





MICRO-DYN Working Paper no. 05/10

Hiring by skill in innovative and non-innovative firms. An explorative comparison using German and Dutch matched employer-employee data bases

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This paper was produced in the framework of MICRO-DYN (<u>www.micro-dyn.eu</u>), an international research project funded by the EU Sixth Framework Programme (<u>www.cordis.lu</u>) with socio-economic sciences and humanities (<u>http://ec.europa.eu/research/social-sciences/index en.html</u>). This publication reflects only the author's views, the European Community is not liable for any use that may be made of the information contained therein.

Hiring by skill in innovative and non-innovative firms

An explorative comparison using German and Dutch matched employer-employee data bases

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Abstract

This paper analyses the nexus between the demand for skilled labour and the innovativeness of firms. Is the hypothesis confirmed that innovative employers hire more highly educated employees than low educated compared to non-innovators? This is the basic principle of the theory of skill biased technological change (SBTC). This guestion is addressed by comparing evidence from matched employer-employee data bases in Germany and The Netherlands. International comparison of these data bases is hampered by differences in design of the data and in availability of information on education. When these difficulties are overcome, we find SBTC to be present in the period 1999-2003 in German industries only. In The Netherlands, labour demand by non-innovators for high skilled workers stands out. This may be related to the build-up to the 2002/3 recession.

> Groningen Tübingen March 2010

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This report was produced in the framework of MICRO-DYN (www.micro-dyn.eu), an international economic research project focusing on the competitiveness of firms, regions and industries in the knowledge-based economy. The project is funded by the EU Sixth Framework Programme (www.cordis.lu). This publication reflects only the author's views, the European Community is not liable for any use that may be made of the information contained therein.

1. Introduction

The demand for low-skilled labour has steadily been decreasing throughout Europe and in the US during the past decades, while demand for high-skilled labour surged. Figure 1 shows the levels of low educated employment between 1970-2004 in the USA and EU-5, comprising Germany, France, Italy, The Netherlands and the UK. Figure 2 shows the corresponding figure for high-educated employment. Clearly, on average the demand in absolute terms for low-educated employees has been declining and that of high-educated has risen.

Labour demand emerges from firms and institutions and very much depends on the prospects of growth these firms envisage.¹ One of the major determining factors for growth is whether a firm innovates. Innovating firms have more potential to grow in terms of output and (labour) input.² In general, the drop in demand for low-educated in favour of high-educated labour is related to increased international competition leading to a skill bias in internationally traded goods and it is related to the skill-biased nature of recent technological changes.³



Figure 1. Employment for low educated, USA and EU-5, 1970-2004

EU-5: Germany, France, Italy, Netherlands, UK (part_rates_edu_gender.xls) Source: own calculation based on BLS, ILO, OECD, SBA, INSEE, ONS, ISTAT, CBS

 $^{^1}$ Output growth is a necessary but not sufficient condition for employment growth. In order to expand jobs, output needs to grow faster than productivity. 2 See M. Pianta (2005) and the references therein.

³ Apart from a fall in demand for low skilled, supply of low skilled also dropped. The opposite is true for demand and supply of high skilled labour. One aspect that received a lot of attention in this respect is the fact that despite this increase of high to low educated labour supply, the corresponding price of labour, i.e. the ratio of high to low educated wages or the skill premium, has actually increased (e.g. Card and DiNardo, 2002; Doms, Dunne and Troske, 1997; Naticchioni, Ricci, and Rustichelli, 2008).



Figure 2. Employment for high educated, USA and EU-5, 1970-2004

EU-5: Germany, France, Italy, Netherlands, UK

Source: own calculation based on BLS, ILO, OECD, SBA, INSEE, ONS, ISTAT, CBS

This paper deals with these phenomena from another perspective. We combine the fact that labour demand has shifted from low to high skills and the fact that labour demand is stronger in innovative firms. The central questions are whether it is true that innovative firms hire more high-skilled workers than non-innovators and whether this relation differs by industry. In other words, is there a skill bias in innovation by industry and how can it be explained?

Several studies have examined these questions on the basis of national datasets, like Bender and Bauer (2004) for Germany, Bresnahan, Brynjolfson and Hitt (2002) for the U.S. or Askenazy and Moreno Galbis (2007) for France. But international comparative evidence is missing so far, mostly due to difficulties of data harmonisation. An additional aim of this paper is to examine the potentials and limitations of using similarly organised micro-level matched employer-employee data for two countries, Germany and The Netherlands, when assessing the above outlined questions.

We find that only the German manufacturing and trade industry indeed reflects the expected skill-biased innovation. Labour demand for highskilled workers in innovating firms exceeds that of low-skilled and of noninnovators. In the German business services on the other hand there appears to be a bias in unskilled labour for innovation: Innovators hire more unskilled than high-skilled workers. The Dutch situation is completely different as innovation does not dominate labour demand as much as it does in Germany. Now, labour demand for high-skilled workers is highest in non-innovating firms of both manufacturing and business services. Dutch trade industry does reflect the unskilled innovation bias, just as the German business services.

These industry-specific results can be explained using the polarisation hypothesis of labour markets. Basically, it asserts that technical change or innovation substitutes routine cognitive and manual tasks but complements non-routine, analytical and interactive tasks.⁴ Routine manual tasks are common in manufacturing, while non-routine interactive tasks are more common in services.⁵

The remainder of the paper is structured as follows: Section 2 presents a short overview of the literature of skill-biased technological change, innovation and polarisation. Section 3 provides the details of the data sets used for Germany and The Netherlands. Section 4 shows the results found with these data bases relating labour demand of workers by skill and firms by innovativeness. Section 5 provides a tentative explanation by considering polarisation as explanation for the (un)skill bias in innovation. Finally section 6 concludes.

2. Literature

2.1. Does innovation create or destroy jobs?

This section considers literature on the impact of innovation on the quantity of jobs. This relation can be studied from the micro, industry and macro perspective for different types of innovation. Usually distinction is made between product and process innovation. In empirical firm-level studies, the evidence on the direct overall employment impact of innovation tends to be positive. Firms that innovate in new products, but also in (production) processes, grow faster and are more likely to expand employment than non-innovators.⁶ Some studies suggest that the positive employment effect of innovation is due to organisational changes.⁷

By their nature, firm-level studies are incapable to determine whether the positive employment effects of innovation occur at the expense of competitors, i.e. they do not determine the net effect on the aggregate industry. It is also often difficult to make an adequate comparison between countries using micro data. By and large, studies at the industry level show that higher growth rates of output (hence demand) of an industry correspond with the importance of innovation. At the same time, there is a positive relationship between the orientation of firms in innovative industries towards product innovation and the employment effects of innovation.⁸

 ⁴ Autor et al. (2003/2005), Goos and Manning (2007), Spitz-Oener (2006).
 ⁵ Routine cognitive tasks and non-routine analytical tasks are less industry-specific. Unfortunately, a distribution of such tasks over industries is not available. Howell and Wolff (1992) do report rankings of tasks by industry, but do not distinguish routine vs. non-routine tasks.

