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The Economic Impact of Capital-Skill Complementarities in German and US Industries Productivity Growth and the New Economy

Thomas Strobel

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Productivity Growth and the New Economy*

Abstract

US labor productivity in ICT-skill intensive industries experienced tremendous increases in post–1995 trend growth compared to Germany, while other (non-ICT-skill intensive) industries showed similar growth trends in both countries. Examining the source of industry productivity growth in German ICT-skill intensive sectors, there is no empirical evidence on the influence of ICT-skill complementarities; rather was productivity growth of German Motor Vehicles & Other Transports driven by Non-ICT-skill complementarities. In case of the US two ICT-skill intensive sectors, Office Machinery & Electronic Equipment and Motor Vehicles & Other Transport, were found to have experienced strong productivity growth via ICT-skill complementarities. These findings shed light on varying sectoral complementarities between physical and human capital and show a decisive disparity in the source of German-US productivity differentials in the goods-producing sector during the New Economy. Such differentials originated from a substantial dissimilarity in production processes as well as from higher ICT intensity and skill endowment in the US.

JEL Code: O3, O4, O5.
Keywords: Industry productivity growth, heterogeneous labor, capital-skill complementarity, information and communication technology.

Thomas Strobel
Ifo Institute for Economic Research
at the University of Munich
Poschingerstr. 5
81679 Munich, Germany
Phone: +49(0)89/9224-1465
strobel@ifo.de

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1. Introduction

Labor productivity (measured as value-added per hour worked) in Germany and the US experienced a persistent divergence in trend growth post 1990. As productivity measurement commenced to allow for effective accounting of information and communication technologies (ICT) in national statistics during the New Economy, starting around the mid–1990s, the origins of the productivity divergence became attributable to a more effective usage of ICT investments in US industries. The immense productivity increases in the US and the country's ability to attract large-scale high-skilled labor associate skill-biased technological change (SBTC) as underlying source of growth. Thereby the SBTC concept expands the notion of *factor-neutral* technological change to *factor-biased*, whereas this bias may be determined endogenously by economic incentives innovators are exposed to, such as firm size or market structure, but also by endogenous changes in the long-run demand for skilled workers and international trade.[1]

Resting on the idea that skilled labor is relatively more complementary to capital equipment than to unskilled (Griliches, 1969), this paper seeks to contribute to the capital-skill complementarity literature and its productivity enhancing effects by examining industry-level data for Germany and the US.[2] In doing so the focus will be on capital-skill effects during the emergence of the New Economy (1991–2005), and in contrast to previous empirical studies Griliches' (1969) idea of capital-skill complementarity will be extended to ICT and Non-ICT capital equipment. Modeling new technologies as entirely embedded in ICT capital goods, the approach accounts for the "IT revolution" which is associated with the New Economy. I then introduce heterogeneous labor to test for possible complementarities between ICT/Non-ICT capital and high-skilled workers and its impact on sectoral productivity growth. Therefore the object of investigation will be roughly the 2-digit NACE industry level for goods-producing industries (see Table A1 in the Appendix).

The implications will be that in industries with higher shares in high skills available, given the complementarity between skills and ICT capital, increases in ICT will raise the marginal productivity of high skills (observed via higher cost shares) and ultimately increases productivity growth. This is due to ICT-skill intensive sectors disposing of the crucial human capital factor necessary to translate new technologies into efficiency gains. Other

[1] Skill-biased technological change is determined as a shift in the production technology that especially favors skilled workers and thereby increases their relative productivity. This increase in productivity, hence, increases relative demand for those workers and their skill premium. A variety of economic models providing the basis for SBTC can be found e.g. in Acemoglu (1998, 2002a, b, 2009), Aghion (2002), and Hornstein et al. (2005).

[2] Papers that provide empirical evidence for capital-skill complementarities are e.g. Bartel and Lichtenberg (1987), Autor, Katz, and Krueger (1998) and Autor, Levy, and Murnane (2003).

(non- ICT-skill intensive) sectors should not display such effects. Those findings may have important implications on the requirements of sectoral skill endowments and governmental policies to attract high-skilled people to jump start economic growth. Determining the effects of capital-skill complementarities in Germany will also become increasingly important with respect to the Lisbon Strategy, which aims of strengthening innovations and advanced technologies in EU countries.

Examining the labor productivity enhancing effects of capital-skill complementarities in German goods-producing industries, I utilize unique German data from the *Ifo Industry Growth Accounting Database* (henceforth IIGAD) covering the period 1991–2005. It provides detailed accounts of 12 assets comprising ICT (Computer and Office Equipment; Communication Equipment; Software) and 8 additional equipment assets (Metal Products; Machinery; Electrical Generation and Distribution; Instruments, Optics and Watches; Furniture, Music and Sports Equipment; Other Machines and Equipment; Automobiles; Other Vehicles) as well as investments in Buildings and Structures. Due to its detailed level of information it allows to construct the most accurate measures of ICT and non-ICT capital services for 52 industries based on actual data. Obtaining methodologically comparable data for the US, growth accounting variables provided by the *EUKLEMS Growth and Productivity Accounts* (henceforth EUKLEMS) are employed.

The empirical investigation reveals that US ICT-skill intensive industries experienced tremendous labor productivity increases post 1995 compared to relatively restrained ICT-skill intensive sectors in Germany. On contrary, other (non-ICT-skill intensive) industries in the US and Germany performed similar during the same period. The econometric analysis corroborates that capital-skill complementarities indeed affected German and US ICT-skill intensive industries' productivity growth, but differently. While there is no empirical evidence of ICT-skill complementarities as source of industry productivity growth in ICT-skill intensive German sectors, productivity growth of German Motor Vehicles & Other Transports was rather driven by Non-ICT-skill complementarities. In the US, the two ICT-skill intensive sectors Office Machinery & Electronic Equipment and Motor Vehicles & Other Transport generated strong productivity growth via ICT-skill complementarities. Those findings support the hypothesis of SBTC being the source of German-US productivity differences in goods-producing sectors during the New Economy. Higher ICT intensity and skill endowment in the US spurred, while Germany's lower factor endowments stifled sectoral productivity growth.

The paper is organized as follows: Section 2 provides descriptive statistics on high-skilled hours worked for German/US industries; it derives the ICT-skill intensive industry taxonomy and juxtaposes labor productivity growth and ICT capital deepening by ICT-skill intensity. Section 3 provides the formally derived empirical models to test capital-skill complementarities and their impact on sectoral productivity growth. Section 4 gives a detailed description of the data, while Section 5 provides the econometric estimation results to the empirical models presented in Section 3. Section 6 concludes.

2. Descriptive Statistics

2.1 ICT-Skill Taxonomy

Data on labor composition provided by EUKLEMS (2008) allows to split hours worked into high-, medium-, and low-skilled. While these definitions are consistent over time within, there might be differences across countries. Being aware of comparability issues between skill types, I chose Germany and the US for comparison as they are classified by similar EUKLEMS skill-type definitions. In Germany the high-skill classification captures “university graduates”, while the US is “college graduates and above”.[3] Low skills is defined as “No formal qualifications” in Germany and “Less then high school and some years of high school (but not completed)” in the US. Hence, medium skills is determined as a residual in both countries comprising of “Intermediate” in Germany and “High school and some years of college (but not completed)” in the US.

As shown in Table 1a and b, there is a striking difference in the level of US/German shares of high-skilled hours worked across goods-producing industries. Inclusion of US bachelor degrees may serve as explanation for such differences; however, the descriptive statistics indicate that US workforce penetration with workers that dispose of higher education is much higher. Due to lack of detailed sectoral labor composition lower industry levels are assumed to dispose of the same high-skilled shares in hours worked as the higher aggregate (Timmer et al., 2007b). Based on average high-skilled shares and average growth rates in ICT capital deepening (measured as ICT capital services per hour worked), I derive a sectoral ICT-skill taxonomy that classifies industries by their similarity of ICT and high-skill endowment. Data on ICT capital deepening is gathered from the IIGAD (2008) for Germany and from EUKLEMS (2008) for the US.

