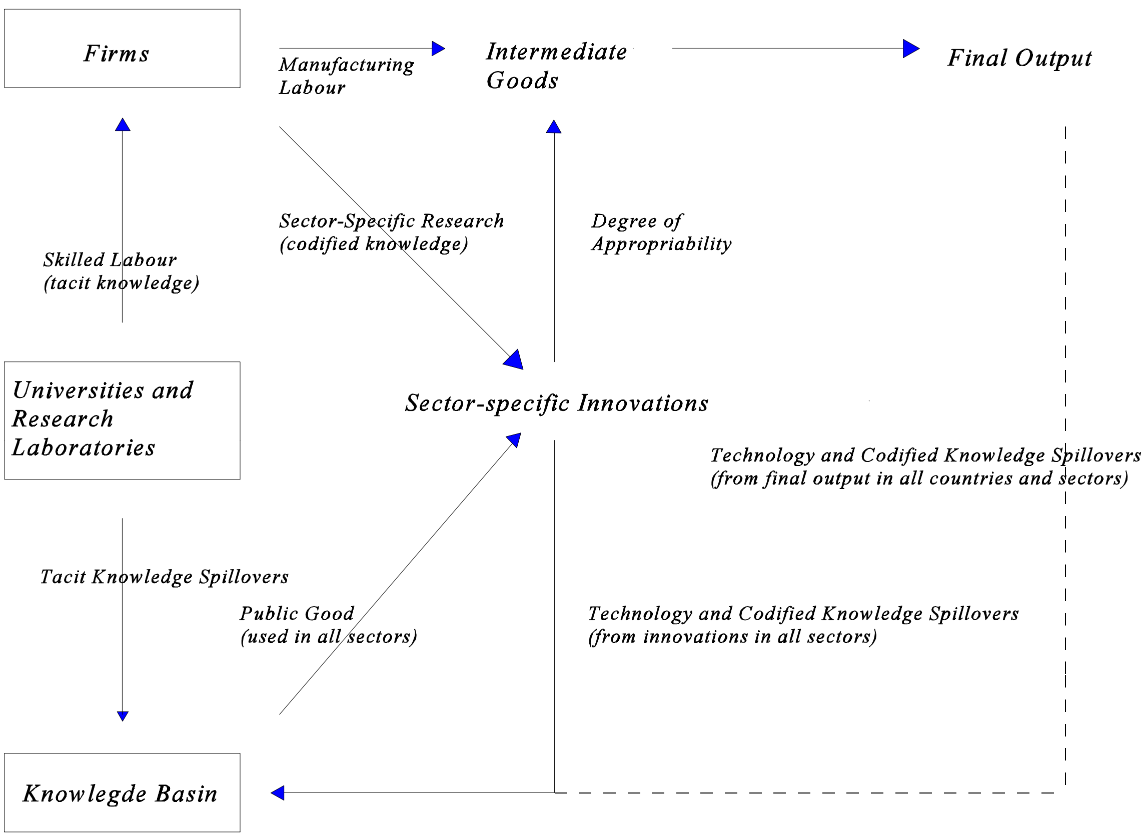
Sector-specific innovations are induced and occur because of the effort of the firm's research department on the one hand, and public knowledge from the public basin on the other hand. Once a firm has invented a new product and/or technology standard, it depends on the degree of appropriability whether the knowledge used to innovate spills over to the public knowledge basin or not. Public knowledge is also enhanced by research performed at universities and other research institutes. Their output in the form of knowledge is often published in scientific journals or transmitted by channels such as conferences. This improves the overall knowledge stock in the economy and induces innovative activities. Moreover, universities educate individuals that

[1] As Edmund Phelps (1998) recently noted at a conference in Barcelona: "... one can argue that the new technologies represent a change in the character of technical progress ..." (p. 11). Hollanders *et al.* (1999) provide a report on the importance of knowledge creation for economic growth. See also Coyle (1998), Herzenberg *et al.* (1998) and Kelly (1998) for contributions concerning the new economy. For other contributions in this regard, see e.g. several papers in Howitt (1996).

[2] See Nelson and Winter (1982) and Winter (1984) for influential contributions with respect to the modelling of Schumpeterian technological regimes. The former is primarily concerned with the basic mechanics of Schumpeterian competition, particularly innovative and imitative strategies and their influence on the evolution of industrial structures, while the latter extended this model with endogenous entry and adaptive R&D strategies of firms, which emphasized the main characteristics of Schumpeter Mark I and Schumpeter Mark II technological regimes.

enter sooner or later the labour force. By means of education the labour force becomes more productive because individuals obtain a higher skill level. These skills can be applied in both the manufacturing division and the research department of the firm. By employing skilled individuals, labour productivity levels are supposed and expected to increase. This in turn leads to higher levels of innovative activities in the research department, on the one hand, and higher levels of production in the manufacturing division, on the other. Of course, these skilled individuals can also be employed at the universities themselves. Employing them at universities leads to a direct positive effect on the stock of public knowledge, while employing skilled individuals at firms or in the business sector leads to possible indirect effects on the stock of public knowledge through the effort put in innovative activities at the firm level.

Figure 1: A Schematic Representation of Knowledge Creating Activities



Source: Adapted from Aghion and Howitt (1998) and Soete and Ter Weel (1999)

This framework clearly explicates arguments stressing the major importance of both codified (through performing R&D) and tacit knowledge (creation of skills) creation. Furthermore, the main problems and challenges put forward by this model are first the means to perform research in order to develop both tacit and codified knowledge, This traditional argument is used to show that some sectors or firms perform worse than others; secondly, and most importantly, the framework provides an argument to acquire knowledge through access to the knowledge basin. This basin consists mainly of codified knowledge measured by e.g. the number of patents, licences and copyrights, but there is also a tacit component involved. Access to the knowledge basin enhances the level of codified knowledge in sectors that do not produce this knowledge, by means of R&D, themselves. This observation stresses an important new opportunity for less-advanced sectors to profit from the knowledge created in the leading sectors by means of spillovers.

Once access to the knowledge basin is obtained, the knowledge has to be articulated and communicated in order to be productively applied in the production process. This cannot be achieved without appropriate skills, and organizational and institutional structures. Of course, skills are needed to unravel the knowledge obtained via access to organizations and institutions in such a manner that the newly acquired production factor can be applied in an efficient way in the production process. Hence, tacit knowledge embodied in human beings and organizations in order to appropriately apply and use codified knowledge has to be present. This observation is in line with the notion of capital-skill complementarity but can be modified as the knowledge-skill complementarity, because the capital used in this setting is codified knowledge and the skills to use this codified knowledge have to be extracted from the tacit knowledge stock in order to fully profit from the appropriated codified knowledge. This means that there has to be a certain level of skills and organizational design in a firm or sector to apply codified knowledge efficiently in the production process. This tacit knowledge can be obtained either by educating the existing stock of employees to acquire the appropriate skills or by attracting high-skilled workers from advanced sectors (tacit knowledge spillovers in terms of Figure 1). Hence, access to codified knowledge has to go hand in hand with the development of tacit knowledge.

In this paper, first the importance of codified knowledge and in particular knowledge spillovers is stressed. The purpose of this analysis is to show how codified knowledge created in one particular sector - either domestic or foreign - is applied and used in the Dutch economy. This analysis gives both a clear picture of the codified knowledge flows within the Dutch manufacturing sector and the dimension or degree to which imported knowledge has an impact on the production process. Section 3 deals with the tacit knowledge creation needed to produce efficiently. This section investigates whether some groups profit more from the creation of tacit knowledge than others by examining the issue of wage inequality. By means of analysing wage inequality it is possible to distinguish between skill groups in order to investigate the returns to tacit knowledge in several manufacturing sectors. Section 4 defines which individuals profit more than others from technical change by answering the following questions: Do knowledge-intensive sectors (as determined in section 2) pay white-collar workers like managers, scientists and engineers a higher wage relative to blue-collar workers than white-collar workers in less knowledge-intensive sectors? This exercise is carried out to build a distinctly and sharply outlined representation of a test for skill-biased technical change based on the type of job in the different sectors. Second, using the same cross-sectional data set the following question with respect to level bias in skill-biased technical change is explored: Do knowledge-intensive sectors pay high-skilled workers a higher wage relative to low-skilled workers than less knowledge-intensive sectors? The objective of this second question is to provide a more comprehensive picture of the relationship between workforce characteristics, technology and job level at the sector level. This paper ends with some concluding remarks.