⁶ See e.g. van Reenen (1997), Smolny (1998) and Brouwer et al. (1993).

⁷ Greenan (2003), Hornstein et al. (2006).

⁸ Pianta (2005).

However, while product innovations may have had positive effects on output and employment, the increased international competition in the 1990s has pushed firms towards restructuring. As a result, industries in many European countries are dominated by process innovations, leading to a prevalence of labour-saving effects. Compared to the USA, employment and output growth of many European countries were lagging far behind.⁹ At a more macro level, innovation becomes one of the many factors that directly or indirectly influence employment.¹⁰

2.2. What type of jobs are created or destroyed by innovation?

This section considers literature regarding the impact of innovation on the quality of jobs. How does innovation affect the skill distribution of jobs within a firm and how does it affect the distribution of wages and income? There exists vast literature arguing that technical change is biased towards the production factor of skilled workers, as new technology or innovation generally replaces unskilled labour, expands skilled labour and increases wage inequality.¹¹

Many studies have argued that the trend of increasing skill intensity of labour in the past decades has accelerated due to the introduction of computers and ICT.¹² Others argue that the gap between developments in skilled and unskilled labour is caused by increasing globalisation and falling barriers to international trade.¹³ This issue is usually studied on the basis of a factor substitution framework showing that measures of trade or technology are important explanatory factors for the relative increase of skilled labour. Which of these two effects – trade or technology – dominates the skill bias in labour is not yet resolved.¹⁴

Haskel and Slaughter (2002) argue that rising wage inequality between high and low-educated employees is concentrated in skill-intensive sectors and vice versa for falling wage inequality. They provide an explicit industry-level dimension to the skill bias, arguing that it is not so much a skill bias we are dealing with, but a sector bias.

Autor et al. (2003) go beyond the traditional industry subdivision and look at the specific tasks that are substituted by the use of computers and more generally ICT. They show that ICT (1) substitutes workers in performing routine cognitive and manual tasks that are accomplished by following explicit (and hence programmable) rules; (2) complements

⁹ The Netherlands did have US-like employment growth rates in the 1990s, opposite to most other EU-countries. Cf. Broersma et al. (2000). ¹⁰ See e.g. Harrison et al. (2008).

¹¹ In fact throughout the whole of the past century, innovation and skills have to a large extent been complementary, contrary to unskilled biased innovations of the 19th century, when mechanisation led to deskilling of artisans.

¹² Berman et al (1994), Krusell et al. (2000), Hornstein et al. (2006) and the references therein.

¹³ Wood (1994/1998), Berman et al. (1998), Feenstra and Hanson (1999).

¹⁴ Baldwin and Cain (2000) conclude from empirical work that it is a combination of both factors.

workers in performing non-routine manual, problem-solving and complex communications tasks. Task changes due to computerisation can explain the majority of the demand shift favouring high educated labour. At the same time, they explain rising labour demand for the low educated in case of non-routine low skilled jobs (see also figure 1 for late 1990's).¹⁵

3. Data

For both countries use is made of a matched employer-employee data base. The specifics of these data bases will next be discussed for each of the two countries and an assessment will be given concerning the comparability of both data sets.

3.1. Germany

For Germany, we use data from the cross-sectional version of the LIAB¹⁶, which is a employer-employee datasets of establishments and individuals in Germany, compiled and maintained by the Research Data Centre of the Federal Employment Agency in Nuremberg (for an overview, see Alda et al., 2005).

3.1.1. Employer side

The employer side of the LIAB is based on the IAB Establishment Panel, a panel dataset of around 16,000 German establishments of all sizes in all sectors which are surveyed by telephone interviews every year since 1993. The selection of firms is based on a representative sample stratified by size and sector of economic activity. The annual questioning is carried out as a longitudinal survey, i.e. most of the participating establishments are interviewed every year. The number of interviews has risen considerably from 4,265 in 1993 to more than 15,500 since 2001.¹⁷

The main contents of the survey comprise various indicators on output and employment and its development over time (e.g. production, turnover, capital assets, and working hours), a set of parameters regarding technical development as well as several measures for firm biography, apprenticeship and productivity, inter alia. Most of the questions are surveyed every year in the same form; however, in nearly every year, emphasis is put on a special feature, e.g. innovation, organisation or collective bargaining.

3.1.2. Employee side

The employee side of the LIAB is based on individual-level information from the Employment and Benefit History (*Beschäftigten-Leistungsempfänger-Historik – BLH*) collected by the Federal Employment

¹⁵ This topic has earlier been addressed in a study by Howell and Wolff (1992). Autor et al. (2003) study the USA, Goos and Manning (2007) the UK and Spitz-Oener (2006) Germany.

¹⁶ "Linked employer-employee data of the Institute for Employment Research (IAB)". For more information see <u>http://fdz.iab.de</u>.

 $^{1^{7}}$ For detailed descriptions of the IAB Establishment Panel see Fischer et al. (2008) or visit www.iab.de.

Agency of Germany. The BLH is maintained since 1975 and it contains, on the one hand, information about every employment relationship subject to obligatory social insurance contribution (the data originates from the Social Insurance Statistics – SIS, see Fritsch and Brixy, 2004). This data consists of yearly obligatory notifications on all employees in all establishments located in Germany, but it also records all changes in existing employment relationships as well as newly starting and terminating relationships.

On the other hand, the BLH contains information about the start date, the duration and the finish date of all kinds of receipts of benefits (for instance unemployment compensation, provisions of reintegration into the labour market) provided by the local employment agencies. All notifications are obligatory; non-response by employers is subject to criminal law. However, a limitation of the data is that it only captures information on employment subject to social security contribution¹⁸ meaning that particularly self-employment and the employment of civil servants is not covered.¹⁹

The BLH does not only contain information about the beginning and end of employment relationships and benefit receipts across all German employees and benefit recipients, but it also covers information on several other variables for these individuals. For example, it includes information on the age and sex of every individual, on the professional status (e.g. apprenticeship), on the educational status (school level and professional education), on the profession itself as well as on wages.