Obtaining the industry taxonomy two cluster techniques are employed: the *k-means* and the *k-medians* approach. The first approach divides observations into four groups start-

[3] In case of high skills, I assume US and German bachelor degrees to represent similar skill levels. For further information on the skill definitions, see Timmer et al. (2007a, b).

ing from an arbitrary grouping of industries from which the absolute difference with the mean of each group is calculated. New groups are then formed by allocating industries to the group with the nearest mean. This process is repeated until no industries change between groups and the intra-group variability is minimized. In case of the k-medians approach industries are allocated to the group with the nearest median, while the selection algorithm works analogously to the k-means approach. For clustering the average high-skilled shares and average growth rates in ICT capital deepening over the periods 1991/1992–2005 are used, respectively. Both cluster techniques serve as robustness check as cluster groups usually react sensitively to the employed cluster techniques and data.

Table A2 in the Appendix shows the industry clusters for German/US goods-producing industries. According to the k-means approach German industries with the highest similarity between high-skilled shares and ICT capital deepening are Office Machinery & Electronic Equipment and Motor Vehicles & Other Transports (denoted C1-1).[4] For the US, highest similarity between the two variables is additionally determined for Mining and Quarrying; Paper, Pulp & Publishing, Printing; Chemicals and Electricity, Gas & Water Supply (denoted C2-1). The alternative k-medians approach specifies an extended set of industries. For Germany, in addition to the k-means industries (C1-1), Mining & Quarrying; Manufacturing n.e.c and Electricity, Gas & Water Supply are classified (C3-1). In case of the US, the same classification as for k-means industries (C2-1) is derived for the k-medians approach (C4-1).

The final ICT-skill taxonomy is chosen according to the k-medians approach as it is less affected by outliers. Industries that are eventually classified as ICT-skill intensive are denoted IS, i.e. those are C3-1 for Germany and C2-1/C4-1 for the US (see Table A2). Non-ICT-skill intensive industries are derived as the residual and are denoted as OTHERS.

2.2 ICT-Skill Intensity By Sample Period and Skill Dynamics

Separation of ICT-skill intensities for Germany and the US by the periods 1991–2005 and 1991–2000 reveals the persistence of stronger skill levels and ICT growth for the US economy (see Table 3). As shown in Table 3 growth of ICT capital deepening in German ICT-skill intensive industries was substantially stronger than in German others, while such a difference is not constituted for US sectors. However, growth of ICT capital deepening was stronger on average in the US than in Germany. Also, independently of ICT-skill intensity

[4] Similarity between high-skilled shares and growth in ICT capital deepening is determined by descending order in highest average high-skilled shares and highest average growth in ICT capital deepening (*y*=1) to lowest average high-skilled shares and lowest average growth in ICT capital deepening (*y*=4). The group classification is C*x*-*y* with *x* being 1 (k-means) and 3 (k-medians) for Germany, and 2 (k-means) and 4 (k-medians) for the US, and *y* being the degree of similarity from 1 to 4.

and country ICT capital deepening increased on average throughout all sectors, but especially during 1991–2000 (New Economy).

The dynamic of labor composition in ICT-skill intensive industries over time is shown in Table A3a in the Appendix. While there was a stagnating share of high skills in German ICT-intensive sectors, the US exhibited a significantly stronger upward dynamic in its high-skilled hours worked. Interestingly, in the US the increase of high-skilled hours worked went to the detriment of the medium skilled, while low skilled stagnated. This is a phenomenon already recognized by Autor et al. (2006) and extensively discussed in Acemoglu and Autor (2010). The recent analysis posits a steadily elimination of medium-skilled job tasks by the introduction of new technologies, as e.g. ICT. The new technologies increased the labor supply of the high skills on the one hand, but left low-skilled job task relatively unaffected on the other. Thus directed technological change created a job polarization that primarily disadvantaged medium-skilled workers. In other sectors the dynamics of labor types was less pronounced for both countries.

Comparing German ICT-skill intensive sectors with the highest shares of high-skilled hours worked (Office Machinery & Electronic Equipment and Motor Vehicles & Other Transports) to their US counterparts (Table A4 and A5) it becomes apparent that in the US exactly those sectors generated much stronger growth in ICT, particularly in Office Machinery & Electronic Equipment. Except in case of Electricity, Gas & Water Supply, German ICT-skill intensive industries generated lower average growth in ICT capital deepening than the US. Strong growth in ICT and high levels of high-skilled hours worked in the US suggest intense complementarities between these two factors.

The dynamic of labor composition for the two selected ICT-skill intensive sectors, Office Machinery & Electronic Equipment and Motor Vehicles & Other Transports, reveals a steady increment in high-skilled hours worked for both US sectors, whereas high-skilled increases in Office Machinery & Electronic Equipment were much more pronounced. Similar to the average labor composition for US ICT-skill intensive sectors, the phenomenon of job polarization is confirmed for the two US sectors once again. On contrary, both German sectors were much more characterized by inertia in labor composition than by dynamic skill reallocation. However, the shares of low-skilled hours worked in both German industries were steadily on the decline and replaced by medium-skilled workers.

2.3 Labor Productivity Growth, Capital Deepening and ICT-Skill Intensity

Juxtaposing average labor productivity (ALP) growth by ICT-skill intensity for German and US industries, Figure 1 shows 5-year averages calculated for the three sample periods 1992–1995, 1996–2000 and 2001–2005.

Comparing ALP growth by ICT-skill intensity it becomes apparent that US ICT-skill intensive industries strongly increased their ALP growth during the periods 1991–1995 and 1996–2000 with 3.62 and 6.64 percent, respectively. On contrary, Germany's ICT-skill intensive industries had weaker and stagnating ALP growth with about 2.9 percent during these periods. While ICT-skill intensive industries' ALP growth dropped post 2000 in the US and Germany, in the US ICT-skill intensive industries still had stronger growth rates with 3.27 percent compared to Germany's 1.56 percent. Regarding other industries, ALP growth constituted no significant differences in both countries. According to these figures productivity growth of goods-producing industries has been much more driven by ICT-skill complementarities in the US than in Germany during the New Economy.

Examination of the relationship between sectoral labor productivity growth and ICT capital deepening separated by ICT-skill intensity shows interesting differences for Germany and the US (Figure 2). While there is obviously no significant relationship between ICT capital deepening and labor productivity growth in other US goods-producing industries, it is quite evident that ICT is the source of labor productivity growth in US ICT-skill intensive industries. On the contrary, in Germany there is no significant difference between the impacts of ICT capital deepening on labor productivity growth by either industry classification. This descriptive analysis further corroborates the association of a more pronounced productivity enhancing complementarity between skills and ICT in US ICT-skill intensive industries.

3. Empirical Models

3.1 Labor Productivity Growth

For the examination of productivity enhancing effects from interaction of ICT and high-skilled workers, I employ a standard neo-classical production function for industry i

$$Y_i = F_i\left(K_i, L_i, A_i\right) , \tag{1}$$

where output Y is generated from the two input factors capital, K, and labor, L, and a disembodied technology parameter, A. In the following industry notation i is omitted due to simplicity. Assuming that disembodied technological change is hicks neutral, labor productivity is derived as

$$\frac{Y}{L} = A\,F\left(\frac{K}{L}\right) . \tag{2}$$

Assigning lower-case letters to per-labor factors the output generating process can be rewritten according to

$$y = A\,F\left(k^{ICT}, k^{NICT}\right) \tag{3}$$

with y being labor productivity, k^{ICT} is ICT capital deepening, and k^{NICT} is Non-ICT capital deepening. Under the assumption that the production function is Cobb Douglas, log-linearizing ends up in the subsequent estimable specification

$$\ln y = \ln A + \alpha_1 \ln k^{ICT} + \alpha_2 \ln k^{NICT} . \tag{4}$$

The final econometric estimation specification that is specified in terms of growth rates, ultimately takes on the form

$$\Delta \ln y_{it} = \Delta \ln A_{it} + \alpha_1 \Delta \ln k_{it}^{ICT} + \alpha_2 \Delta \ln k_{it}^{NICT} + \Delta \ln \varepsilon_{it} \tag{5}$$

for industry i and time t, with the error term structure assumed to be

$$\Delta \ln \varepsilon_{it} = \Delta \ln a_{it} + \Delta \ln d_t + \Delta \ln \upsilon_{it} \tag{6}$$

where a_{it} are time-variant unobserved industry effects, d_t common time effects and υ_{it} a stochastic i.i.d. component.