2. Codified Knowledge

Economic theory has traditionally recognized the crucial role of codified knowledge accumulation in the process of economic growth. Without technical change, which results from innovation and performing R&D, capital accumulation will not be sustained - its marginal productivity declining - and the equilibrium (per capita) growth rate will inexorably tend towards zero, inducing rising inequality and unemployment rates - cf. Roland Bénabou (1996) and Piet Keizer and Ter Weel (1999). Philippe Aghion and Peter Howitt (1998a, pp. 123-143) show that it is because of inventions of new machines and intermediate goods that opportunities for new investment are provided and exploited. Hence, as has been shown in many empirical studies, the efficiency gains, following the introduction, diffusion and continuous improvement of new production processes and techniques, have been the major factor behind the rise in wealth (for some groups in society) over the post-war period in the OECD economies.[3]

Hence, codified knowledge plays a crucial role in a country's growth performance. This means that countries can directly increase their codified knowledge base by spending resources on R&D, but countries - and the industrial sectors within a country - can also benefit indirectly from the R&D performed in other sectors and/or countries. These knowledge or R&D spillovers play an ever more important role in explaining economic growth. The creation of knowledge will thus be characterized by significant spillovers, because knowledge created will not be fully appropriated and will flow to other firms in the same sector, to other using sectors, and of course to other countries, as shown in Figure 1. Econometric studies have established how such R&D spillovers play a significant role in explaining economic growth.[4] E.g., David Coe and Elhanan Helpman (1995) study international R&D spillovers in a long-run equilibrium model and conclude that R&D spillovers play a prominent role in the explanation of productivity growth and productivity convergence across countries. This long-run equilibrium model is a useful tool to investigate the extent to which a country's productivity level depends on domestic and foreign R&D capital stocks. Jeffrey Bernstein and Pierre Mohnen (1991) have shown that it is important to account for temporary deviations from long-run equilibrium growth paths in measuring productivity growth because simply assuming that producers are always employing their long-run equilibrium capital stock can lead to biases in measured productivity growth. Bernstein and Mohnen (1998) account for these deviations from long-run equilibrium by using adjustment costs. Their results are in line with other studies associated with domestic R&D spillovers - see Zvi Griliches (1992), as well as the social rates obtained by Coe and Helpman (1995) in a multi-country context and Coe, Helpman and Alexander Hoffmaister (1997) in a North-South model.

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[3] See the macroeconomic models by e.g. Layard and Nickell (1986), Fitoussi and Phelps (1988), Layard *et al.* (1991), Sarantis (1993) and Phelps (1994). See Madsen (1998) for an interesting overview of the explanatory capabilities of these models. See also Soete and Ter Weel (1999) for a contribution regarding the continuous improvement of new policy instruments to enhance economic growth.

[4] Griliches (1998) provides an interesting overview of econometric evidence with respect to R&D and productivity.

Griliches (1992) defines in his analysis, on the one hand, rent spillovers generated by international trade and, on the other hand, knowledge spillovers generated by blue prints like patent information, scientific literature and imitation. Particularly the latter is of main importance for the analysis carried out here.

The remainder of this section explores and stresses the importance of the impact of knowledge spillovers on labour productivity in the Netherlands, from 1973 to 1995, using the 'technology flow matrix', developed in Bart Verspagen (1997a) and (1997b), to describe knowledge flows from the knowledge producing to the knowledge consuming sectors.

The analysis is built on the following simple Cobb-Douglas production function

$$Y_{j,t} = A_j K_{j,t}{}^{\alpha} L_{j,t}{}^{\beta} CK_{j,t}{}^{\rho} ICD_{j,t}{}^{\delta} ICF_{j,t}{}^{\phi} \qquad (1)$$

where subscript j refers to sector j and t is the time indicator. The data used refer all to manufacturing sectors and are taken from the OECD STAN, ANBERD and BITRA databases.[5] Y is defined as value added generated in the production process, A is a scale variable, K is the capital stock, L the amount of labour used in the production process, CK the codified knowledge created and applied in sector j, ICD is the codified knowledge available from the public knowledge basin in the Netherlands, and ICF is the codified knowledge available from the public knowledge basin in the rest of the world, i.e. indirect knowledge spillovers from abroad. The parameters α, β, ρ, δ, ϕ are the elasticities with respect to each of them.

The physical capital and codified knowledge stock are determined by using the perpetual inventory method, i.e.

[5] The following 22 sectors are included in our analysis (ISIC code in brackets): Food, beverages and tobacco (31), Textiles, apparel and leather (32), Wood products and furniture (33), Paper, paper products and printing (34), Pharmaceuticals (3522), Other Chemicals (351+352-3522), Refined oil and related products (353+354), Rubber and plastic products (355+356), Glass, stone and clay (36), Ferrous metals (371), Non-ferrous metals (372), Metal products (381), Non-electrical machinery (382-3825), Office and computing equipment (3825), Radio, TV and communication equipment (3832), Electrical machinery (383-3832), Shipbuilding (3841), Automobiles (3843), Aerospace (3845), Other transport equipment (384-3841-3843-3845), Instruments (385) and Other manufacturing (39).

$$K_t = (1-\varphi)K_{t-1} + I_{K,t} \tag{2}$$

and

$$CK_t = (1-\chi)CK_{t-1} + I_{CK,t} \tag{3}$$

where φ and χ are the depreciation rates with respect to the physical capital and codified knowledge stock, respectively, while $I_{K,t}$ and $I_{CK,t}$ are defined as the (annual) investments in both stocks. For K_t and CK_t a depreciation rate of 5% and 15% is assumed, respectively.[6]

The indirect codified knowledge stocks are constructed using the technology flow matrix.[7] The domestic indirect codified knowledge stock for sector k is defined as

$$ICD_k = \sum_j \omega_{jk} CK_j (1-m_j) \tag{4}$$

and the foreign codified knowledge stocks for the same sector are defined as

$$ICF_k = \sum_F \sum_j \omega_{jk} CK_{Fj} s_{Fj} m_j \tag{5}$$

Following the analysis in Figure 1, ω_{jk} is defined as the part of sector-specific part of R&D performed by sector j that spills over to sector k; m_j is the import share of sector j in terms of intermediary goods.[8] The number of countries included in F is limited to the following set: Australia, Canada, Denmark, Finland, France, Germany, Italy, Japan, Norway, Spain, Sweden, UK and US. The variable labelled s_{Fj} gives the import share of sector j in the Netherlands from country F.

Finally, equation (1) is rewritten in log-form in order to perform the estimations. This is done by dividing every variable, except *ICD* and *ICF*, by L and subsequently taking logarithms. This

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[6] The initial capital and knowledge stocks are defined in the following manner $K_0 = (I_{K,1})/ (\varphi + 0.05)$ and $CK_0 = (I_{CK,1})/ (\chi + 0.05)$. This is in line with definitions suggested in Griliches (1980).

[7] Annex 1 provides the technology flow matrix.

[8] It is important to note that the diagonal of the technology flow matrix with respect to the calculation of the domestic knowledge stock is put at zero to exclude the problem of multicollinearity, i.e. $\omega_{jj} = 0$.

leads to equations (6)[9] which is subject to further estimation:

$$y_{j,t} - l_{j,t} = a + \alpha(k_{j,t} - l_{j,t}) + \lambda l_{j,t} + \rho(ck_{j,t} - l_{j,t}) + \delta\, icd_{j,t} + \phi\, icf_{j,t} \tag{6}$$

The database constructed to estimate equation (6) is a panel database. Hence the so-called 'within' regression method is used.[10] The reason to use the 'within' regression method is that it gives a strong and comprehensive picture of the development over time; in this case 1973-1995. The results of the regressions are displayed in Table 1.[11]

Table 1: Regression results knowledge spillovers

	α	ρ	δ	φ	**R^2 adj.**
	k-l	*ck-l*	*icd*	*icf*	
(1)	0.379 (0.033)	0.102 (0.023)			0.425
(2)	0.199 (0.045)	0.106 (0.022)	0.210 (0.037)		0.463
(3)	0.214 (0.037)	0.079 (0.022)		0.165 (0.020)	0.496
(4)	0.140 (0.044)	0.085 (0.022)	0.117 (0.038)	0.139 (0.022)	0.505

Note: Standard errors in brackets.

Regression (1) shows the regression results without taking into account domestic and international codified knowledge spillovers. The coefficient of the capital-labour ratio is 38% and the direct codified knowledge stock has a positive and significant effect on labour productivity: 10%. The second row shows the effect of including domestic codified knowledge spillovers. The

9 to which an error term is added.

10 This method is in essence an OLS-regression in which per sector the average value of the variable is subtracted from the variable's actual value.