3.1.3. Longitudinal vs. cross-section

Via an establishment-ID, the individual level employment data can be matched with the establishment level data from the IAB Establishment Panel. There are two versions of the LIAB differentiated by the method of matching the data sets. The longitudinal version makes use of the fact that the employee-level data is available as spell data with exact dates of beginning and end of every employment (and unemployment) notification. This version then contains, for a subsample of establishments, all spells of all employees who have been employed in the establishment in a given period (see Alda et al., 2005, for a more detailed description of this version of the LIAB).

For the present paper, we use the cross-sectional version of the LIAB. It links information for all employees employed on June 30 in one of the sample establishments to the establishment-level information from the IAB Establishment Panel. It allows for tracking employees as long as they work in one of the panel firms, but, contrary to the longitudinal version, it neither contains information about what employees do before or after an employment (in one of these establishments) nor on the exact duration of

¹⁸ Since 1999, it also contains data on marginal employment.

¹⁹ The coverage of total employment on the basis of the SIS ranges from only less than 24% in the agricultural sector to about 50% in the public sector, 80% in the service sector and up to more than 90% in manufacturing (see, for example, Fritsch and Brixy, 2004, p. 183).

the employment. However, the advantage of using the cross section version is that it allows for analysing a larger number of establishments consistently over a longer period of time. Moreover, it permits determining the number of gained and lost employees relative to the previous or following year – which can be interpreted as hires and separations.²⁰

3.1.4. Selection of data

For the present study, we use only a part of the available data in the cross-sectional version, mainly due to the objective of making data comparable with the Dutch data.

Regarding the establishment-level data, we do not have information about entering and exiting establishments, as we cannot determine whether an establishment is entering/exiting the data due to entry or exit from the market or due to not being surveyed in the respective year or due to other reasons. Thus, we only include establishments which have been in the data continuously between 1998 and 2004. We further exclude establishments with extremely high growth rates (depending on firm size) as well as, certainly, establishments which do not match to any employee in the individual-level data or which display employee numbers diverging by more than 60% from that of the aggregate individual level data.

From the individual-level data, we exclude all individuals aged younger than 16 and older than 65 years, and, certainly, all observations which do not match any of the establishments. Furthermore, we exclude all employment relationships not subject to social security contribution, i.e. marginal employment, which is part of the data since 1999.

We end up with a sample of 1,968 establishments with observations for all years from 1998 to 2004. The sample contains a yearly average of 454,202 employees, declining from 472,572 in 1998 to 434,784 in 2004. Hires and separations can be identified in the data from 1999 to 2003. All employment relationships new to an establishment in a given year are interpreted as hires, all employment relationships being assigned to an establishment for in year *t* but not in year t+1 are interpreted as separations.

The information on the educational levels of employees is derived from the employee-level data and it originates from the information provided by the employers to the Employment Agency at the time employing a person.²¹ We are able to distinguish in total six educational levels:

²⁰ There ate two noticeable drawbacks in the data: First, employment relationships beginning after June 30 of year *t* and ending before June 30 of year *t*+1 cannot be observed in the data. Second, we cannot consider the exact duration of employment relationships: an employment beginning on June 30 and ending on July 1st would be weighted equally as an employment beginning on June 30 an ending on December 31.

²¹ As the original information is incomplete, particularly at the beginning of the job careers of individuals in the establishments, we use the imputation methodology proposed by Fitzenberger et al. (2005). Thereby, we are able to reduce the share of observations with unknown skills from 5.81% to 4.74%.

- no degree,
- vocational training,
- high-school,
- high-school + vocational training,
- technical college,
- university.

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We consider all employees with a technical college or a university degree as high-skilled. The information on innovation, on the other hand, stems from the establishment-level data. We use information on investments in ICT measured as share of total investments to determine whether an establishment is seen as an innovator or not.²²

3.2. The Netherlands

For the purpose of this paper, a matched employer-employee data base for The Netherlands was compiled by linking a number of micro-level data bases of Statistics Netherlands. Figure 3 shows the data base structure.

At the heart is the so-called Social Statistical Jobs Data base (*SSB-Jobs*), which contains information on all jobs of all Dutch employees at the business unit they work in, dates they start or end their jobs and the business unit's main activity (NACE). We have information on all employees in the Netherlands in the period 1999-2005. Some indicators in this data base, like wages, are however not available for all employees, but only for a sample. On the employer side it comprises all business units with personnel between 1999 and 2005.²³ Hence, the SSB-Jobs is basically (the core of) a matched employer-employee census.

In principal, the SSB-Jobs is set up as a longitudinal data base containing all employment spells of all employees in The Netherlands. This implies that there are about 10 million jobs of employees included for a period of a year, i.e. including jobs starting and ending within that same year. At any fixed point in time in the period under consideration, there are about 7 million employee jobs in The Netherlands. Hence there are roughly 3 million that appear and vanish within one year. This data based on the number of jobs at a fixed point in time is called the cross-section data base. The fixed point in time is set at September 30 of each year.²⁴

²² Indeed, the German establishment level data contains better measures of innovation (like, e.g., the R&D investments or the number of different types of innovations). However, we use ICT investments in order to provide comparability with the Dutch data in this respect.

²³ Statistics Netherlands divides companies into business unit. A business unit is the lowest level of identification at which data on any given economic activity are collected by Statistics Netherlands.

²⁴ This is because Statistics Netherland also used this date as reference date in its employer surveys to which the SSB will be linked. The fact that the Dutch and German reference dates are not the same is an inheritance from the past as both dates were already set prior to this research. We feel this does not really affect the outcomes.

We have experimented extensively with whether to use the longitudinal or the cross-section version of this data base for The Netherlands. The question is the importance of the so called 'double flow jobs', i.e. the jobs that appear and disappear in the period between two reference dates. In case of the longitudinal version, they are included and to get the appropriate hiring rates, the inflow of new employees has to be scaled by the total jobs in a given year of roughly 10 million. In case of the cross section version, they are not included and the denominator of the hiring rate then equals the number of jobs at that fixed point of roughly 7 million. We found that the hiring rates between the two versions – longitudinal or cross-section – do not differ very much.²⁵ This, plus the fact that for the German data base the cross section version allows for more establishment observations over a longer period of time than the longitudinal version, made us decide to use the cross-section version of both data bases for our comparative analyses.

3.2.1. Employer side

At the employer side, there exists only survey information on business units from e.g. Production Statistics (PS), containing balance sheet information, Investment Statistics (IS) on investments in fixed assets or the Community Innovation Survey (CIS) on innovation (cf. figure 3). On average these surveys include about 60,000 business units, which represent about 8% of all Dutch business units. Basically, the PS and IS comprise all business units with 50 or more employees and a sample of the smaller ones.