Employing an alternative production function specification for robustness three different skill types (high-, medium- and low-skill) are introduced into the Cobb-Douglas framework. This renders equation (1) into

$$Y = F(K, L^{HS}, L^{MS}, L^{LS}, A) . \tag{7}$$

In terms of labor productivity equation (7) can be rewritten as

$$\frac{Y}{L} = A\,F\left(\frac{K}{L}, \frac{L^{HS}}{L}, \frac{L^{MS}}{L}, \frac{L^{LS}}{L}\right) \tag{8}$$

and thus in lower-case letters as

$$y = A\,F\left(k^{ICT}, k^{NICT}, l^{HS}, l^{MS}, l^{LS}\right) \tag{9}$$

with y, k^{ICT} and k^{NICT} resembling the variable definition of equation (3), and l^m being the hours worked share of skill type m in total hours worked for m being high skilled (HS), medium skilled (MS) and low skilled (LS), respectively. Log-linearization turns the Cobb-Douglas specification of equation (9) into

$$\ln y = \ln A + \alpha_1 \ln k^{ICT} + \alpha_2 \ln k^{NICT} + \beta_1 \ln l^{HS} + \beta_2 \ln l^{MS} + \beta_3 \ln l^{LS} . \tag{10}$$

The final econometric estimation specification, as specified in growth rates, has the subsequent form

$$\Delta \ln y_{it} = \Delta \ln A_{it} + \alpha_1 \Delta \ln k_{it}^{ICT} + \alpha_2 \Delta \ln k_{it}^{NICT} + \beta_1 \Delta \ln l_{it}^{HS} + \beta_2 \Delta \ln l_{it}^{MS} + \beta_3 \Delta \ln l_{it}^{LS} + \Delta \ln \varphi_{it} \quad (11)$$

for industry i and time t, with an error term structure given analogously to equation (6)

$$\Delta \ln \varphi_{it} = \Delta \ln a_{it} + \Delta \ln d_t + \Delta \ln \theta_{it} \quad (12)$$

with time-variant unobserved industry effects, a_{it}, common time effects, d_t , and a stochastic i.i.d. component, θ_{it}.

3.2 Capital-Skill Complementarities

In order to examine the extent of capital-skill complementarities during the period of the New Economy on the sectoral level, I start by setting up a cost function for each industry i

$$C_i = F_i\left(Y_i, K_i, P_i\right) \quad (13)$$

with C representing total production costs, Y is output, K capital input, and P the factor prices of the variable input factors. Besides capital input, which is treated as quasi-fixed, the cost function exhibits three additional variable input factors: high-skilled (1), medium-skilled (2) and low-skilled labor (3), which are chosen optimally subject to their given factor prices.

Treating capital as quasi-fixed enables replacing the price of capital by the quantity of capital employed, and thus represents the cost function in a short-term perspective (e.g. Brown and Christensen, 1981) instead of long-run.[5] Modeling the effect of new technologies that have emerged during the New Economy as well as the technology interaction with high-skilled workers, I allow capital input to differ by ICT and Non-ICT, analogously as in the production function framework. Thereby, ICT is intended to capture embodied technological change associated with newly developed high-tech products (primarily information technology, communication and software). Non-ICT investment captures all other types of technological change that is embedded in other investment goods. The prices for the three variable labor types are approximated by each type's real hourly wages.

The nature of the cost function is assumed to be translog and industry notation is omitted due to simplicity

[5] For a detailed description of the cost functional form and its assumptions, see e.g. Bond and Van Reenen (2007).

$$
\begin{aligned}
\ln C = {} & \ln\alpha_0 + \sum_{m=1}^{3}\beta_m \ln P_m + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3}\gamma_{mn}\ln P_m \ln P_n \\
& + \alpha_Y \ln Y + \frac{1}{2}\gamma_{YY}(\ln Y)^2 + \sum_{m=1}^{3}\gamma_{mY}\ln P_m \ln Y + \gamma_{K^{ICT}Y}\ln K^{ICT}\ln Y + \gamma_{K^{NICT}Y}\ln K^{NICT}\ln Y \\
& + \gamma_{K^{ICT}}\ln K^{ICT} + \frac{1}{2}\gamma_{K^{ICT}K^{ICT}}\left(\ln K^{ICT}\right)^2 + \sum_{m=1}^{3}\gamma_{mK^{ICT}}\ln P_m \ln K^{ICT} \\
& + \gamma_{K^{NICT}}\ln K^{NICT} + \frac{1}{2}\gamma_{K^{NICT}K^{NICT}}\left(\ln K^{NICT}\right)^2 + \sum_{m=1}^{3}\gamma_{iK^{NICT}}\ln P_m \ln K^{NICT} \\
& + \rho_\tau t + \frac{1}{2}\rho_{\tau\tau}t^2 + \rho_{\tau Y} t \ln Y + \sum_{m=1}^{3}\rho_{\tau P_i}\ln P_m t + \rho_{\tau K^{ICT}} t \ln K^{ICT} + \rho_{\tau K^{NICT}} t \ln K^{NICT}
\end{aligned}
\tag{14}
$$

where m (n) reflects the three labor inputs by skill type (high skill = 1, medium skill = 2 , low skill = 3). Utilizing Shephard's (1953) Lemma for the variable factors and imposing homogeneity and symmetry assumptions, the first order conditions of the variable cost share equations are derived by

$$
\frac{\partial \ln C}{\partial \ln P_m} = \beta_m + \sum_{n=1}^{3}\gamma_{mn}\ln P_n + \alpha_{mY}\ln Y + \gamma_{mK^{ICT}}\ln K^{ICT} + \gamma_{mK^{NICT}}\ln K^{NICT} + \rho_{\tau P_m} t \ . \tag{15}
$$

Since the first order derivates can be written in terms of cost shares

$$
\frac{\partial \ln C}{\partial \ln P_m} = \frac{\partial C}{C}\Big/\frac{\partial P_m}{P_m} = \frac{P_m}{C}\frac{\partial C}{\partial P_m} = \frac{P_m X_m}{C} = S_m \tag{16}
$$

with X being the minimizing choices of input demands, S resembles the share of one of the three labor-type factors in total variable costs. As the derivation of equation (15) is obtained under the assumption of homogeneity of degree one in factor prices and of symmetry in the cross-elasticities following restrictions are required to hold: For homogeneity it is

$$
\sum_{m=1}^{3}\alpha_m = 1 \ ; \ \sum_{m=1}^{3}\gamma_{mY} = 0 \ ; \ \sum_{n=1}^{3}\gamma_{mn} = \sum_{m=1}^{3}\gamma_{mn} = \sum_{n=1}^{3}\sum_{m=1}^{3}\gamma_{mn} = 0 \tag{17a}
$$

and for symmetry

$$
\gamma_{mn} = \gamma_{nm} \ . \tag{17b}
$$

Under these restrictions equation (15) can be formulated for the high-skilled workers cost share equation as

$$
\begin{aligned}
S_{HS} = {} & \beta_{HS} + \gamma_{HS,HS}\ln P_{HS} + \gamma_{HS,MS}\ln P_{MS} + \gamma_{HS,LS}\ln P_{LS} \\
& + \alpha_{HS,Y}\ln Y + \gamma_{HS,K^{ICT}}\ln K^{ICT} + \gamma_{HS,K^{NICT}}\ln K^{NICT} + \rho_{\tau P_{HS}} t
\end{aligned}
\tag{18}
$$