11 Note that $\lambda = \alpha + \beta + \rho - 1$. Including the λ-term in these regressions results in statistically insignificant coefficients (the hypothesis of constant returns to scale is thus not rejected). Hence, we have excluded the λ-term in the regression results shown in Table 1.

elasticity of the capital-labour ratio is now 20%, whereas the elasticity of the direct codified knowledge stock increases to 11%, The indirect domestic codified knowledge stock shows a large significant effect on labour productivity: 21%. The fact that the elasticity of the domestic indirect codified knowledge stock is twice as large as the elasticity of the direct codified knowledge stock, indicates the importance of the public knowledge basin for labour productivity.

International codified knowledge spillovers also have a large and significant effect on labour productivity, as shown in the third row: 17%. The elasticity of the capital-labour ratio is now 21% and that of the direct codified knowledge stock has decreased to 8%. International codified knowledge spillovers thus have an effect on labour productivity which is twice as large as that of the sectors' own direct codified knowledge stock. Finally, the fourth row in Table 1 shows the regression results when we include both domestic and international codified knowledge spillovers. Both spillovers are of central importance to Dutch manufacturing, with the elasticity of international spillovers not only being about 20% larger than that for domestic spillovers, but also being of the same size as that for the capital-labour ratio.

Table 1 has shown the importance of domestic and international codified knowledge spillovers as the elasticities of these spillovers are about twice as large as that of the direct knowledge stock. However, the latter still dominates these indirect knowledge stocks in absolute terms. From 1973 to 1995 the ratio of the direct to the sum of both the domestic and foreign indirect knowledge stocks has decreased from 1.3 to 1.0. The importance of codified knowledge spillovers for Dutch manufacturing thus seems to be increasing over time, particularly with regard to spillovers originating from abroad. Whereas the direct and indirect domestic codified knowledge stocks rose almost twofold between 1973 and 1995, the foreign codified knowledge stock rose threefold.

Table 2 shows the relative contribution of each sector to the domestic direct and indirect codified knowledge stocks, which are calculated as follows:

$$\frac{CK_j / \sum_j CK_j}{Y_j / \sum_j Y_j} \tag{7a}$$

and

$$\frac{ICD_j / \sum_j ICD_j}{Y_j / \sum_j Y_j} \qquad (7b)$$

A value larger than 1 in equations (7a) and (7b) indicates a more than average contribution to the direct or indirect codified knowledge stock. Table 2 shows that this value exceeds 1 for the following 7 sectors: Pharmaceuticals (3522), Office and computing equipment (3825), Radio, TV and communication equipment (3832), Aerospace (3845),[12] Other chemicals (351+352-3522), Electrical machinery (383-3832) and Automobiles (3843).[13]

The last part of Table 2 shows for each sector the relative contribution to the indirect codified knowledge stock divided by that of the direct codified knowledge stock, i.e. the elasticity of an increase in the indirect codified knowledge stock as a result of an increase in the direct codified knowledge stock. For most manufacturing sectors this value exceeds 1. This emphasizes the important role of knowledge spillovers in generating labour productivity and thus economic growth. Each additional dollar which is spent on increasing the direct knowledge stock, will lead to an increase of the indirect knowledge stock of more than one dollar.[14]

[12] These are defined by the OECD as high-technology sectors (OECD, 1998).

[13] These are defined by the OECD as medium-high-technology sectors (OECD, 1998).

[14] The exceptional high values in Table 2 for the sector Electrical Machineries is due to Philips. All spendings on R&D are computed in this sector, while the production of Philips takes place in many sectors.

Table 2: Knowledge and relative sector importance

Sectors		Relative contribution Direct knowledge stock / value added				Relative contribution Indirect knowledge stock / value added				Indirect/ direct			
		76-80	81-85	86-90	91-95	76-80	81-85	86-90	91-95	76-80	81-85	86-90	91-95
High-technology													
Pharmaceuticals	3522	5.13	5.17	3.87	4.43	4.72	4.55	3.48	4.02	0.92	0.88	0.90	0.91
Office and computing equipment	3825	4.72	2.76	3.38	5.82	4.15	2.47	3.67	6.02	0.88	0.89	1.08	1.03
Radio, TV and communication equipment	3832	1.72	1.66	1.70	1.75	1.30	1.30	1.31	1.30	0.76	0.78	0.77	0.74
Aerospace	3845	0.88	2.28	3.34	2.25	1.34	3.18	4.14	2.68	1.52	1.40	1.24	1.19
Medium-high-technology													
Other chemicals	351+352-3522	1.84	2.28	1.81	1.90	1.43	1.78	1.40	1.45	0.78	0.78	0.77	0.76
Non-electrical machinery	382-3825	0.56	0.49	0.42	0.41	0.28	0.23	0.20	0.20	0.50	0.48	0.49	0.49
Electrical machinery	383-3832	31.70	18.33	28.68	27.10	36.37	21.69	33.48	30.76	1.15	1.18	1.17	1.14
Automobiles	3843	1.28	1.14	1.32	1.77	1.59	1.46	1.79	2.41	1.24	1.29	1.36	1.37
Instruments	385	0.76	0.60	0.49	0.64	0.77	0.60	0.53	0.69	1.01	0.99	1.06	1.08
Medium-low-technology													
Refined oil and related products	353+354	0.84	0.64	0.49	0.43	1.33	0.98	0.79	0.74	1.57	1.52	1.61	1.72
Rubber and plastic products	355+356	0.31	0.31	0.26	0.27	0.62	0.65	0.54	0.58	2.01	2.07	2.09	2.18
Glass, stone and clay	36	0.11	0.10	0.10	0.09	0.14	0.14	0.13	0.13	1.29	1.33	1.31	1.43
Ferrous metals	371	0.43	0.44	0.42	0.52	0.50	0.49	0.47	0.61	1.14	1.10	1.13	1.16
Non-ferrous metals	372	0.66	0.45	0.28	0.41	0.86	0.59	0.39	0.72	1.30	1.31	1.39	1.77
Metal products	381	0.07	0.11	0.14	0.16	0.08	0.12	0.16	0.19	1.19	1.13	1.16	1.13
Shipbuilding	3841	0.20	0.21	0.16	0.13	0.30	0.29	0.21	0.20	1.51	1.36	1.37	1.50
Low-technology													
Food, beverages and tobacco	31	0.45	0.43	0.40	0.41	0.62	0.58	0.55	0.60	1.37	1.35	1.39	1.46
Textiles, apparel and leather	32	0.11	0.11	0.11	0.12	0.14	0.15	0.16	0.18	1.31	1.37	1.41	1.46
Wood products and furniture	33	0.06	0.03	0.02	0.02	0.10	0.05	0.04	0.04	1.63	1.59	1.80	1.94
Paper, paper products and printing	34	0.05	0.04	0.03	0.03	0.07	0.06	0.05	0.05	1.45	1.47	1.48	1.56

Except for Pharmaceuticals, Radio, TV and communication equipment, Other Chemicals and Non-electrical machinery, all sectors show an elasticity larger than 1. Aerospace and Office and computing equipment are the only high-technology sectors having an elasticity larger than 1. The fact that all low-technology and medium-low technology sectors show an elasticity exceeding 1, stresses the (growing) importance of codified knowledge spillovers, which not only originate in the high-technology sectors, but especially in all low- and medium-low-technology sectors in Dutch manufacturing.

In general, the results stress the importance of R&D efforts and codified knowledge spillovers for productivity growth. However, the results also suggest that codified knowledge easily spills over from one sector and one country to another, pointing to the difficulties in internalizing the fruits of innovating activities. In the next section tacit knowledge (skills) is under consideration. In section 5 the two types of knowledge are combined in what we call a knowledge-skill complementary framework.

3. Tacit Knowledge

Whereas the embodiment of technology in physical capital has long been recognized, the increasing importance of tacit knowledge embodied in organizations and people has been recognized much more recently in the pioneering contributions by Gary Becker (1962) and Theodore Schultz (1961). Yet, there is little doubt that the way to apply and use a particular technology is fully part of that specific technology: human skills are essential and important complementary assets to implement, maintain, adapt to and use new physically embodied technologies. From this perspective, as noted recently by Daron Acemoglu (1998) and Claudia Goldin and Lawrence Katz (1998), and already initiated by an early contribution of Griliches (1969), human capital and technology are two faces of the same coin, two non-separable aspects of knowledge accumulation.