Figure 3. Structure of Dutch matched employer employee data base

Note: The hexagon is the key data base linking persons to business units, rectangular is a census, ovals are surveys.

²⁵ This is corroborated by hiring rates reported by Statistics Netherlands based on the longitudinal version of SSB-Jobs, which hardly differ from the ones we found with the cross-section version.

The PS and IS that will be used in this study are limited to business units in manufacturing, in trade and hotels and in business services.²⁶ For these industries, a sufficiently long time period is available, pertaining from 1999 to 2005. For other industries PS information is either not available or it is limited to few years.

3.2.2. Employee side

From the employee side this SSB-Jobs can be linked to person-information from the Municipality Base Register (MBR), comprising information on gender, age, marital status, children and ethnicity of all 16 million inhabitants of all Dutch municipalities. Since the MBR comprises characteristics of all employees, the linkage to the SSB-Jobs keeps the matched employer-employee census intact (see figure 3).

The only piece of information the MBR does not cover is the level of education attained by Dutch citizens. This immediately brings us to the one major flaw in this matched employer-employee data base, which is the lack of information on education for each of the workers in the SSB. The only publicly available source of the education attainment of workers in the Netherlands is the Labour Force Survey (LFS). This LFS is a rolling panel, where only a small part of the persons questioned are followed in time and the other part is a random sample that differs each year. The LFS covers about 1% of the employees of the SSB. Given the large cross-section component of the LFS, linking the LFS to the SSB-Jobs means that not one single business unit with employees will be covered for all years and that the data base would hence be empty.

3.2.3. Construction of education/skill indicator for The Netherlands This lacking information made it necessary to construct an approximation for the level of education of each of the workers in the SSB for whom wage information was available. This holds true for about 2.5 million out of the 7 million employees in the cross section version of the SSB-Jobs data base. The wage information of this selection of employees will be used to approximate the number of high educated among them.

This approach is motivated by the literature on human capital externalities. Basically, this literature states a positive relation between the educational level and wages. An additional year of schooling raises the individual wage with x%.²⁷ In fact, we have reversed this way of reasoning by assuming that individual wages beyond a certain threshold in the wage distribution imply the wage earner has a high education or at least is highly skilled. This is of course a tricky assumption as higher wages also represent increased job tenure. This approach is therefore

²⁶ Manufacturing is NACE 15-37, trade comprises traded and hotels, (NACE 50-55) and business services are NACE 70-74 (plus 93).

²⁷ This analysis is usually based on a so-called Mincerian wage equation. Rauch (1993) finds x is about 5%, Acemoglu and Angrist (2000) find x equals 1-3%, Moretti (2004) finds x is 0.4%, Winter Ebmer (1994) finds returns x of 4-9%. So the actual size of the returns to human capital differs by country, sample and the way human capital is defined. But generally a significant positive effect is found.

perhaps more an approximation for high skills or work experience than for high education. We therefore refer to it as an education/skill indicator. It is a mere dummy variable referring to each employee for whom wages are available in the SSB-Jobs and returns a value of 1 in case the individual is assumed to have a high education or to have a high skill-level and a value of 0 otherwise.

Next, we will briefly set out how this indicator has been constructed. We have three sources of micro data that will be used in the construction of the education/skill indicator. First, the CIS-3 (1998-2000) contains a question asking employers to report the share of high educated workers they employ. Second, the SSB-Jobs contains pre-tax wages for about 2.5 million employees. Eventually our construction method will result in an education/skill indicator for each of them. Third, the PS contains the total gross wage costs each of the employers in the survey incurs.

The share of high educated workers from the CIS-3 is an important piece of information, as it enables us to construct 2-digit industry shares of high educated labour. These industry averages play a crucial role in comparing the industry aggregates of our constructed individual indicators.

Information on wages of employees from SSB-Jobs are linked to the age of these employees drawn from the MBR. Since the SSB-Jobs also comprises information for which firm these employees work, linking SSB-Jobs to ages from the MBR makes it possible to generate annual wage distributions for 2-digit industry classes by 10-year age groups. Thereby, the fact that wages rise with age is mitigated.

Given this wage distributions for each of the 2-digit industries and years, the CIS-3 share determines where the cut-off point of each distribution is located: above this point employees are assumed to have a high education (or high skills). Therewith, we can determine for each employee by age class if he has a wage above the reference wage based on the CIS-3 share. Any employee with a wage above the reference level in any year is assumed to be high educated/high skilled.

As an alternative, we also considered the wage distribution without considering the age of employees, but instead looked at the wage costs the business units have to cover and again in terms of the wage (costs) distribution per year and per 2-digit industry. The CIS-3 now determines a sort of skill premium for each industry, above which the associated employee is high educated/high skilled and below which he is not. In order to compare this business level wage costs to the wages per employee, we assume employees to be high educated/high skilled, when their wage is above the average business wage times the industry skill premium.²⁸ Again, if an employee receives a wage above this reference wage in any year, he is assumed to be high educated/high skilled.

²⁸ In order to get comparable figures for gross employee wages (before taxes) and business wage costs (before taxes and employer costs), we also divide the wage costs by the average Dutch employer costs to labour, which is 25%.

The data base without the education skill indicator comprises 75,000 business units and roughly 2.5 million jobs for the period 1999-2003. Because of linkage to the IS to yield the innovation indicator, these businesses and jobs are limited to the industries manufacturing, trade and hotels and business services. When the education/skill indicator is included, we are end up with 2,300 business units and on average 28,000 jobs over the period 1999-2003. This implies that the average firm size in the small data base including education is smaller than when it is excluded. This casts doubt on the representativeness of the data base with the education/skill indicator. The large data base without education is a representative sample because the SSB-Jobs is a census and the IS is representative.

3.3. Comparability

Even at the aggregate level, data of different countries are difficult to compare, let alone data at the micro-level. In this subsection, we list a few of these difficulties that we have encountered in this study during the preparation and comparison of the Dutch and German matched employeremployee data bases.

Comparing employer activity

The first difficulty pertains to the actual definition of the employer-side of the data bases. In order to make this difficulty clear, we need to elaborate on the different types of activities statistical agencies can distinguish. At the heart of the activities is the so-called *kind-of-activity unit* (KAU) as set out in the ESA95 guidelines.²⁹

The KAU covers all parts of an institutional unit in its capacity as producer contributing to the performance of an activity at NACE-4 or 5 level and corresponds to one or more operational subdivisions of the institutional unit. Statistics Netherlands prioritises the second part of this definition. In many cases it is also possible to distinguish a more or less local KAU.³⁰

Figure 4 relates these concepts. It shows different types of units involved in production activity according to ESA 95 guidelines and indicates their links. On the left side, the institutional perspective is described; the right side displays the functional perspective. The rows show three levels of analysis: aggregate, elementary and local referenced.