The econometric estimation specification ultimately is specified in terms of growth rates and takes on the following form

$$
\begin{aligned}
\Delta\ln S_{HS,i,t} = {} & b + \gamma_1\Delta\ln P_{HS,i,t} + \gamma_2\Delta\ln P_{MS,i,t} + \gamma_3\Delta\ln P_{LS,i,t} \\
& + \alpha_1\Delta\ln Y_{it} + \gamma_4\Delta\ln K_{it}^{ICT} + \gamma_5\Delta\ln K_{it}^{NICT} + \rho\Delta\ln t_{it} + \Delta\ln\xi_{it}
\end{aligned}
\tag{19}
$$

with S_{HS} being measured as high-skilled shares in total labor compensation[6] for industry i at time t, P_m is real hourly wages (deflated by VA deflator) for the three labor types m, Y is real value-added, and K^{ICT} and K^{NICT} are ICT and Non-ICT capital services. The error term, ξ_{it}, is assumed to be of structure

$$\Delta \ln \xi_{it} = \Delta \ln a_{it} + \Delta \ln d_t + \Delta \ln \omega_{it} \tag{20}$$

with time-variant unobserved industry effects, a_{it}, common time effects, d_t , and a stochastic i.i.d. component, ω_{it}. Since I do not explicitly model the technological parameter t in equation (15) applying first-differences via system GMM will eliminate technological differences between sectors.

As I will explicitly account for ICT-skill intensive and other industries, I will introduce sector dummies allowing for parameter heterogeneity among these two groups in equation (5), (11) and (19). This is due to standard pooled regressions without accounting for cross-sectoral heterogeneity in parameters may cause estimators to be less precise and/or biased. Moreover, besides controlling for parameter heterogeneity by ICT-skill intensity, the three econometric estimation specifications will be modified to investigate the effects of single ICT-skill intensive industries, respectively. These estimations will be conducted for Germany and the US separately.

4. Data

For the subsequent analysis of formally testing the complementarity effects between new technologies (as embedded in ICT investment) and high-skilled labor on sectoral labor productivity growth during the New Economy, I focus on two industrialized economies Germany and the US. Therefore growth accounting data for both countries for the period 1991–2005 are obtained.

As shown in the previous section, I will commence the analysis by employing a neoclassical production function approach (Solow, 1956) seeking to determine the impact of ICT-skill complementarities on sectoral productivity growth. For that reason, I implement output measured as real value-added and input factors capital and labor measured as capital services and total hours worked by persons engaged. Output and input factors are provided by IIGAD (2008)[7] in case of Germany at a 28 goods-producing industry level, while US output and input data is obtained from EUKLEMS (2008)[8] on a 17 goods-producing industry

[6] Since only the three skill types are assumed to be variable factors, total variable costs are total labor compensation.
[7] For a detailed description of the data, see Roehn et al. (2007).
[8] For a detailed description of the data, see Timmer et al. (2007a, b).

level. To achieve comparable industry aggregates sectoral IIGAD data is cumulated via value-added weighting industry growth rates within aggregates to match the US classification. The reason for choosing German growth accounting data provided by IIGAD over EUKLEMS is due to the more detailed disaggregation of different asset types and marginal productivities (measured as user costs) on the sectoral level that allows me to construct most accurate measures of German ICT and Non-ICT capital services. Particularly in case of German software (one of the ICT assets) industry-level investments are obtained from an Ifo study (Herrmann and Müller, 1997) and surveys conducted by the *Ifo Investment Survey*[9]. As detailed in Herrmann and Müller (1997) the software estimates are based on specific questions that solicited information on industry-level investment in purchased and own account software in 1995, 1998, 1999, and 2000. In a subsequent robustness test, I will additionally account for different skill types in total hours worked within the production function framework. Sectoral skill composition data for hours worked are obtained from EUKLEMS for both countries.

Seeking to determine whether capital-skill complementarities are indeed confirmed on the sectoral level via a cost function approach variable factors such as high-skilled shares in total labor compensation, VA-deflated hourly wages by skill type, real value-added, ICT and Non-ICT capital services are gathered. Regarding high-skilled shares and hourly wages by skill type, those are derived from EUKLEMS (2008)[10] for Germany and the US. Nominal value-added and implicit price deflators as well as ICT and Non-ICT services are derived from IIGAD (2008) and EUKLEMS (2008) for Germany and the US, respectively.

Importantly, as the period of analysis coincides with the launching phase of the New Economy during the second half of the 1990s, both databases account for productivity effects stemming from new technologies in ICT capital services. Moreover, the sectoral nature of the data enables disaggregation of both economies into 17 goods-producing industries (see Table A1, Appendix) and accounting for industry-specific trends in labor productivity growth and high-skill cost shares. Jorgenson (2005), for example, argues that the magnitude of the US growth resurgence outpaced all but the most optimistic expectations. After advances in the productivity measurement allowed for effective accounting of information technology in national statistics (Schreyer, 2001), it became clear that the recent productivity increases originated mainly with ICT investments in ICT-intensive industries.

[9] The *Ifo Investment Survey* follows the EU guidelines for harmonized business surveys and contains 70,000 German firms, 5000 of which are surveyed for each sample period. It is established as an excellent leading indicator of German investment; it is also incorporated in a number of other leading indicators, most prominently the European Commission's *Economic Indicators of the Euro Zone*.

[10] For a detailed description of the data, see Timmer et al. (2007a, b).

5. Econometric Estimations

5.1 Sectoral Labor Productivity Growth and ICT-Skill Intensity

Due to potential endogeneity issues stemming from simultaneity or/and contemporary unobservable factors that influence labor productivity growth and cost-minimization behavior (Acemoglu, 1998, 2002a, b) as well as the problem of reverse causality, I implement the system-GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998; Roodman, 2005). Therefore, I assume explanatory variables to be predetermined in nature and thus employ them as valid instruments.[11] The system-GMM estimator is chosen over first-difference GMM (Arellano und Bond, 1991) for its increased efficiency in the context of short panels.

Starting the analysis of formally testing productivity growth by ICT-skill intensity, Table 4 reveals no statistically significant growth effect from ICT capital deepening in German ICT-skill intensive and other (non-ICT-skill intensive) industries (column Ia–c). However, Non-ICT capital deepening appears to be the main driver of other German industries, while ICT-skill intensive sectors experienced statistically significant lower growth effects from Non-ICT (column Ib). Disaggregation of ICT-skill intensive industries shows that productivity enhancing effects and the reduced Non-ICT effect mainly originated from substitution of ICT for Non-ICT in Manufacturing n.e.c. (column Ic). Motor Vehicles & Other Transports and Energy, Gas & Water Supply also generated higher productivity growth from ICT investments, without showing negative effects from increased Non-ICT.

Reducing the sample and focusing on the formation phase of the New Economy (1991–2000), the positive growth effects from ICT in Motor Vehicles & Other Transports reverse (column Ie). Now, exactly those industries exhibited strong productivity growth from substitution of Non-ICT for ICT. Moreover, additionally to the previously found growth effects from substituting ICT for Non-ICT in Manufacturing n.e.c., which is supported here, German Office Machinery & Electronic Equipment also managed to reap productivity gains from substituting ICT for Non-ICT (column Ie). Those findings confirm that German ICT-skill intensive industries indeed generated higher productivity growth from increased ICT investment during the emergence of the New Economy, when the growth effects are traced to their sectoral origin.

In case of the US the estimation results disclose that Non-ICT capital deepening, similar to Germany, had been the main driver of industries' labor productivity growth and that aggregate ICT-skill intensive industries show no statistically significant productivity differ-

[11] Due to the assumption of all input variables being predetermined and being given in growth rates, I employ longer lags in input variables, i.e. t-3 and longer, as instruments. Time dummies are assumed to be strictly exogenous and are implemented as instruments as well.

ential for Non-ICT as well as for ICT capital deepening (column IIb). Nevertheless, disaggregation of US ICT-skill intensive industries reveals positive growth effects from substitution of ICT for Non-ICT capital in Chemicals and Office Machinery & Electronic Equipment. Additionally, the ICT-skill intensive sectors Paper, Pulp & Publishing, Printing and Electricity, Gas & Water Supply generated productivity growth from increased Non-ICT, while they were lacking those effects for ICT investments (column IIc).