Accumulation of human capital that goes along with the introduction of new technologies, can involve as well an increase in tacit knowledge embodied in skilled workers as an increase in the number of skilled workers working in a specific plant or industry. This observation clearly has non-negligible effects on employment and wages, because when introducing new technologies leads to an increase in the knowledge and human capital embodied in a specific part of the existing stock of employees, lower levels of employment and wage inequality will be the result.[15]

This idea is obviously closely related to the contemporary discussions on skill-biased technical change and (wage) inequality - cf. Chinhui Juhn, Kevin Murphy and Brooks Pierce (1993). Since a higher proportion of skilled workers in the labour force implies a large market for high-skilled technology, an increase in the supply of skills induces skill-biased technical change, as a result of the employment of these skilled workers, despite rising relative wages.[16] In the econometric literature concerning the impact of technical change on employment and wages, much evidence has been brought together highlighting the reduction of the demand for low-skilled labour relative to the demand for high-skilled labour. This skill bias can be explained by various factors. For instance, in Griliches (1969) it is due to the relative decline of the price of capital, while Michael Denny and Melvyn Fuss (1983) attribute the skill bias to the specific effects of technical change. Murphy, Craig Riddell and Paul Romer (1998) conclude that new technologies are relative complements with more educated labour, which is closely related to the thesis that machinery and new technologies harm low-skilled workers. In general the rationale for the argument put forward is that high-skilled workers and advanced capital equipment are complements - reinforcing the argument that tacit and codified knowledge development have to go hand in hand - whereas high-skilled labour and low-skilled labour are substitutes - pointing towards the insurmountable dispersion within the creation of tacit knowledge in the production process.

The debate on the wage premium on skills and tacit knowledge due to new technologies at the individual level has been initiated by an influential study of Alan Krueger (1993), but the

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[15] Wood (1998) and Francois and Nelson (1998) enter the debate on wage inequality by referring to the increasing globalization and the subsequent new opportunities for trade as a major cause of (wage) inequality.

[16] See e.g. Berman *et al.*(1998) and Machin and Van Reenen (1998) for recent empirical evidence in this regard and Acemoglu (1998), Aghion and Howitt (1998b) and Hollanders and Ter Weel (1998) for an elaborate theoretical framework.

evidence from several studies is not conclusive. Krueger shows that in the US the use of computers brought the workers surveyed a wage premium of some 15%. Such a premium could be attributed either to an increase in productivity or to user's personal characteristics, which led them in all cases to receive significantly higher wages. Krueger favours the first explanation, even though cross-section data did not allow for such conclusions to be drawn. By contrast, Horst Entorf and Francis Kramarz (1997) show for France that workers using computers did already receive a higher wage before they started using one. Moreover, John DiNardo and Jorn-Steffen Pischke (1997) - in a critical assessment of Krueger's results - observe for Germany that the use of pencils has a similar effect on the wage rate as computer use has. Only Brian Bell (1996), using a sample of one thousand individuals finds a net increasing effect on wages for those using computers at work.[17]

The recognition of the importance of the much broader notion of knowledge accumulation - including alongside capital, in the form of codified knowledge, and human embodied technical change, in the form of tacit knowledge, also disembodied technical change, is challenging not only the traditional focus on the R&D process, but the whole spectrum of scientific and technical activities from invention to diffusion, from basic research to technical mastery. Such a view of technical change rejects the orthodox definition of technical capabilities in terms of knowledge or information with the connotation that industrial technology is like a recipe; understood by particular individuals and readily articulatable and communicable from one individual to another with the requisite background training and skills. Knowing how to produce a product, is as much experienced tacit skill as articulatable knowledge. Contrary to the implicit general theory, tacit skills of a skilled worker in the art are not interchangeable: who works with the recipe makes a difference. Therefore, training new workers has become much more expensive when one takes these arguments into account and the human capital of a firm will increasingly be embodied in less high-skilled individuals, thereby further increasing the gap between high-skilled an low-

[17] Other empirical work carried out by e.g. Baldwin, Divery and Johnson (1995) for Canada, Bellman and Boeri (1995) for Germany, Vainiomaki and Laaksonen (1995) for Finland, Entorf and Kramarz (1997) for France, Bruinshoofd and Ter Weel (1998) for the Netherlands, Chennells and Van Reenen (1997) and Hildreth (1998) for the UK and Doms, Dunne and Troske (1997) for the US find that there exists a technology wage premium. See also e.g. Autor, Katz and Krueger (1998), Bartel and Sicherman (1995), Bound and Johnson (1992), Heckman, Lochner and Taber (1998), Heckman and Sedlacek (1985), Katz and Murphy (1992), Meghir and Whitehouse (1996) and Nickell and Bell (1995) and (1996).

skilled workers. Moreover, this trend can also induce a sector bias in technical change, since some sectors might have more resources and scope to invest in knowledge, both codified and tacit, which can lead to large differences in the accumulation of tacit knowledge, inducing an absorbing effect on high-skilled labour from other sectors - cf. Bruinshoofd and Ter Weel (1998) and Jonathan Haskel and Matthew Slaughter (1998) for one of the initial empirical assessments of the sector bias of technical change.

In this section the evolution and creation of tacit knowledge over the last decade in the Netherlands is under empirical investigation. This is performed by analysing the perception of increased wage inequality during the past years. The main objective is to carefully make a distinction between the sector bias component in wage inequality and the job level measure, i.e. high-skilled versus low-skilled workers. In this manner it is possible to distinctly and sharply judge whether in some sectors wage divergence is due to the type of job an individual performs and the knowledge involved (i.e. white-collar versus blue-collar) or whether wage divergence is a consequence of job levels (i.e. high-skilled versus low-skilled jobs). To do so, first the following standard wage equation is constructed and estimated for 1996:[18]

$$\ln WH_i = \alpha_i + AGE_i + D_i^{WBEAA} + D_i^{GENDER} + ED_i + LEV_i + \sum_{i=1}^{n} D_{j,i}^{SECTOR} + \sum_{i=1}^{n} D_{k,i}^{OCCUP} \qquad (8)$$
$$with\ \ j = 1 \ldots 4,\ \ k = 1 \ldots 9$$

where $\ln WH_i$ is defined as the log of the hourly wage individual *i* earns, D_i^{WBEAA} is a dummy variable including individuals originally from Surinam, the Dutch Antils, Aruba, Turkey and Morocco, D_i^{GENDER} refer to either male or female, AGE_i is the age group a particular individual is included in, ED_i is defined as the type of education individual *i* has attained, while LEV_i[19] is

[18] Empirical studies often use proxies based on education and occupation. Education is categorised by years of schooling or final degree obtained. Occupations sometimes provide more information on the skills requirement for workers because it also takes into account on-the-job training and experience. Here, the OSA database of 1996 (2317 observations) for the Netherlands is used, which is a panel database and defines five levels of occupations: elementary, low, medium, high and scientific level.

[19] Note: LEV_i (job level) is based on employer's perceptions subdivided into seven broad classes. In contrast, skill-level and worker collar are determined by the Statistics Netherlands (CBS) occupational classification. The distinction between the two variables ameliorates the bias that emanates from over- or under-education, which is not corrected for in the analysis carried out here.

the individual's job level. In addition, we have included a sector dummy, $D_{j,i}^{SECTOR}$ to analyse the influence of being employed in a certain sector on individual *i*'s hourly wage. The number of sectors included is equal to the aggregated sectors described in Table 2. Following the OECD classification, we have summed the data from the different sectors into the four categories: High-technology, Medium-high technology, Medium-low technology and Low-technology sectors. Finally, occupational levels have been distinguished which have been divided, i.e. Elementary, Low, Medium, High and Scientific jobs, of which the latter four are subdivided into blue- and white-collar jobs, obtaining a total of nine types of occupations.

Table 3: Benchmark results from estimating equation (8)

Variables		Coefficients
General		
Constant	(α)	3.359 (0.111)*
Age	(AGE)	0.074 (0.009)*
Gender	(D^{GENDER})	-0.194 (0.051)*
Education	(ED)	0.081 (0.025)*
Level of job	(LEV)	0.008 (0.020)
Non-Dutch WBEAA	(D^{WBEAA})	-0.273 (0.253)
Sectors		0.075 (0.046)
Medium-low technology sector		0.023 (0.050)
Medium-high technology sector		0.064 (0.052)
High technology sector		
Occupations		
Elementary		-0.023 (0.078)
Low administrative and commercial		0.119 (0.083)
Medium		0.077 (0.060)
Medium administrative and commercial		0.208 (0.067)*
High		0.189 (0.111)**
High administrative and commercial		0.283 (0.103*
Scientific		0.328 (0.177)**
Scientific administrative and commercial		0.589 (0.142)*

Note: R^2 adj. 35.8%
Standard errors in brackets
* significant at a five percent level
** significant at a ten percent level

The results from estimating equation (8) are shown in Table 3. First, for the data set as a whole a relative high degree of wage discrimination (19.4%) in favour of male workers is observed, whereas discrimination with regard to race does not seem to be present. In addition, it can be concluded from Table 3 that the level of the job has no significant impact on an individual's. The returns to education are about eight percent which is in line with findings of other studies.[20]

Table 3 also carries out a sector analysis for the four ‘technology’ sectors in the database relative to the low-technology sector. However, no significant results can be obtained. In the third part of Table 3 an occupations analysis ranging from elementary to scientific occupations is shown; the overall trend is upward relative to the reference point, a low level job.