²⁹ See e.g. EC/Eurostat (2002, p. 45-48).

³⁰ The SSB does contain information on the municipality of each business unit, but the employer-side survey data (PS, IS, CIS) do not.

Figure 4. Types of production units in ESA 95



Source: Eurostat, ESA 95 Input-Output Manual (EC/Eurostat, 2002, p. 47)

Statistical agencies register as many local KAU's as there are secondary activities performed by the institutional unit (usually the company). However, when accounting documents needed to describe such activities are not available, a local KAU may include one or several secondary activities.³¹ The group of all local KAU's or KAU's engaged in the same or similar kind-of-activities constitute an industry. The local (institutional) unit of production is a site producing goods or services or a part thereof situated in a geographically identified place (usually the establishment). This may correspond to a (local) KAU, but not necessarily. A local establishment may comprise different activities (and hence KAU's).

In the Dutch situation, the employer side of the data base refers to the so-called business-unit level, which corresponds to the functional KAU. The German employer side of the data base refers to the institutional establishment level. However, the relation between KAU's and establishments is complex. An establishment may comprise several KAU's, depending on the (identifiable) secondary activities of the establishment. It is however also feasible that one KAU comprises several establishments of one company, as far as these establishments perform the same activity.

In most cases however, the KAU or business unit level of the Netherlands data base will to a large extent correspond to the establishment level of the German data base. The main reason for this premise is the fact that this study links the SSB–Jobs data base to the PS and IS (see figure 3). The latter surveys comprise all business units with more than 50

³¹ The statistical requirements for each institutional unit's information system must include for each KAU its value of production, intermediate consumption, compensation of employees, operating surplus, employment and gross capital formation.

employees and sample the smaller ones. Most of these larger business units are (part of) a company and hence an establishment, while the number of establishments comprising several KAU's are limited. Therefore despite the statistical differences between the Dutch and German way of collecting employer level data, we feel that for our purposes this aspect of the data does not pose much of a threat.

Comparing hiring rates

Apart from possible differences in the level at which employers are identified, it is also important to know how a hire of a (new) employee at an employer can be identified. For every employer in the data base - be it establishment or business unit – we can identify each employee. A hire is identified here as the appearance of a new employee at an employer.

We have already argued that this research is based on the cross-sectional version of the matched employer-employee data bases in both Germany and the Netherlands. Table 1 presents a simple representation of how a hire (and a separation) is identified within these data bases. None of the job movements between dates t and t-1 or t+1 are observed.

Point in time	t-1	t	t+1	identified as
employee	out	out	in	hire in <i>t+1</i>
employee	out	in	in	hire in <i>t</i>
employee	out	in	out	hire in t, separation in t+1
employee	in	out	out	separation in <i>t</i>
employee	in	out	in	separation in t , hire in $t+1$
employee	in	in	out	separation in <i>t+1</i>

Table 1. Identification of hires and separations in cross sectiondata bases of Germany and The Netherlands

Comparing innovation

We also need a similar definition of innovation of these employer-side units. One way to look at innovation is to link the employer-side to various waves of the Community Innovation Survey (CIS), which among others states whether employers are innovators or not.³² However, CIS data for Germany are neither part of the LIAB nor of the IAB Establishment panel, and as both data bases are relatively small samples, one can expect the potential rate of watches to be very small

Instead, we define innovativeness by the extent to which a business unit or establishment has higher ICT investments than the sectoral (2-digit) average over the period 1999-2003.³³ When a business unit or establishment has higher than average ICT investment during those years, it is labelled an innovator, else it is a non-innovator. This definition can be applied to both Germany and The Netherlands. Table 2 compares

³² The CIS is a bi-annual survey conducted under auspices of EUROSTAT in EU member states for a number of years now (starting in 1994-96).

³³ In the Dutch case these investments are drawn from the IS, in the German case they are an integral part of the matched database. The Dutch case does indeed refer to 1999-2003, while for Germany this is 2000-2003.

the share of innovating firms in The Netherlands according to this definition and the share of innovating firms according to published data of Statistics Netherlands. Innovation in manufacturing is underestimated as it often goes beyond ICT application and involves R&D and related technological activities. The innovation rates in trade and business services match very well. To a large extent, service innovations correspond to ICT applications.

	ICT investment	Stat.Neth CIS
Manufacturing	25.2	41.5
Trade/hotels	19.0	19.4
Business service	s 29.5	30.5

Table 2. Comparison of share of innovating firms, Netherlands

Source: own definition and CIS3 (share of innovators)

Comparing education

We now turn to issues of comparability on the employee side. The crucial variable in our study is the level of education of each of the employees in the data base. This information is an integral part of the German data base, but it is not present in the Dutch data. The previous subsection already demonstrated how we have constructed an approximation of the education/skill level for a large portion of the employees in the Dutch data base.

This constructed education/skill level causes a sample bias. There are two reasons for that. First, the education/skill indicator cannot be constructed for all employees, but only for those with wage information. Hence, for a large part of the employees it is not possible to construct this index. Second, each employer in a matched employer-employee data base should contain information on all his employees. If one employee of such an employer is missing, this would cause the employer to drop out of the data base. These two points imply that business units with large numbers of employees will be underrepresented. For these businesses, it is more likely that wage information of one single employee is missing and hence the employer drops from the data base. This implies that it is unlikely that the Dutch matched employer-employee data including the education/skill indicator is in fact a representative sample.³⁴ This has repercussions for the interpretation of the results with these data.

This study does however have the option of assessing the reliability of the constructed education indicator. The German data base contains both education and wages. We have hence constructed the education/skill indicator for Germany in the same way as we did for The Netherlands. Next, this German indicator can be compared to the observed education for German employees. If this observed and constructed indicator match well, we may conclude that – assuming a similar employment structure in

³⁴ Without the education/skill indicator it is a representative sample, since the PS and IS are both representative and the SSB-Jobs is a census.

both neighbouring countries – the Dutch constructed education/skill indicator will also converge to the true level of education.