During the emergence of the New Economy, US Office Machinery & Electronic Equipment maintained their positive growth effects from ICT (column IIe). Also, it turns out that US Motor Vehicles & Other Transports generated strong productivity growth from substitution of ICT for Non-ICT capital (column IIe). This is a somewhat interesting result as it posits totally the opposite to the German case. Typical beacons of the German economy, namely the Motor Vehicles & Other Transports industry, generated their productivity gains via increased Non-ICT during the New Economy instead of ICT. Those discrepancies in productivity enhancing mechanisms reveal substantial differences in the underlying production process in these two leading economies.

5.2 Robustness Check: Labor Productivity Growth and Heterogeneous Labor

Allowing for different skill types in productivity growth regressions (see Table 5), qualitatively does not change the results of Table 4. This indicates no severe omitted variable bias in the original specification from ignoring to account for the labor composition. Nevertheless, the introduction of different skill types reveals interesting insights into the relationship between productivity growth and varying skill endowments in US and German goods-producing industries.

For Germany the estimations results reveal no statistically significant growth effects throughout all samples (total and pre–2001) for different skill types. On contrary, in the US high-skilled labor exhibits statistically significant productivity growth effects, which are estimated relatively robust across sample coverage. Other skill types show no statically significant effect for the 1991–2005 period, but interestingly pre–2001 medium-skilled labor affected US productivity growth significantly and even exceeded the impact of the high skills. Remembering the tremendous labor productivity increases in US ICT-skill intensive industries during the emergence of the New Economy, such increases suggest to be attributed to the potential of US institutions to better succeed in reaping productivity gains from a well educated workforce – beyond the employment of physical capital.

5.3 Sectoral Capital-Skill Complementarities

Seeking to explain the origins of German and US productivity growth as determined in Table 4 and 5 via capital-skill complementarities, Table 6 provides the relevant cost share regressions for the highly skilled.

For Germany the cost share regressions reveal that increases in high-skill cost shares of other (non-ICT-skill intensive) industries stem from substitution of Non-ICT for ICT (column Ia–c). ICT-skill intensive industries did not experience a different effect on high-skill cost shares through ICT than other industries, but analogously to the productivity growth regressions a less strong increase for Non-ICT (column Ib). Splitting ICT-skill intensive industries again by sectors shows that the reduced impact for Non-ICT primarily stems from Mining & Quarrying and Manufacturing n.e.c. (column Ic), similar to productivity growth in Table 4 and 5 in case of Manufacturing n.e.c.

This picture changes when the sample focuses on the formation phase of the New Economy (1991–2000). Obviously, during this period there was only one but strong substitution effect of Non-ICT for ICT leading to increased high-skill cost shares in ICT-skill intensive industries, namely in the Motor Vehicles & Other Transports industry (column Ie). Comparing those results to the findings of Table 4 and 5 suggests that during the pre–2001 period it was Non-ICT-skill complementarities that spurred productivity growth in Motor Vehicles & Other Transport. On the contrary, the productivity growth effects from substitution of ICT for Non-ICT as detected in Manufacturing n.e.c. and Office Machinery & Electronic Equipment cannot be explain by capital-skill complementarities univocally, as there are no statistically significant effects on high-skilled cost shares for those industries prior to 2001, neither for ICT nor Non-ICT (column Ie).

In case of other US industries effects from ICT and Non-ICT on high-skill cost shares are estimated as statistically insignificant (Table 5, column IIa–c) compared to Germany. However, for ICT-skill intensive industries increases in ICT show a statistically significant reduction in high-skill cost shares (column IIb). This reduction is mainly driven by a strong substitution of Non-ICT for ICT in Chemicals and Energy, Gas & Water Supply (column IIc). Especially in case of US Chemicals the findings contradict the productivity growth effects from ICT and Non-ICT capital deepening as determined in Table 4 and 5. It seems as if an ICT substitution for Non-ICT enhanced US Chemical productivity growth on the one hand, while capital-skill complementarities worked through Non-ICT instead of ICT on the other.

For the pre–2001 period, the picture changes remarkably. Now the two ICT-skill intensive sectors Office Machinery & Electronic Equipment and Motor Vehicles & Other Transports exhibit strong increases in high-skill cost shares from substituting ICT for Non-ICT. Those findings match the productivity growth effects from ICT in those sectors, indicating strong ICT-skill complementarities as source of productivity growth (column IIe). Furthermore, the findings corroborate the suggestion that there had been considerably different capital-skill complementarities in US goods-producing industries during the New Economy than it has been the case in Germany. While US ICT-skill intensive sectors provide empirical evidence that they had been driven by ICT-skill complementarities, German ICT-skill intensive sectors reveal Non-ICT-skill complementarities as source of productivity growth, particularly in Motor Vehicles & Other Transports.

Taking a closer look at the substitution elasticities between high-skilled workers and other skill types, Table 6 displays that increases in medium-skilled productivity (indicated by increases in medium-skilled hourly wages) led to decreasing high-skilled cost shares in German goods-producing industries (column Ia–c). The same is true for the US; however, the substitution elasticity between high- and medium-skilled workers is estimated much stronger for the US. Moreover, for the US even increases in low-skilled productivity generate statistically significant decreases in high-skilled cost shares, although sizably lower than in case of medium skills. Nevertheless, the determined substitution elasticities for Germany and the US are estimated robustly across different sample periods.

Comparing the effects of increased high-skilled productivity on high-skilled cost shares between Germany and the US, it becomes apparent that high-skilled productivity seemingly affected high-skilled cost shares substantially less in Germany. Putting it differently, the impact of increased high-skilled productivity in US sectors is about three times the size of Germany's! These and the previous findings on inter-skill elasticities indicate a) more flexibility in the substitution between different skill types and b) more easily affected high-skilled cost shares by adjustments in high-skilled productivity in the US. Hence, the substitution elasticities point to less rigid labor market regulations as well as less strong wage compression in the US economy.

6. Conclusion

US ICT-skill intensive industries experienced tremendous increases in labor productivity growth post 1995 compared to relatively restrained ICT-skill intensive sectors in Germany. In contrast, other (non-ICT-skill intensive) industries in the US and Germany performed relatively similar during the same period. Moreover, in Germany no significant differences in trend growth of labor productivity between ICT-skill intensive and other industries are identified, and even as labor productivity growth in ICT-skill intensive industries decreased post 2000 in both countries, US growth rates were still more than twice as high than in Germany.

These stylized facts pose important questions about the underlying mechanisms that determined labor productivity growth in these two countries. This paper focuses on the interaction effect of physical capital, especially ICT and Non-ICT capital, and human skills as main source of productivity growth during the New Economy. Testing for such capital-skill complementarities shows that German and US industries' productivity growth was affected substantially different by those complementarities. Regarding ICT-skill intensive German sectors, there is no empirical evidence of ICT-skill complementarities as main source of industry productivity growth. However, productivity growth of the ICT-skill intensive Motor Vehicles & Other Transports industry in Germany was rather driven by Non-ICT-skill complementarities. In case of the US the two ICT-skill intensive sectors Office Machinery & Electronic Equipment and Motor Vehicles & Other Transport were found to have experienced strong increments in productivity growth via ICT-skill complementarities prior to 2001.

Interestingly, regarding the substitution elasticities between different skill types it seems as if the US managed a better reallocation of factors within the goods-producing sector. Germany's underdeveloped low-skilled labor sector and a less distinctive wage dispersion, which prevented low-skilled workers to be absorbed into lower productive job tasks, serve as potential explanations. Furthermore, regarding the varying capital-skill complementarities on the sectoral level, trade dependent countries like Germany and the US are prone to changes in international trade patterns and industry restructuring that affects skill endowments and SBTC endogenously (Acemoglu, 2003). Empirical studies that exactly determine the relationship between countries' skill endowments, institutions and the impact of international trade on sectoral capital-skill complementarities are scarce, and thus prepare the ground for future research.