Table 4: Testing for wage differentials between blue- and white collar workers

Variables		Coefficients
General		
Constant	(α)	3.206 (0.091)*
Age	(AGE)	0.079 (0.008)*
Gender	(D^{GENDER})	-0.211 (0.050)*
Education	(ED)	0.102 (0.023)*
Level of job	(LEV)	0.041 (0.013)*
Non-Dutch WBEAA	(D^{WBEAA})	-0.300 (0.252)
Sectors		
Medium-low technology sector		0.083 (0.045)
Medium-high technology sector		0.019 (0.049)
High technology sector		0.068 (0.051)
D_i^{WC}		0.149 (0.042)*

Note: R^2 adj. 35.0%
Standard errors in brackets
* significant at a five percent level
** significant at a ten percent level

Next, equation (8) is amended to make a distinction between job types. We distinguish here between blue-collar and white-collar jobs in order to analyse whether there are wage differences between these two types of jobs. Hence the following equation is estimated:

$$\ln WH_i = \alpha_i + AGE_i + D_i^{WBEAA} + D_i^{GENDER} + ED_i + LEV_i + \sum_{i=1}^{n} D_{j,i}^{SECTOR} + D_i^{WC} \qquad (9)$$

[20] E.g. Bruinshoofd and Ter Weel (1998) obtain returns to education ranging from 6 to 13 percent; Cohn and Kahn (1995) find a return to education of 7.7%, Groot (1993) obtains a return of 5.3%, Hartog and Jonker (1996) find returns ranging from 5.8 to 8.4 percent, Hartog and Oosterbeek (1988) observe returns for females to be 5.2% and returns for males to be 7.6%, Oosterbeek and Webbink (1996) estimate that the returns to education are 9.2%, Rumberger (1986) finds results ranging from 4.1% to 10.9% depending on gender and type of education, and Sicherman (1991) obtains a result of 4.8%.

where D_i^{WC} is defined as a white-collar job dummy variable.[21] The results from equation (9) are shown in Table 4. It is observed that a white-collar worker earns a 14.9% higher wage than his blue-collar colleagues. Hence, there is a strong and statistically significant difference in wages between white-collar and blue-collar workers.

Finally, to test the presence of a wage premium based on job level we estimate:

$$\ln WH_i = \alpha_i + AGE_i + D_i^{WBEAA} + D_i^{GENDER} + ED_i + LEV_i + \sum_{i=1}^{n} D_{j,i}^{SECTOR} + D_i^{HS} \qquad (10)$$

where D_i^{HS} is defined as a high-skilled dummy variable. The results which are depicted in Table 5 show no significant evidence for differences in wages between sectors when we compare the same jobs in different sectors. However, comparing blue- and white-collar workers at the same level, it is observed that white-collar workers obtain a wage premium of almost fourteen percent.

Table 5: Testing for wage differentials between high- and low-skilled jobs

Variables		Coefficients
General		
Constant	(α)	3.247 (0.103)*
Age	(AGE)	0.073 (0.009))*
Gender	(D^{GENDER})	-0.161 (0.049))*
Education	(ED)	0.105 (0.024))*
Level of job	(LEV)	0.033 (0.015))*
Non-Dutch WBEAA	(D^{WBEAA})	-0.367 (0.254)
Sectors		
Medium-low technology sector		0.089 (0.046)
Medium-high technology sector		0.015 (0.050)
High technology sector		0.073 (0.052)
D_i^{HS}		0.139 (0.063)*

Note: R^2 adj. 33.8%
Standard errors in brackets
* significant at a five percent level
** significant at a ten percent level

[21] Note that D_i^{WC} is defined without taking into account the different sectors defined in equation (8). So we implicitly assume at this point that white-collar workers receive a wage premium that is sector-independent.

In conclusion it can stated that there is significant wage divergence in the Netherlands in 1996 based on both job type and job level. This clearly points into the direction of concentration of tacit knowledge in few high-skilled individuals at the expense of the other workers.

4. Knowledge-Skill Complementarity

This section combines the analyses of section 2 and 3 this section to investigate whether sectors creating and or absorbing high levels of codified knowledge also embody high levels of tacit knowledge.

Jan Tinbergen already characterized in 1975 the evolution of the wage structure as a "race between technological development and access to education" (Tinbergen, 1975). Since access to education is in industrialized countries like the Netherlands of no concern, technological development is the major force behind inequality in society that can be measured by wage inequality. This development can be split up, as is shown in the previous two sections, in the development and evolution of codified and tacit advancement. This section tests whether sectors embodying relatively large amounts of codified knowledge, either by performing research themselves or profiting from research performed in other sector and or countries, employ relatively large numbers of high-skilled workers, i.e. contain a relatively large proportion of the total tacit knowledge present in the Netherlands.

In the previous section it turned out that white-collar workers and high-skilled workers receive a wage premium of some fourteen percent. However, in that analysis there is no distinction being made between the four different sectors that are defined and that section. This means that only a regression analysis is carried out on all white-collar versus blue-collar and high-skilled versus low-skilled workers without taking into account in which sector they are employed. Here, first a regression is performed to investigate whether the wage premium of white-collar and high-skilled workers is sector specific or a general phenomenon observed in all Dutch manufacturing sectors. To do so, consider the following equations, where an interaction dummy is added to equations (9) and (10) to test for a so-called sector bias within the wage premium for both white-collar (equation (11a)) and high-skilled (equation (11b)) workers:

$$\ln WH_i = \alpha_i + AGE_i + D_i^{WBEAA} + D_i^{GENDER} + ED_i + LEV_i + \sum_{i=1}^{n} D_{j,i}^{SECTOR} + \sum_{i=1}^{n} D_i^{WC} D_{j,i}^{SECTOR} \quad (11a)$$

and

$$\ln WH_i = \alpha_i + AGE_i + D_i^{WBEAA} + D_i^{GENDER} + ED_i + LEV_i + \sum_{i=1}^{n} D_{j,i}^{SECTOR} + \sum_{i=1}^{n} D_i^{HS} D_{j,i}^{SECTOR} \quad (11b)$$

where the interaction dummies are $D_i^{WC}D_{j,i}^{SECTOR}$ and $D_i^{HS}D_{j,i}^{SECTOR}$, summed over all individuals in the dataset. The results of estimating equations (11a) and (11b) are shown in Table 6.

Table 6: Estimating sector bias

Variables		equation (11a)	equation (11b)
General			
Constant	(α)	3.205 (0.093)*	3.258 (0.103)*
Age	(AGE)	0.078 (0.008)*	0.075 (0.009)*
Gender	(D^{GENDER})	-0.209 (0.050)*	-0.170 (0.049)*
Education	(ED)	0.102 (0.024)*	0.103 (0.024)*
Level of job	(LEV)	0.041 (0.013)*	0.032 (0.015)*
Non-Dutch WBEAA	(D^{WBEAA})	-0.302 (0.253)	-0.382 (0.256)
Sectors			
Medium-low technology sector		0.033 (0.006)*	0.068 (0.006)*
Medium-high technology sector		0.071 (0.006)*	0.089 (0.006)*
High technology sector		0.086 (0.005)*	0.093 (0.049)**

Note: R^2 adj. equation (11a) 34.5% and equation (11b) 34.1%
Standard errors in brackets
* significant at a five percent level
** significant at a ten percent level

Table 6 shows that the sectors embodying higher levels of codified knowledge, as determined by Table 2 and classified accordingly so, pay both their high-skilled and white-collar (presumably their scientists and engineers) a significant higher wage premium than sectors embodying less codified knowledge. That is to say, the wage premia are an increasing function of the technology intensity of the sector.

This result already implies the suggested knowledge-skill complementarity. Following the analysis of the activities creating both codified and tacit knowledge, laid out in Figure 1 - where it is already explicated that the creation of codified knowledge, as the result of performing R&D by a particular sector - implies that both access to the knowledge basin and a certain level of skills is required to innovate. In order to attract labour in the research department of a particular firm, this firm has to pay a wage premium. This premium of course increases when more high-skilled and white-collar workers are needed. Hence, we have already established, in a similar way that Murphy, Riddell and Romer (1998) do, that there is, to a certain extent a knowledge-skill complementarity in the manufacturing sector in the Netherlands.