Table 3 assesses the comparison of the constructed and observed education indicator for Germany. This constructed indicator has a large error of the first kind in terms of appointing the high educated. Of each 100 individuals who are attributed a high education according to the indicator, in reality 70 did not have a high education. Hence, our index seems to point to other worker characteristics than education.³⁵

Table 3.	Comparison between constructed and observed educatior
	indicators, Germany 1999-2003 (x 1000)

		Constructed level of education					
		Not high High		h To		otal	
		× 1000	%	\times 1000	%	\times 1000	%
Observed	Not high	3389.6	96.3	244.1	69.9	3633.8	93.9
level of	High	130.0	3.7	105.3	30.1	235.3	6.1
education	Total	3519.6	100.0	349.5	100.0	3869.1	100.0

Source: own calculations based on LIAB data base

We conclude from table 3 that education is only partly captured by our indicator. A large part of it also reflects job experience or tenure. So our indicator is more a reflection of education and skill than solely of education. This is in fact an advantage over mere education, because in the theory of skill-biased technical change or skill-biased international trade, which lie at the heart of our study, it is not so much education that is substituted for cheap workers abroad or machines, but that is much more a matter of skills.

Concluding remarks on the (im)possibility of international comparison This section shows that for Dutch and German matched employeremployee data a useful comparison is difficult if not impossible to make. The German definition of employees by social insurance payment may create some problems. However, since we are looking at only three market industries (manufacturing, trade/hotels and business services), these problems are only minor compared to the Dutch data base.

The matched employer-employee data base that we have constructed for The Netherlands has the major drawback that no viable information on education of all employees is publicly available.³⁶ This makes comparison of the actual level of the hiring rates between the two countries impossible. What can be done, with due caution, is to consider the rankings of the hiring rates for the nexus of innovativeness and education/skill. We can then assess possible differences in dominance of the hiring rates between the two countries, without looking at their actual size.

³⁵ This line of reasoning is also followed by Schlitte (2009). He uses a similar argument to come up with an alternative measure based on education and skills, developed by Brandt and Cordes (2007).

³⁶ Statistics Netherlands does have that information, but only for internal use.

4. Results

The main focus of this paper lies in the analysis of demand for skilled (high-educated) labour by innovating and non-innovating firms. This implies that hiring of new employees is the key variable here. Hiring is determined as the occurrence of a new worker with a certain level of education in a firm.³⁷ The hiring rate in any firm *i* by education level *j* (*j*=high, non-high) is then defined as

$$h_{i,j} = \frac{\sum_{k} H_{k,j,t}}{1/2 \cdot \left(\sum_{k} E_{k,j,t-1} + \sum_{k} E_{k,j,t}\right)}$$

where $H_{k,j,t}$ is any worker k with education j that appears for the first time in firm i in period t. The denominator is the average number of employees E_k working in firm i and having education level j.³⁸ This hiring rate can be calculated for each firm i, where the firms can be subdivided in two groups: innovators and non-innovators.

Table 4 shows the hiring rates of high and non-high education by innovators and non-innovators in Germany and The Netherlands in three different industries, averaged over the period 1999-2003. This is the period covered by the data sets in both countries. It shows the extent to which innovators hire more high educated/high skilled workers than noninnovators.

These results show that for the period 1999-2003 the hiring rate – i.e. labour demand – is larger in innovating firms than in non-innovators in Germany. For The Netherlands this is only true for trade. Both in Dutch manufacturing and business services, labour demand is highest for non-innovators. Table 4 also shows that for both countries, labour demand for high educated exceeds that for non-high educated for all industries, with the Dutch business services as sole exception. Here, labour demand for intermediate and low educated is the larger category. So, even before looking at the nexus of innovation and education, we can already conclude there is a large difference between Germany and The Netherlands with respect to the structure of business services and possibly manufacturing.

Zooming in on the employment structure of business services in both countries in table 5, we find that particularly temporary employment agencies form the main difference. In The Netherlands these are by far the largest industry class within business services comprising roughly 40% of the employment in NACE-class 74. In Germany this is a mere 13%.

³⁷ We use the expression 'firm' for both business units (in The Netherlands) and establishments (in Germany).

³⁸ This form is chosen following the denominator used in the job flow rates by Davis and Haltiwanger (1992) and helps to evade possible regression to the mean bias.

Table 4. Hiring rates by in	nnovation intensity of the firm a	and education/skill level o	f the newly hired worker,
averages over the	period 1999-2003		

Table 4. Hiring rates by innovation averages over the period 1	on intensity of the firm and education/s .999-2003	ski	ill level of the newly hired worker,
	Germany		Netherlands

		Non-innovators	Innovators	All firms	Non-innovators	Innovators	All firms
Manufacturing	No high skills	6.4	7.1	6.6	12.4	11.8	12.3
	High skills	10.1	11.0	10.4	17.0	16.0	16.7
	All hires	6.8	7.7	7.1	12.9	12.4	12.7
Trade	No high skills	11.8	10.3	11.3	18.0	22.4	18.7
	High skills	13.1	16.6	14.8	21.0	18.4	19.7
	All hires	12.1	10.8	11.8	18.5	21.5	18.9
Business services	No high skills	8.7	19.0	11.6	32.0	26.6	29.2
	High skills	14.9	14.5	14.8	32.6	15.0	22.5
	All hires	13.0	17.9	14.5	32.0	21.4	26.4

Note: Cells shaded green indicate skill biased innovation, cells shaded red indicate unskill biased innovation as maximum hiring rates. Neither is found to be dominant in Dutch manufacturing or business services

Source: Own calculations from a matched employer-employee data base for The Netherlands, compiled from different data bases of Statistics Netherlands and own calculations from the German LIAB matched employer-employee data base.

This is one of the major causes of the relatively low share of knowledge intensive business services (KIBS) of The Netherlands. These KIBS usually comprise NACE 72, 73 and 741-744, which yields 38% of total business services for The Netherlands and 45% for Germany.³⁹ In other words, the complement, or non-KIBS share, is much larger in the Netherlands (62%) than in Germany (55%). This corroborates the non-high educated nature of Dutch business services.