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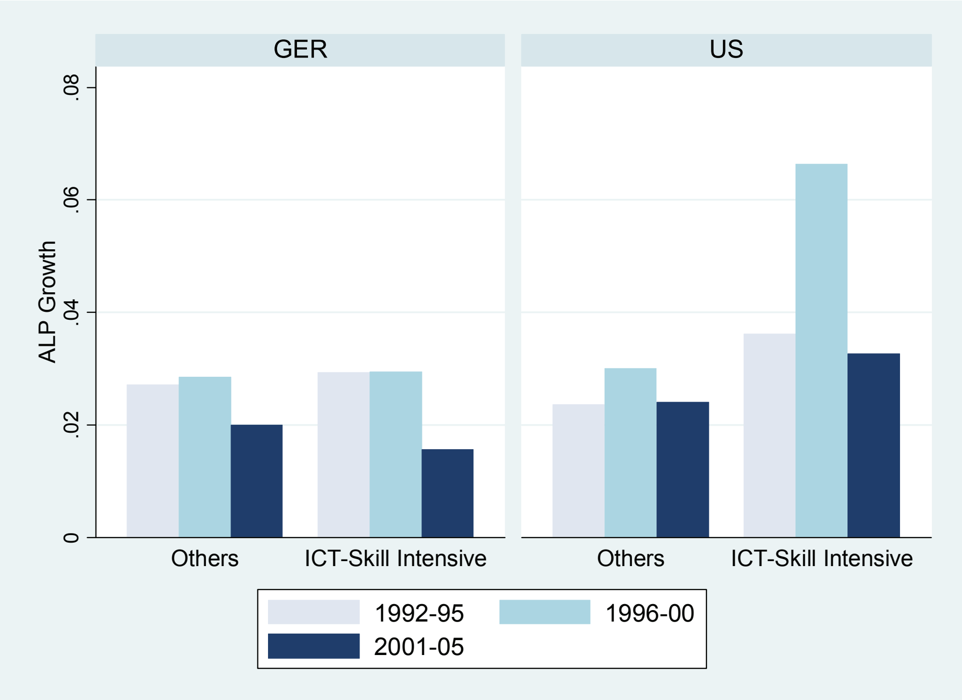
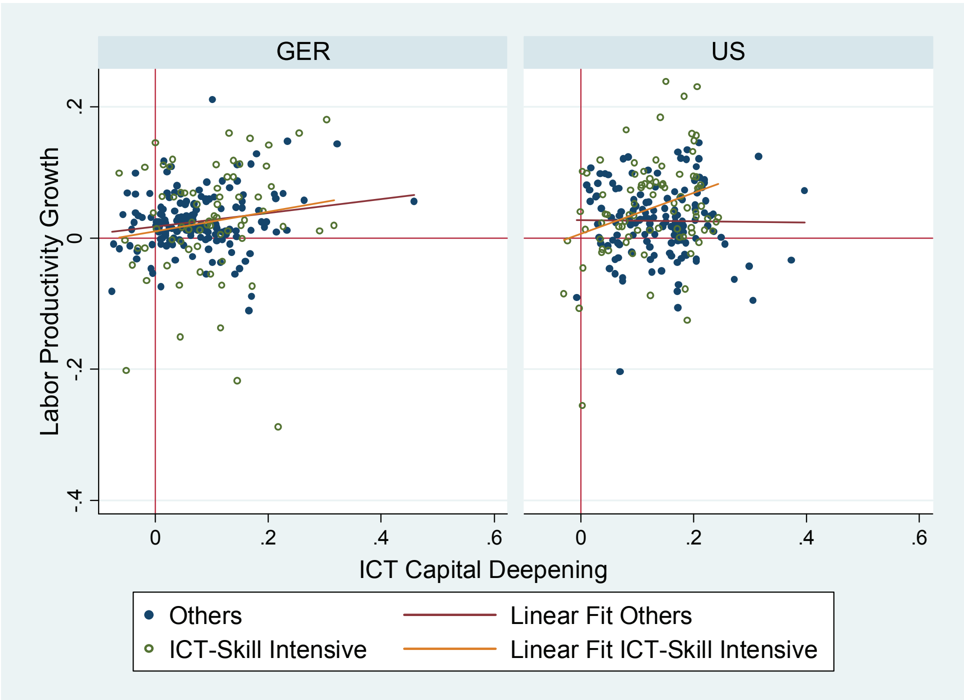
Figure 1:
Average Labor Productivity Growth,
by ICT-Skill Intensity, Germany vs. US



Notes: Average labor productivity (ALP) growth is 5-year averages over the three sub-periods 1992–1995, 1996–2000, and 2001–2005. Outliers excluded. *Sources:* EUKLEMS (2008) and IIGAD (2008).

Figure 2:
Labor Productivity Growth and ICT Capital Deepening,
by ICT-Skill Intensity, Germany vs. US (1992–2005)



Note: Outliers excluded. *Sources:* EUKLEMS (2008) and IIGAD (2008).

Table 1a: Shares of High-Skilled Hours Worked, Germany

	High-Skilled Shares in Total Hours Worked			
	1991–1995	**1996–2000**	**2001–2005**	**1991–2005**
Agriculture, Hunting and Forestry	3.60	3.30	3.42	3.44
Mining and Quarrying	6.82	8.12	8.73	7.89
Food and Tobacco	1.96	2.40	2.71	2.36
Textiles, Apparel, and Leather	1.96	2.40	2.71	2.36
Wood Products	5.44	6.24	7.01	6.23
Paper, Pulp, Publishing, Printing	5.44	6.24	7.01	6.23
Chemicals	5.44	6.24	7.01	6.23
Rubber and Plastics	5.44	6.24	7.01	6.23
Other Non-metallic Mineral Products	5.44	6.24	7.01	6.23
Basic and Fabricated Metals	5.44	6.24	7.01	6.23
Machinery	5.44	6.24	7.01	6.23
Office Machinery and Electronic Equip.	12.50	13.96	13.85	13.44
Motor Vehicles and Other Transport	12.50	13.96	13.85	13.44
Manufacturing n.e.c.[a)]	6.82	8.12	8.73	7.89
Electricity, Gas & Water Supply	6.82	8.12	8.73	7.89
Construction	3.60	3.88	4.29	3.92
Mean	**5.92**	**6.75**	**7.25**	**6.64**
Median	**5.44**	**6.24**	**7.01**	**6.23**

Notes: a) consists of the sectors Furniture, Recycling, and Manufacturing n.e.c. Figures represent period averages. High-skilled shares are available for seven goods-producing aggregate industries. For lower levels the same high-skilled shares as the higher aggregate are assumed. Outliers excluded. *Source:* EUKLEMS (2008).

Table 1b: Shares of High-Skilled Hours Worked, US

	High-Skilled Shares in Total Hours Worked			
	1991–1995	**1996–2000**	**2001–2005**	**1991–2005**
Agriculture, Hunting and Forestry	14.37	14.05	15.56	14.66
Mining and Quarrying	23.85	21.43	23.50	22.92
Food and Tobacco	15.24	16.67	17.10	16.34
Textiles, Apparel, and Leather	9.53	11.94	12.69	11.39
Wood Products	7.51	7.79	8.64	7.98
Paper, Pulp, Publishing, Printing	25.49	29.21	30.48	28.39
Chemicals	35.62	41.00	43.53	40.05
Rubber and Plastics	13.25	14.62	15.32	14.40
Other Non-metallic Mineral Products	12.09	13.37	14.95	13.47
Basic and Fabricated Metals	11.60	12.19	13.55	12.45
Machinery	15.72	15.79	21.75	17.75
Office Machinery and Electronic Equip.	31.39	33.46	39.52	34.79
Motor Vehicles and Other Transport	22.38	26.11	26.76	25.08
Manufacturing n.e.c.[a)]	13.46	15.38	16.54	15.13
Electricity, Gas & Water Supply	25.17	27.48	29.50	27.38
Construction	11.08	10.83	11.31	11.07
Mean	**17.98**	**19.46**	**21.29**	**19.58**
Median	**14.81**	**15.59**	**16.82**	**15.73**

Notes: a) consists of the sectors Furniture, Recycling, and Manufacturing n.e.c. Figures represent period averages. Outliers excluded. *Source:* EUKLEMS (2008).