Next, we want to investigate the sector bias based on job type and job level by not just using a dummy variable or the four sector we have defined, but by including the codified knowledge intensity into the analysis above. First, the total codified knowledge intensity is computed as the sum of the codified knowledge stock (*CK*), the domestic indirect codified knowledge stock (*ICD*) and the foreign codified knowledge stock (*ICF*) divided by value added. The results are shown in Table 7.

Table 7: Overall codified knowledge intenisity

Sector	76-80	81-85	86-90	91-95
Low technology sector	0.09	0.11	0.11	0.11
Medium-low technology sector	0.17	0.20	0.20	0.21
Medium-high technology sector	0.91	0.91	0.81	1.12
High technology sector	1.01	1.05	1.07	1.22

Adapted from Table 2

From this table it can be observed that the overall codified knowledge intensity remains fairly constant over time. Hence, we only include the figures for the period 1991-1995 in the regression analysis.

The regression equations (11a) and (11b) have to be amended in order to include the codified knowledge intensities in the following manner:

$$\ln WH_i \;=\; \alpha_i + AGE_i + D_i^{WBEAA} + D_i^{GENDER} + ED_i + LEV_i + \sum_{i=1}^{n} D_{j,i}^{\;SECTOR} + D_i^{WC} OCK_{j,i}^{\;SECTOR} \quad (12a)$$

and

$$\ln WH_i \;=\; \alpha_i + AGE_i + D_i^{WBEAA} + D_i^{GENDER} + ED_i + LEV_i + \sum_{i=1}^{n} D_{j,i}^{\;SECTOR} + D_i^{HS} OCK_{j,i}^{\;SECTOR} \quad (12b)$$

where $OCK_{j,\,i}^{\;SECTOR}$ is defined as the overall codified knowledge stock in sector j. The regression results from estimating equations (12a) and (12b) are shown in Table 8. From this table it can be observed that a sector bias with regard to job type of 12% is obtained, while the sector bias with respect to job level just exceeds fifteen percent. These results indicate that first of all that white-collar workers, when taking into account codified knowledge intensities in the four sectors, obtain a wage premium of 12% relative to their blue-collar colleagues. In addition, high-skilled workers in codified knowledge-intensive sectors obtain a wage premium of more than fifteen percent relative to high-skilled workers in relatively less codified knowledge-intensive sectors.

Table 8: Knowledge-skill complementarity

Variables		equation (12a)	equation (12b)
General			
Constant	(α)	3.143 (0.090)*	3.180 (0.094)*
Age	(AGE)	0.081 (0.008)*	0.079 (0.009)*
Gender	(D^{GENDER})	-0.180 (0.049)*	-0.169 (0.049)*
Education	(ED)	0.118 (0.023)*	0.115 (0.023)*
Level of job	(LEV)	0.044 (0.013)*	0.043 (0.013)*
Non-Dutch WBEAA	(D^{WBEAA})	-0.343 (0.254)	-0.347 (0.254)
Sectors			
Medium-low technology sector		0.041 (0.052)	0.026 (0.597)
Medium-high technology sector		0.096 (0.054)**	0.083 (0.053)**
High technology sector		0.109 (0.023)*	0.096 (0.047)*
$OCK_{j,\,i}^{\;SECTOR}$		0.120 (0.059)*	0.151 (0.088)**

Note: R^2 adj. equation (12a) 33.6% and equation (12b) 33.4%
Standard errors in brackets
* significant at a five percent level
** significant at a ten percent level

These results also clearly answer, stress the importance and make explicit the two questions that this paper tries to answer and explain. First, do knowledge-intensive sectors pay workers a higher wage relative to workers in less knowledge-intensive sectors? The answer can be obtained from Table 8, column two, by investigating the coefficients for the three estimated sectors dummies to the low-technology intensive sector. These results indicate that the higher the level of knowledge-intensity, the higher the wage for workers. On top of that, white-collar workers receive a wage premium. The regression coefficients in Table 8 for the different sectors have to be multiplied by the values computed in Table 7 for the period 1991-1995 to obtain the 'real' wage premium observed by white-collar workers. These premiums are shown in Table 9: Workers in the Medium-low technology sector obtain a wage premium of 2,5 percent; white-collar workers employed in the Medium-high technology sector observe a wage premium of 13.4%; and, High technology sector white-collar workers obtain a wage premium of more than fourteen percent.

Secondly, do knowledge-intensive sectors pay workers a higher wage relative to low-skilled workers than less knowledge-intensive sectors? The objective of this second question is to provide picture of the relationship between technology and job level at the level of the four sectors defined. The regression results (column 3) show that high-skilled workers in technology-intensive sectors observe a significantly higher wage premium than high-skilled workers in relatively less knowledge-intensive sectors. Again Table 9, column three, shows the 'real' wage premium: High-skilled workers in the Medium-low technology sector obtain a wage premium of 3.2% over their colleagues in the low-technology sector; Medium-high technology sector high-skilled workers have a wage premium of some seventeen percent; and high-skilled workers employed in the High technology sector observe a wage premium of nearly twenty percent.

Table 9: Wage premiums

Variables	White-collar	High-skilled
Medium-low technology sector	0.025	0.032
Medium-high technology sector	0.134	0.169
High technology sector	0.146	0.184

In conclusion it is possible to state that the analysis of Dutch manufacturing proves that knowledge-intensive sectors in the Netherlands pay higher wage premiums based on both job type and job level. The analysis shows that the position with regard to this premium of both high-skilled workers and white-collar workers is significantly better. Furthermore, we observe that the wage premium is slightly more important with regard to the job level of an individual than on the proper use of skills, *i.e.* the position of high-skilled workers is better than the position of white-collar workers.

5. Concluding Remarks

In this paper we have presented evidence that sectors embodying and creating relatively high levels of codified knowledge, by performing R&D and building a sector-specific knowledge stock pay their workers a wage premium proportional to the extend of knowledge advancement. Our data show that (a) knowledge-intensive sectors pay white-collar workers like managers, scientists and engineers a higher wage relative to blue-collar workers, than white-collar workers in less knowledge-intensive sectors; and (b) knowledge-intensive sectors pay high-skilled workers a higher wage relative to low-skilled workers than less knowledge-intensive sectors.

The debate in the literature over the related field of the effects of skill-biased technical change on relative wages has often turned on the relevance of the substitution of low-skilled labour with high-skilled labour and capital, assuming a complementary relation between capital and high-skilled labour. This relation already explored in Griliches (1969) and put in a historical perspective by Goldin and Katz (1998) has recently been picked up in economics both on the empirical side of the econometric spectrum (Bruinshoofd and Ter Weel, 1998 and Haskel and Slaughter, 1998) and theoretical side of economic modelling (Acemoglu, 1998). The results of these studies are that capital-skill complementarity is observed to an ever greater extent, reinforcing the arguments in favour of skill-biased technical change.

Here, it is shown that this property can be extended by not only investigating the substitution effects of low-skilled labour with high-skilled labour and capital, and the complementary relationship between capital and high-skilled labour, but to go one step further and analyse whether or not the creation and use of codified knowledge induces both substitution of low-skilled labour with tacit knowledge and codified knowledge, and whether or not a complementary relationship can be obtained between the latter to. The major contribution of this approach is that by analysing the creation of codified knowledge, from the analysis underlying Figure 1, a clear picture can be obtained with regard to the mechanisms involved in the production process in manufacturing. The results show that there exists a large sector bias with regard to codified knowledge creation in Dutch manufacturing leading to a large bias in the reward of both white-collar and high-skilled labour.

In addition, the importance of knowledge creation, both codified and tacit, shows that a boost in the level of either codified or tacit knowledge creates a further gap between low-skilled and high-skilled labour, inducing further inequality (see also Bénabou, 1996). Particularly low-skilled workers may be disproportionately affected by an increase in codified knowledge creation. These effects will only increase since knowledge becomes more important in the process of economic growth.

References

Acemoglu, D. (1998), Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality, *Quarterly Journal of Economics*, vol. 113, no. 4, pp. 1055-1089.

Aghion, P. and P. Howitt (1998a), *Endogenous Growth Theory*, MIT Press, Cambridge MA.

Aghion, P. and P. Howitt (1998b), On the Macroeconomic Effects of Major Technological Change, in: Helpman, E. (ed.) *General Purpose Technologies and Economic Growth*, MIT Press, Cambridge MA, pp. 121-144.

Autor, D. H., L. F. Katz and A. B. Krueger (1998), Computing Inequality: How Computers Have Changed the Labor Market, *Quarterly Journal of Economics*, vol. 113, no. 4, pp. 1169-1214.

Baldwin, J. R., B. Diverty and J. Johnson (1995), Success, Innovation, Technology and Human Resource Strategies an Interactive System, Paper presented at the conference on the effects of technology and innovation on firm performance and employment, Washington

DC.