NACE-2	NACE-3	Description	Germany	Netherlands
70		Real estate	12.2	5.0
71		Renting of movables	2.0	1.5
72		ICT services	8.4	8.7
73		R&D services	3.4	2.1
74		Other business services	74.0	82.7
	of which			
		Legal, accounting services		
	741	and the like	18.8	19.3
		Architects and technical		
	742	engineering services	8.1	5.9
	743	Testing and control	1.3	0.7
	744	Advertising agencies	5.2	2.1
	745	Temporary work agencies	12.8	39.4
	746	Security services	3.6	2.2
	747	Cleaning	16.5	9.3
		Fotography, packaging		
	748	and the like	7.8	3.8

Table 5. Employment structure of business service industry in Germany and The Netherlands, 2006 (% jobs in NACE-7)

Source: Statistics Netherlands and IAB (Establishment History Panel)

In fact, the large employment growth The Netherlands experienced in the late 1990's – sometimes referred to as the Dutch Miracle – was to a large extent employment growth for low-educated. Many of these low- educated jobs were situated at the bottom part of the business services industry of table 3, particularly at temporary work agencies.⁴⁰

Figure 5 corroborates these premises by presenting the development of low educated employment in both Germany and The Netherlands for the period 1994-2000. There is a marked increase for low educated labour for The Netherlands, thereby offsetting the general falling pattern of figure 1 for that period.⁴¹

³⁹ For this industry definition of KIBS see Miozzo and Grimshaw (2006, p. 3) ⁴⁰ Evidence of Statistics Netherlands shows that, between 1994-1999, the average number of employee jobs grew 4% on average per year, while temporary agency jobs grew at 10% in that period. The study of Broersma (2009a) corroborates the low educated nature of this employment growth.

⁴¹ Note that US employment for low educated (Figure 1) also showed a slight increase from halfway the 1990's to the early 2000's.



Figure 5. Low educated employment, Germany, The Netherlands

Source: own calculation based on ILO, OECD, SBA, CBS

Another outcome of table 4 that catches the eye is the much larger hiring rates in The Netherlands compared to those in Germany. Is this a statistical artefact due to the non-representativeness of our dataset or is it a real phenomenon? As argued before, the Dutch data is based on a nonrepresentative sample of business units, which may affect the hiring rates.

Nevertheless, is there any reason for the higher level of job dynamics in the Dutch labour market than in the German? Hiring of new personnel can be subdivided in (i) hires to a new job or (ii) hires to an existing job that for whatever reason is abandoned by its previous occupant and is eligible for refilling. The first factor equals the gross job creation rate. We know the job creation rates between Germany and the Netherlands are in the same range.⁴² The second factor is of a more complex nature, particularly because it is difficult to assess whether or not an abandoned job will be refilled. An important part of abandoned jobs is due to voluntary job movements. Rates of job to job movement for the two countries are also similar.⁴³ The rate of abandoned jobs that are refilled depends on a host of factors, like entrepreneurship and risk aversion, but also on institutional issues. These may differ between the two countries.

 ⁴² See e.g. OECD (1994), Burda and Wyplosz (1987), Broersma and Gautier (1997), Broersma and Rekveldt (2007).
 ⁴³ For Germany, Koch and Boockman (2008) as well as Steffes (2008) report job-

⁴³ For Germany, Koch and Boockman (2008) as well as Steffes (2008) report jobto job flow rates of about 7-9%, which are roughly the same as reported by Statistics Netherlands.

Finally, we look at the actual cross results of hiring rates by innovativeness and education/skills in table 4, as in the diagram below.

	Non-innovators	Innovators
No high skills	(i)	(ii)
High skills	(iii)	(iv)

Although comparison of the actual hiring rates between the two countries may be hampered by various problems, we can still identify the dominant hiring rates from the diagram:

(i) hiring rates for non-high educated/skilled by non-innovating firms,

(ii) hiring rates for non-high educated/skilled by innovating firms,

(iii) hiring rates for high educated/skilled by non-innovating firms or (iv) hiring rates for high educated/skilled by innovating firms.

Given the increasing demand for high educated workers of the past decades (see figure 2) and the fact that innovation has a positive effect on employment (and hence hiring of new personnel), we expect the hiring rate for high educated/skilled workers in innovating firms (i.e. iv) to be dominant over the other three cells. This corresponds to the theory of skill-biased technological change (SBTC).

Table 4 indeed shows that the hiring rates of cell (iv) are largest for manufacturing and trade in Germany. For business services in Germany cell (ii) is largest, just as for trade industry in The Netherlands. For manufacturing and business services in The Netherlands the hiring rate of cell (iii) is dominant. Therefore, for the period 1999-2003, table 4 does point towards SBTC in German manufacturing and trade, but not in German business services. On the other hand, in none of the Dutch industries we find cell (iv) to dominate, so SBTC seems to be less of an issue here than in Germany.⁴⁴

In other words, only hiring rates in German manufacturing and trade industries corroborates our hypothesis and do point towards skill biased innovation. Hiring rates in the German business services, on the other hand, refute it, exhibiting an unskill bias in innovation. The same holds true for Dutch trade, where hiring of non-high skilled also dominates, while in Dutch manufacturing and business services hiring rates for high skilled in non-innovating firms dominate.

⁴⁴ One could argue that hiring rates tell only part of the story as it may very well be that separation rates are also larger for non-innovators or non-high educated/skilled workers. To counteract such arguments we also looked at the net employment growth rates, i.e. hiring minus separation rates. This yields for Germany that hiring rates in all three industries are highest for cell (iv). For The Netherlands this holds true for manufacturing, but the ranking in Dutch trade and business services remains unchanged. Nevertheless, the concept of labour demand is in our opinion better served with gross hiring inflows than with net employment changes. The latter can for instance be negative and negative labour demand does not make sense.

5. Reconciliation with theory

This section discusses the results of table 4 in terms of recent theoretical considerations. The results we find for German manufacturing and trade neatly fit the literature on skill-biased technological change. This literature states that ICT and low educated/skilled workers are substitutes, whereas ICT and high educated/skilled workers complement each other. Therefore, manufacturing firms with high ICT investments (i.e. innovators in manufacturing), have a depressing effect on the demand for lower educated, but increasing effect on demand for high educated.

Apart from being replaced by ICT capital, low and intermediate skilled jobs in manufacturing may also be outsourced to low wage countries. The low skilled intermediate products they produce are next imported again for further assembly in the home country. This globalisation due to falling trade barriers is also an ongoing process, just like the increasing trend in the use of ICT-capital due to relatively falling ICT-prices.

These phenomena can be explained by the fact that many low skilled employees in manufacturing basically perform routine manual tasks that are accomplished by following explicit (and hence programmable) rules. Their tasks can either be replaced by a programmable machine (computer) or can be 'exported' and carried out by cheaper low skilled labour abroad.

What remains in manufacturing in Western economies, like in Germany, are more non-routine manual, analytical and communication tasks. These involve much more co-ordination as production comes from different parts of the world and is assembled in a more high-tech environment than previously was the case. Also these tasks are more concerned with the generation of new ideas, design and R&D-like activities. These are all typically tasks for higher educated/skilled personnel.

This line of reasoning fits the strand of literature on the skill bias in technological change and the skill bias in international trade.⁴⁵ The explanation of these phenomena in terms of tasks is based on the theory introduced by Autor et al. (2003).