Table 2: Industry ICT-Skill Intensity

		GER			US		
		Taxonomy	High Skills	ICT	Taxonomy	High Skills	ICT
1	Agriculture, Hunting and Forestry	OTHER	3.44	0.19	OTHER	14.66	0.17
2	Mining and Quarrying	IS	7.89	0.11	IS	22.92	0.12
3	Food and Tobacco	OTHER	2.36	0.04	OTHER	16.34	0.12
4	Textiles, Apparel, and Leather	OTHER	2.36	0.03	OTHER	11.39	0.16
5	Wood Products	OTHER	6.23	0.02	OTHER	7.98	0.12
6	Paper, Pulp, Publishing, Printing	OTHER	6.23	0.11	IS	28.39	0.15
7	Chemicals	OTHER	6.23	0.11	IS	40.05	0.15
8	Rubber and Plastics	OTHER	6.23	0.06	OTHER	14.40	0.15
9	Other Non-metallic Mineral Products	OTHER	6.23	0.08	OTHER	13.47	0.10
10	Basic and Fabricated Metals	OTHER	6.23	0.02	OTHER	12.45	0.11
11	Machinery	OTHER	6.23	0.06	OTHER	17.75	0.13
12	Office Machinery and Electronic Equipment	IS	13.44	0.08	IS	34.79	0.14
13	Motor Vehicles and Other Transport	IS	13.44	0.08	IS	25.08	0.10
14	Manufacturing n.e.c.[a)]	IS	7.89	0.05	OTHER	15.13	0.13
15	Electricity, Gas & Water Supply	IS	7.89	0.16	IS	27.38	0.08
16	Construction	OTHER	3.92	0.09	OTHER	11.07	0.20

Notes: a) consists of the sectors Furniture, Recycling, and Manufacturing n.e.c. Outliers excluded. IS = ICT-skill intensive industries, OTHERS = non-ICT-skill intensive industries. High skills is average high-skilled hours worked in total hours, while ICT resembles average growth of ICT capital deepening over the periods 1991–2005 and 1992–2005, respectively. *Sources:* EUKLEMS (2008) and IIGAD (2008).

Table 3: Industry ICT-Skill Intensity, By Sample Period

	GER				US			
	High Skills		ICT		High Skills		ICT	
	1991-05	1991-00	1992-05	1992-00	1991-05	1991-00	1992-05	1992-00
Other Industries	5.06	4.77	0.07	0.09	13.46	12.82	0.14	0.16
ICT-Skill Intensive Industries	10.11	9.77	0.10	0.13	29.77	28.55	0.13	0.15
Mining and Quarrying	7.89	7.47	0.11	0.15	22.92	22.64	0.12	0.18
Paper, Pulp, Publishing, Printing	---	---	---	---	28.39	27.35	0.15	0.17
Chemicals	---	---	---	---	40.05	38.31	0.15	0.19
Office Mach. and Electronic Equip.	13.44	13.23	0.08	0.10	34.79	32.43	0.14	0.17
Motor Vehicles & Other Transport	13.44	13.23	0.08	0.08	25.08	24.24	0.10	0.11
Manufacturing n.e.c.[a)]	7.89	7.47	0.05	0.08	---	---	---	---
Electricity, Gas & Water Supply	7.89	7.47	0.16	0.22	27.38	26.32	0.08	0.08

Notes: a) consists of the sectors Furniture, Recycling, and Manufacturing n.e.c. Outliers excluded. High skills is average high-skilled hours worked in total hours, while ICT resembles average growth of ICT capital deepening over the periods 1991–2005/1991–2000 and 1992–2005/1992–2000, respectively. *Sources:* EUKLEMS (2008) and IIGAD (2008).

Table 4:
Labor Productivity Growth Regressions, System GMM

Δ ln y	GER					US				
	1991-05			*1991-00*		*1991-05*			*1991-00*	
	Ia	Ib	Ic	Id[a)]	Ie	IIa	IIb	IIc	IId	IIe
α_1	0.036	0.003	-0.006	-0.022	-0.023	-0.143	-0.160	-0.069	-0.114	-0.015
	[0.081]	[0.054]	[0.056]	[0.092]	[0.084]	[0.147]	[0.142]	[0.143]	[0.138]	[0.180]
$\alpha_1 \times$ IS		0.119		-0.063			0.121		-0.023	
		[0.118]		[0.206]			[0.112]		[0.081]	
MQ			**-0.458*** **		**-0.791*** **			0.015		-0.022
			[0.064]		[0.097]			[0.057]		[0.070]
PP								-0.045		-0.058
								[0.063]		[0.067]
CH								**0.194*** **		-0.073
								[0.057]		[0.082]
OE			0.011		**0.806*** **			**1.197*** **		**0.574*** **
			[0.053]		[0.070]			[0.061]		[0.112]
MO			**0.213*** **		**-0.377*** **			0.077		**0.193*** **
			[0.048]		[0.070]			[0.055]		[0.056]
MN			**0.483*** **		**0.520*** **					
			[0.063]		[0.094]					
EGW			**0.185** **		**0.177* **			-0.084		-0.024
			[0.067]		[0.094]			[0.069]		[0.172]
α_2	**0.411*** **	**0.788*** **	**0.814*** **	**0.901** **	**0.819** **	**0.618** **	**0.552** **	**0.492** **	**0.754*** **	**0.613* **
	[0.128]	[0.159]	[0.175]	[0.322]	[0.314]	[0.211]	[0.189]	[0.205]	[0.250]	[0.302]
$\alpha_2 \times$ IS		**-0.541* **		0.074			0.105		0.879	
		[0.277]		[0.392]			[0.259]		[0.731]	
MQ			-0.373		**0.880** **			0.152		0.436
			[0.220]		[0.317]			[0.185]		[0.292]
PP								**0.591** **		0.366
								[0.253]		[0.375]
CH								**-1.413*** **		0.090
								[0.273]		[0.497]
OE			**0.342** **		**-0.967*** **			**-1.329*** **		0.682
			[0.157]		[0.247]			[0.201]		[0.465]
MO			-0.242		**1.556*** **			0.216		**-1.509*** **
			[0.146]		[0.260]			[0.230]		[0.310]
MN			**-1.719*** **		**-2.084*** **					
			[0.167]		[0.299]					
EGW			-0.273		-0.233			**0.602** **		0.489
			[0.192]		[0.319]			[0.251]		[0.425]
Obs.	224	224	224	128	144	224	224	224	144	144
# Ind.	16	16	16	16	16	16	16	16	16	16
AR1	0.071	0.065	0.058	0.028	0.025	0.010	0.010	0.009	0.038	0.031
AR2	0.511	0.498	0.432	0.346	0.561	0.954	0.909	0.856	0.612	0.535
Hansen	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Notes: All variables reflect exponential growth rates. IS is a dummy with 1 for ICT-skill intensive industries and 0 otherwise. Time dummies included. Outliers excluded. AR1, AR2 and Hansen indicate p-values. Robust standard errors in brackets allow for intra-industry correlation. a) Specification includes t-1 lagged dependent variable according to autocorrelation tests. Significance levels: * significant at 10, ** significant at 5, *** significant at 1 percent. *Sources:* EUKLEMS (2008) and IIGAD (2008).