Bartel, A. and N. Sicherman (1995), Technological Change and the Skill Acquisition of Young Workers, *National Bureau of Economic Research*, Working Paper No. 5107.

Becker, G. S. (1962), Investment in Human Capital: A Theoretical Analysis, *Journal of Political Economy*, vol. 70, no. 1, pp. 9-49.

Bell, B. D. (1996), Skill-Biased Technical Change and Wages: Evidence from a Longitudinal Data Set, *Institute of Economics and Statistics*, University of Oxford, mimeo.

Bellman, L. and T. Boeri (1995), Internal and External Creative Destruction: Determinants of Changes of Employment and Productivity, Paper presented at the conference on the effects of technology and innovation on firm performance and employment, Washington DC.

Bénabou, R. (1996), Inequality and Growth, in: Bernanke, B.S. and J. Rotemberg (eds.), *NBER Macroeconomics Annual*, vol. 11, The MIT Press, Cambridge MA, pp. 11-74.

Berman, E., J. Bound and Z. Griliches (1994), Changes in the Demand for Skilled Labor within US Manufacturing: Evidence from the Annual Survey of Manufactures, *Quarterly Journal of Economics*, vol. 109, no. 2, pp. 367-397.

Berman, E., J. Bound and S. Machin (1998), Implications of Skill-Biased Technological Change: International Evidence, *Quarterly Journal of Economics*, vol. 113, no. 4, pp. 1245-1279.

Bernstein, J. I. and P. Mohnen (1991), Price-Cost Margins, Exports and Productivity Growth: With an Application to Canadian Industries, *Canadian Journal of Economics*, vol. 24, pp. 638-659.

Bernstein, J. I. and P. Mohnen (1998), International R&D Spillovers between US and Japanese R&D Intensive Sectors, *Journal of International Economics*, vol. 44, pp. 315-338.

Bound, J. and G. Johnson (1992), Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations, *American Economic Review*, vol. 82, no. 2, pp. 371-392.

Bruinshoofd, W. A. and B. J. Ter Weel (1998), Skill-Biased Technical Change: On Technology and Wages in the Netherlands, *MERIT Research Memorandum 98-025*, MERIT, Maastricht University, Maastricht.

Chennells, L. and J. van Reenen (1997), Technical Change and Earnings in British Establishments, *Economica*, vol. 64, pp. 587-604.

Cohn, E. and S. Kahn (1995), The Wage Effect of Overschooling revisited, *Labour Economics*, vol. 2, no. 1, pp. 66-76.

Coe, D. T. and E. Helpman (1995), International R&D Spillovers, *European Economic Review*, vol. 39, pp. 859-887.

Coe, D. T., E. Helpman and A. Hoffmaister (1997), North-South R&D Spillovers, *Economic Journal*, vol. 107, pp. 134-149.

Coyle, D. (1998), *The Weightless World*, MIT Press, Cambridge MA.

Denny, M. and M. Fuss (1983), The Effects of Factor Prices and Technological Change on the Occupational Demand for Labour: Evidence from Canadian Telecommunications, *The Journal of Human Resources*, vol. XVII, no. 2, pp. 161-176.

DiNardo, J. E. and J.-S. Pischke (1997), The Returns to Computer use Revisited: Have Pencils Changed the Wage Structure Too?, *Quarterly Journal of Economics*, vol. 112, no. 1, pp. 291-303.

Doms, M., T. Dunne and M. Roberts (1997), Workers, Wages and Technology, *Quarterly Journal of Economics*, vol. 112, no. 1, pp. 253-290.

Entorf, H. and F. Kramarz (1997), Does Unmeasured Ability Explain the Higher Wages of New Technology Workers, *European Economic Review*, vol. 41, pp. 1489-1509.

Fitoussi, J.-S. and E. S. Phelps (1988), *The Slump in Europe: Open Economy Macro-Economics Reconstructed*, Basil Blackwell, Oxford.

Francois, J.-F. and D. Nelson (1998), Trade, Technology, and Wages: General Equilibrium Mechanics, *Economic Journal*, vol. 108, pp. 1483-1499.

Goldin, C. and L. F. Katz (1998), The Origins of Technology-Skill Complementarity, *Quarterly Journal of Economics*, vol. 113, no. 3, pp. 693-732.

Griliches, Z. (1969), Capital-Skill Complementarity, *The Review of Economics and Statistics*, vol. 51, no. 4, pp. 465-468.

Griliches, Z. (1980), R&D and Productivity Slowdown, *American Economic Review*, vol. 70, pp. 343-348.

Griliches, Z. (1992), The Search for R&D Spillovers, *Scandinavian Journal of Economics*, vol. 94, pp. 29-47.

Griliches, Z. (1998), *R&D and Productivity: The Econometric Evidence*, Chicago University Press, Chicago.

Groot, W. (1993), Overeducation and the Returns to Enterprise-Related Schooling, *Economics of Education Review*, vol. 12, no. 2, pp. 21-40.

Hartog, J. and N. Jonker (1996), A Job to Match Your Education: Does it Matter? ROA, Maastricht.

Hartog, J. and H. Oosterbeek (1988), Education, Allocation and Earnings in the Netherlands: Overschooling? *Economics of Education Review*, vol. 7, no. 2, pp. 185-194.

Haskel, J. E. and M. J. Slaughter (1998), Does the Sector Bias of Skill-Biased Technical Change Explain Changing Wage Inequality?, *National Bureau of Economic Research*, Working Paper No. 6565.

Heckman, J., L. Lochner and C. Taber (1998), Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogenous Agents, *National Bureau of Economic Research*, Working Paper No. 6384.

Heckman, J. and G. Sedlacek (1985), Heterogeneity, Aggregation and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market, *Journal of Political*

Economy, vol. 98, no. 4, pp. 1077-1125.

Herzenberg, S. A., J. A. Alic and H. Wial (1998), *New Rules for a New Economy*, Cornell University Press, Ithaca.

Hildreth, A. (1998), Rent-Sharing and Wages: Product Demand or Technology Driven Premia?, *Economics of Innovation and New Technology*, vol. 5, pp. 199-226.

Hollanders, H., L. L. G. Soete and B. J. Ter Weel (1999), *World Knowledge Report*, Edward Elgar, London, forthcoming.

Hollanders, H. and B. J. Ter Weel (1998), Skill-Biased Technological Change in an Endogenous Growth Model, *MERIT Research Memorandum 98-019*, MERIT, Maastricht University, Maastricht.

Howitt, P. (ed.) (1996), *The Implications of Knowledge-Based Growth for Micro-Economic Policies*, University of Calgary Press, Calgary.

Juhn, C., K. Murphy and B. Pierce (1993), Wage Inequality and the Rise in Returns to Skill, *Journal of Political Economy*, vol. 101, no. 2, pp. 410-442.

Katz, L. and K. M. Murphy (1992), Changes in Relative Wages, 1963-1987: Supply and Demand Factors, *Quarterly Journal of Economics*, vol. 107, no. 1, pp. 35-78.

Keizer, P. K. and B. J. Ter Weel (1999), Justice and Stability in Western Welfare States, Maastricht University/ MERIT, mimeo.

Kelly, K. (1998), *New Rules for the New Economy*, Penguin Putman Inc., New York.

Krueger, A. B., 1993, How Computers Have Changed the Wage Structure: Evidence from Micro Data 1984-1989, *Quarterly Journal of Economics*, vol. CVIII, no. 1, pp. 33-60.

Layard, R. and S. J. Nickell (1986), Unemployment in Britain, *Economica*, vol. 53, pp. S121-S169.

Layard, R., S. J. Nickell, S. J. and R. Jackman (1991) *Unemployment: Macroeconomic Performance and the Labour Market*, Oxford University Press, Oxford.

Machin, S. and J. Van Reenen (1998), Technology and Changes in Skill Structure: Evidence from Seven OECD Countries, *Quarterly Journal of Economics*, vol. 113, no. 4, pp. 1215-1244.

Madsen, J. (1998), General Equilibrium Macroeconomic Models of Unemployment: Can They Explain the Unemployment Path in the OECD?, *Economic Journal*, vol. 108, no. 2, pp. 850-867.

Meghir, C. and E. Whitehouse (1996), The Evolution of Wages in the United Kingdom: Evidence from Micro Data, *Journal of Labor Economics*, vol. 14, no. 1, pp. 1-25.

Murphy, K. M., W. C. Riddell and P. M. Romer (1998), Wages, Skills and Technology in the United States and Canada, in: E. Helpman (ed.), *General Purpose Technologies and Economic Growth*, MIT Press, Cambridge MA.