In fact, these phenomena are also put forward to explain the rising importance of business services as source of employment and the decline in manufacturing. The idea is that low skilled jobs in manufacturing are lost, while in services, particularly business services, there is a growing need for high-educated workers. This would then create an underclass of low-educated/low-skilled workers being permanently locked out from labour. As the outcome for business services of table 4 shows, this is not the case, neither in Germany nor in The Netherlands.

How can this phenomenon be explained in the light of the dominant theories of skill-biased technological change and skill-biased international trade? First, we have to realise that both these theories emphasise the

⁴⁵ cf. Berman et al. (1994, 1998), Krusell (2000), Hornstein et al. (2006).

demand side of the labour market. Basically, firms make the decisions about if and how to replace workers by skill for machines or by outsourcing their work. But whether this worsens the labour market position of low educated also depends on their labour supply. Supply of low educated labour has also decreased because of the participation rise in education from the 1960's onwards. If labour supply of low educated drops faster than demand, their relative labour market position will in fact improve, as they become more scarce. Second, empirical evidence of figure 5 shows that employment for low educated has increased in the second half of the 1990's and that the structure of business services in The Netherlands favours low educated because of the large share of non-KIBS.

These observations can be related to an extension of Autor et al. (2003) towards polarisation of labour markets.⁴⁶ Here, focus is on providing an explanation for the stabilisation or slightly rising demand for low skilled employed workers, which can be seen from the second half of the 1990's in figure 1. This can also explain the rise for Germany and The Netherlands in that period of figure 5. Like Goos and Manning (2007) showed for the UK, Autor et al. (2006) show for the US that in the 1990's employment growth was concentrated at the lower and upper tail of the wage distribution resp. the lower and upper tail of the skill distribution, reflected in the distribution of the years of schooling.

Hence, both low and high-educated jobs indeed increased not just in the USA and the UK, but this also appears to be the case in The Netherlands and Germany (figure 5). This goes at the expense of employment growth for intermediately educated. In Anglo-Saxon countries the wage rate of intermediately educated falls relative to that of low and high-educated (Autor et al. 2006, Goos and Manning 2007) In continental European countries their unemployment rises relative to that of low and high-educated (Broersma 2009b). This difference is in line with the Krugman thesis that the more flexible labour markets in Anglo-Saxon countries reflect this phenomenon in falling wage rates, while in the more rigid European labour markets this is reflected in higher unemployment.

We will not pursue this line of reasoning any further here and return to the role of polarisation for the explanation of the unskill bias in innovation of business services and trade of table 4. Autor et al. (2006) go on to argue that non-routine manual tasks like of a (truck) driver, waiter, cleaner or security guard, are no substitute of ICT capital. This however still does not explain why their employment has not just stabilised, but in fact increased. An explanation can be found in the theory of increasing polarisation of Sassen (1991). She argues that a rise in jobs for high educated/skilled workers provides a stimulus for job creation at the lower end of the skill distribution. High-earning knowledge workers exert a large demand for all kinds of low-skilled (personal) services, like for cleaners,

⁴⁶ Autor et al. (2006), Goos and Manning (2007), Spitz-Oener (2006)

homecare services, guards, child care services, waiters, hair dressers, taxi drivers and concierges (cf. de Beer, 2006).⁴⁷

6. Concluding remarks

This paper has studied the differences in labour demand for innovating and non-innovating firms by education/skill level. This is conducted in an international comparative manner, by applying this issue to matched employer-employee data bases in Germany and The Netherlands. In these data sets, each individual employee is matched to an employer and for each employer we know exactly how many and which employees are in his work force. Labour demand is then defined as each realised gross hire in a firm, i.e. any employee appearing in the work force of a firm for the first time.

As far as possible, a common methodology was used to capture this labour demand. Nevertheless, we conclude that a useful comparison between the data bases for Germany and The Netherlands is difficult if not impossible to make. The matched employer-employee data base that we have constructed for The Netherlands has the major drawback that no information on education of employees is attainable. An approximation for this education makes the data base non-representative. Hence, comparison of the actual levels of the hiring rates between the two countries is then impossible. What still can be done, however, is to look at the ranking of the hiring rates for the nexus of innovativeness and education/skill. We can then assess possible differences in dominance of the hiring rates between the two countries, without looking at their actual size.

We then find that only for the German industries of manufacturing and trade, labour demand is largest for high educated/skilled employees in innovating firms. Hence, these firms reflect signs of a skill bias in innovation, i.e. innovation goes along with elevated hiring rate of skilled personnel, possibly at the expense of low educated. However, for German innovators in business services, hiring rates are largest for non-high educated/skilled workers. The same holds for trade in The Netherlands. This points towards an unskill bias in innovation for these industries, i.e. innovation goes with hiring of non-skilled personnel.

For Germany, these phenomena can be explained by the fact that many low and medium-skilled employees in manufacturing and trade basically

⁴⁷ We have so far neglected the innovative character of the unskilled business services. We merely state here that firms, or individual entrepreneurs, being capable to open up these new markets should be regarded as innovative, maybe not so much in ICT-terms but in organisational-terms. Business services are known to be good at just these organisational innovations; usually related to KIBS (see Broersma and van Ark, 2007). Note however that this type of innovation is by no means characteristic for high education. So non-KIBS may be innovative as well.

perform routine manual tasks that are accomplished by following explicit (and hence programmable) rules. Their tasks can relatively easy be replaced by either a computer or be exported and carried out by cheaper labour abroad. What remains are the more non-routine co-ordination and communication tasks, as production is more and more assembled from different parts of the world and administration is increasingly being standardized. These are typically tasks for higher educated/skilled personnel.

The pattern in German business services and Dutch trade is explained by the fact that in these industries low-skilled tasks also more often have a non-routine nature. Tasks performed by waiters, shop-assistants, cleaners or security guards, home and child care services are no substitute of ICT capital, nor can they be outsourced. This explains the rising importance of low skilled jobs not just in business services, but in all services. Demand for these types of jobs increased due to the increasing trend in employment for high educated. These high-earning, high-educated, knowledge workers exert a large demand for all kinds of low-skilled (personal) services.

The fact that Dutch manufacturing and business services fit neither the skilled nor the unskilled biased innovation hypothesis may be caused by the flaws in the construction of our education/skill indicator, but also because of the relatively short time period that is covered by the data. Basically 1999-2003 is a period of economic decline, culminating in the (mild) recession of 2002-3. In the build-up to this recession, Dutch firms have been focused more on cutting down on innovation than on hiring less high-skilled personnel. In Germany, this is much less the case.

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