Nelson, R. R. and S. Winter (1982), *An Evolutionary Theory of Economic Change*, Harvard University Press, Cambridge MA.

Nickell, S. J. and B. D. Bell (1995), The Collapse in Demand for the Unskilled and Unemployment across the OECD, *Oxford Review of Economic Policy*, vol. 11, no. 1, pp. 40-62.

Nickell, S. J. and B. D. Bell (1996), Changes in the Distribution of Wages and Unemployment in OECD Countries, *American Economic Review*, vol. 86, no. 2, pp. 302-308.

OECD (1998), *Science, Technology and Industry Outlook 1998*, OECD, Paris.

Oosterbeek, H. and D. Webbink (1996), Over Scholing, Overscholing en Inkomen, *Economisch Statistische Berichten*, vol. 81, pp. 240-241.

Phelps, E. S. (1994), *Structural Slumps: The Modern Equilibrium Theory of Unemployment, Interest and Assets*, Harvard University Press, Cambridge MA.

Phelps, E. S. (1998), New Technologies and the Less-Qualified Worker: Intervening to Shore Up Inclusion and Releasing Enterprise to Rekindle Development, Paper presented at the fourth conference on Job Creation, Employment and New Technologies, University of Navarra, Barcelona, June.

Rumberger, R. W. (1986), The Impact of Surplus Schooling on Productivity and Earning, *The Journal of Human Resources*, vol. XXII, no. 1, pp. 24-50.

Sarantis, N. (1993), Distribution, Aggregate Demand and Unemployment in the OECD Countries, *Economic Journal*, vol. 103, no. 2, pp. 459-467.

Schultz, T. W. (1961), Investment in Human Capital, *American Economic Review*, vol. 51, no. 1, pp. 1-17.

Sicherman, N. (1991), Overeducation in the Labor Market, *Journal of Labour Economics*, vol. 9, no. 2, pp. 101-122.

Soete, L. L. G. and B. J. Ter Weel (1999), Innovation, Knowledge Creation and Technology Policy in Europe, *De Economist*, vol. 147, forthcoming June 1999.

Tinbergen, J. (1975), *Income Differences: Recent Research*, North Holland, Amsterdam.

Vaniniomaki, J. and S. Laaksonen (1995), Inter-industry Wage Differentials in Finland: Evidence from Longitudinal Census Data for 1975-85, *Labour Economics*, vol. 2, no. 2, pp. 161-173.

Verspagen, B. (1997a), Estimating International Technology Spillovers Using Technology Flow Matrices, *Weltwirtschaftliches Archiv*, vol. 133, no. 2, pp. 226-248.

Verspagen, B. (1997b), Measuring Inter-Sectoral Technology Spillovers: Estimates from the European and US Patent Offices Databases, *Economic Systems Research*, vo. 9, no. 1, pp. 49-67.

Winter, S. (1984), Schumpeterian Competition in Alternative Technological Regimes, *Journal of Economic Behaviour and Organization*, vol. 5, pp. 287-320.

Wood, A. (1998), Globalisation and the Rise in Labour Market Inequalities, *Economic Journal*, vol. 108, pp.1463-1482.

Annex 1. Technology Flow Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	0.000	0.007	0.000	0.004	0.284	0.263	0.001	0.000	0.002	0.000	0.000	0.019	0.091	0.000	0.002	0.003	0.000	0.001	0.000	0.000	0.039	0.010
2	0.006	0.000	0.002	0.026	0.085	0.005	0.001	0.016	0.018	0.002	0.091	0.042	0.249	0.003	0.012	0.013	0.000	0.006	0.002	0.004	0.050	0.083
3	0.003	0.017	0.000	0.204	0.074	0.008	0.000	0.020	0.017	0.001	0.000	0.247	0.096	0.004	0.004	0.018	0.001	0.006	0.002	0.016	0.092	0.061
4	0.003	0.088	0.003	0.000	0.105	0.022	0.003	0.006	0.011	0.008	0.003	0.034	0.163	0.041	0.006	0.024	0.001	0.004	0.001	0.001	0.105	0.087
5	0.013	0.018	0.000	0.011	0.000	0.167	0.025	0.002	0.039	0.004	0.002	0.018	0.085	0.004	0.007	0.013	0.000	0.001	0.000	0.001	0.043	0.014
6	0.025	0.002	0.000	0.003	0.261	0.000	0.006	0.000	0.001	0.000	0.000	0.003	0.031	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.023	0.002
7	0.005	0.003	0.000	0.007	0.371	0.070	0.000	0.000	0.029	0.005	0.000	0.042	0.111	0.004	0.005	0.046	0.000	0.001	0.000	0.000	0.106	0.004
8	0.006	0.126	0.025	0.016	0.046	0.005	0.005	0.000	0.012	0.002	0.001	0.119	0.142	0.007	0.007	0.156	0.000	0.093	0.001	0.023	0.144	0.029
9	0.003	0.004	0.007	0.042	0.135	0.008	0.001	0.001	0.000	0.005	0.001	0.107	0.212	0.002	0.008	0.020	0.001	0.005	0.001	0.001	0.049	0.020
10	0.000	0.003	0.000	0.002	0.035	0.002	0.001	0.000	0.024	0.000	0.187	0.095	0.123	0.001	0.001	0.030	0.000	0.007	0.000	0.000	0.021	0.004
11	0.000	0.002	0.000	0.016	0.069	0.007	0.003	0.001	0.020	0.298	0.000	0.085	0.092	0.002	0.008	0.043	0.000	0.007	0.000	0.001	0.015	0.010
12	0.004	0.003	0.016	0.034	0.027	0.004	0.002	0.004	0.038	0.012	0.009	0.000	0.187	0.004	0.016	0.052	0.002	0.026	0.002	0.004	0.051	0.024
13	0.029	0.020	0.002	0.016	0.069	0.014	0.003	0.002	0.020	0.007	0.006	0.110	0.000	0.005	0.007	0.024	0.002	0.039	0.003	0.004	0.060	0.030
14	0.000	0.001	0.001	0.006	0.006	0.001	0.000	0.000	0.001	0.000	0.000	0.008	0.012	0.000	0.075	0.027	0.000	0.004	0.000	0.002	0.075	0.019
15	0.000	0.002	0.000	0.001	0.017	0.001	0.000	0.000	0.004	0.001	0.001	0.011	0.010	0.056	0.000	0.187	0.000	0.001	0.001	0.005	0.065	0.008
16	0.001	0.002	0.001	0.005	0.008	0.000	0.000	0.001	0.009	0.002	0.007	0.038	0.029	0.020	0.355	0.000	0.000	0.012	0.001	0.006	0.059	0.005
17	0.000	0.004	0.001	0.002	0.004	0.000	0.000	0.001	0.004	0.000	0.000	0.038	0.088	0.002	0.001	0.012	0.000	0.444	0.010	0.049	0.035	0.015
18	0.001	0.005	0.005	0.057	0.019	0.001	0.000	0.044	0.039	0.002	0.001	0.085	0.194	0.003	0.007	0.027	0.003	0.000	0.004	0.080	0.033	0.023
19	0.000	0.000	0.003	0.004	0.008	0.000	0.000	0.005	0.005	0.001	0.000	0.062	0.153	0.006	0.014	0.028	0.029	0.133	0.000	0.015	0.077	0.024
20	0.000	0.001	0.002	0.003	0.002	0.000	0.000	0.001	0.003	0.001	0.000	0.044	0.061	0.003	0.005	0.065	0.004	0.479	0.003	0.000	0.041	0.007
21	0.011	0.003	0.001	0.022	0.071	0.111	0.005	0.001	0.005	0.002	0.001	0.026	0.085	0.044	0.038	0.035	0.000	0.005	0.002	0.002	0.000	0.019
22	0.009	0.076	0.003	0.034	0.026	0.002	0.001	0.004	0.009	0.001	0.001	0.041	0.121	0.189	0.042	0.031	0.003	0.008	0.001	0.006	0.110	0.000

1. Food, beverages and tobacco, 2. Textiles, apparel and leather, 3. Wood products and furniture, 4. Paper, paper products and printing, 5. Pharmaceuticals, 6. Other chemicals, 7. Refined oil and related products, 8. Rubber and plastic products, 9. Glass, stone and clay, 10. Ferrous metals, 11. Non-ferrous metals, 12. Metal products, 13. Office and computing equipment, 14. Non-electrical machinery, 15. Radio, TV and communication equipment, 16. Electrical machinery, 17. Shipbuilding, 18. Automobiles, 19. Aerospace, 20. Other transport, 21. Instruments, 22. Other manufacturing

Where columns are defined as absorbing or receiving knowledge spillovers and rows are defined as generating knowledge.

Source: Verspagen (1997a).