Table 5:
Labor Productivity Growth Regressions and Heterogeneous Labor, System GMM

Δ ln y	GER					US				
	1991-05			*1991-00*		*1991-05*			*1991-00*	
	Ia	Ib	Ic	Id [a)]	Ie	IIa	IIb	IIc	IId	IIe
α_1	0.024	0.031	0.040	-0.019	-0.022	-0.136	-0.147	-0.095	-0.115	-0.067
	[0.100]	[0.051]	[0.059]	[0.108]	[0.115]	[0.126]	[0.125]	[0.127]	[0.114]	[0.156]
$\alpha_1 \times$ IS		0.058		-0.037			0.142		0.035	
		[0.173]		[0.227]			[0.114]		[0.082]	
MQ			**-0.559***		**-0.758***			0.023		0.000
			[0.102]		[0.110]			[0.051]		[0.071]
PP								-0.035		-0.051
								[0.058]		[0.061]
CH								**0.205***		-0.044
								[0.057]		[0.086]
OE			-0.018		**0.876***			**1.218***		**0.610***
			[0.141]		[0.226]			[0.067]		[0.112]
MO			**0.169**		**-0.335**			0.070		**0.211***
			[0.067]		[0.122]			[0.056]		[0.058]
MN			**0.397***		**0.541***					
			[0.120]		[0.111]					
EGW			0.090		0.183			-0.066		-0.016
			[0.110]		[0.105]			[0.074]		[0.168]
α_2	**0.418***	**0.738***	**0.746***	**0.869**	**0.808**	**0.656**	**0.527**	**0.491**	**0.718**	**0.638**
	[0.125]	[0.140]	[0.145]	[0.331]	[0.319]	[0.232]	[0.188]	[0.199]	[0.245]	[0.294]
$\alpha_2 \times$ IS		**-0.494***		0.105			0.094		0.704	
		[0.261]		[0.397]			[0.266]		[0.737]	
MQ			-0.230		**0.862**			0.170		0.324
			[0.243]		[0.307]			[0.178]		[0.313]
PP								**0.611**		0.566
								[0.240]		[0.373]
CH								**-1.380***		0.137
								[0.275]		[0.564]
OE			0.295		**-1.061***			**-1.353***		0.619
			[0.326]		[0.528]			[0.220]		[0.451]
MO			-0.244		**1.483***			0.258		**-1.580***
			[0.203]		[0.380]			[0.248]		[0.364]
MN			**-1.698***		**-2.027***					
			[0.197]		[0.287]					
EGW			-0.119		-0.188			**0.545**		0.418
			[0.227]		[0.358]			[0.235]		[0.437]
β_1	-0.167	-0.133	-0.070	0.055	0.020	0.128	**0.177**	**0.129**	**0.248**	**0.221**
	[0.229]	[0.193]	[0.156]	[0.222]	[0.270]	[0.089]	[0.062]	[0.055]	[0.107]	[0.081]
β_2	-0.163	-0.319	-0.112	0.249	-0.464	0.243	0.399	0.240	**0.824**	**0.582***
	[0.928]	[0.880]	[1.010]	[1.760]	[1.647]	[0.319]	[0.244]	[0.231]	[0.379]	[0.295]
β_3	-0.302	-0.422	-0.322	0.282	-0.015	0.013	0.048	0.009	0.109	0.040
	[0.533]	[0.528]	[0.559]	[0.698]	[0.714]	[0.064]	[0.057]	[0.060]	[0.111]	[0.066]
Obs.	224	224	224	128	144	224	224	224	144	144
# Ind.	16	16	16	16	16	16	16	16	16	16
AR1	0.070	0.063	0.056	0.028	0.028	0.012	0.011	0.011	0.041	0.037
AR2	0.533	0.533	0.457	0.238	0.573	0.936	0.878	0.887	0.559	0.439
Hansen	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Notes: All variables reflect exponential growth rates. IS is a dummy with 1 for ICT-skill intensive industries and 0 otherwise. Time dummies included. Outliers excluded. AR1, AR2 and Hansen indicate p-values. Robust standard errors in brackets allow for intra-industry correlation. a) Specification includes t-1 lagged dependent variable according to autocorrelation tests. Significance levels: * significant at 10, ** significant at 5, *** significant at 1 percent. *Sources:* EUKLEMS (2008) and IIGAD (2008).

Table 6:
High-Skilled Cost Share Regressions, System GMM

$\Delta \ln S_{HS}$	GER					US				
	1991-05			*1991-00*		*1991-05*			*1991-00*	
	Ia	Ib	Ic	Id	Ie	IIa	IIb	IIc	IId	IIe
γ_4	**-0.087****	**-0.108*****	**-0.112*****	**-0.110***	**-0.125****	-0.065	-0.044	-0.074	-0.032	-0.072
	[0.040]	[0.036]	[0.034]	[0.055]	[0.055]	[0.069]	[0.073]	[0.086]	[0.061]	[0.062]
$\gamma_4 \times$ IS		0.054		0.061			**-0.050****		-0.027	
		[0.052]		[0.057]			[0.023]		[0.055]	
MQ			-0.037		**0.198****			-0.038		**-0.125*****
			[0.041]		[0.078]			[0.045]		[0.027]
PP								-0.007		0.041
								[0.027]		[0.042]
CH								**-0.151****		-0.080
								[0.060]		[0.131]
OE			**-0.141***		-0.184			0.060		**0.632****
			[0.068]		[0.110]			[0.161]		[0.270]
MO			0.006		**-0.717****			-0.189		**1.227****
			[0.036]		[0.252]			[0.112]		[0.466]
MN			0.015		0.040					
			[0.043]		[0.067]					
EGW			0.031		0.102			**-0.184****		-0.145
			[0.049]		[0.068]			[0.082]		[0.089]
γ_5	**0.148***	**0.232****	**0.231****	0.081	0.107	0.122	0.049	0.083	0.003	0.081
	[0.075]	[0.089]	[0.083]	[0.187]	[0.180]	[0.197]	[0.164]	[0.176]	[0.134]	[0.147]
$\gamma_5 \times$ IS		**-0.202***		0.107			0.160		0.105	
		[0.105]		[0.165]			[0.255]		[0.387]	
MQ			**-0.316*****		**0.567***			0.266		1.169
			[0.084]		[0.298]			[0.489]		[1.301]
PP								**0.640****		-1.635
								[0.283]		[1.756]
CH								**1.796****		1.399
								[0.614]		[1.075]
OE			0.282		0.824			-0.374		**-1.619****
			[0.307]		[0.649]			[0.353]		[0.556]
MO			-0.171		**2.409****			0.531		**-5.615****
			[0.105]		[0.874]			[0.476]		[1.976]
MN			**-0.977*****		-0.485					
			[0.210]		[0.424]					
EGW			**0.487****		0.063			**1.717****		**3.830*****
			[0.214]		[0.257]			[0.660]		[0.774]
γ_1	**0.219*****	**0.194*****	**0.232*****	0.036	0.097	**0.683*****	**0.690*****	**0.699*****	**0.737*****	**0.715*****
	[0.070]	[0.058]	[0.063]	[0.084]	[0.109]	[0.056]	[0.056]	[0.059]	[0.092]	[0.106]
γ_2	**-0.360*****	**-0.303*****	**-0.368*****	-0.051	-0.111	**-0.955*****	**-0.952*****	**-0.976*****	**-1.191*****	**-1.370*****
	[0.112]	[0.092]	[0.094]	[0.147]	[0.166]	[0.113]	[0.115]	[0.122]	[0.125]	[0.133]
γ_3	0.070	0.042	0.070	-0.088	-0.071	**-0.169*****	**-0.166*****	**-0.165*****	**-0.130***	**-0.147***
	[0.045]	[0.060]	[0.056]	[0.063]	[0.063]	[0.054]	[0.054]	[0.051]	[0.070]	[0.073]
α_1	-0.055	**-0.051***	-0.053	-0.042	-0.028	0.019	0.011	0.014	0.023	-0.039
	[0.032]	[0.028]	[0.032]	[0.043]	[0.055]	[0.046]	[0.055]	[0.070]	[0.143]	[0.182]
Obs.	224	224	224	144	144	224	224	224	144	144
# Ind.	16	16	16	16	16	16	16	16	16	16
AR1	0.049	0.051	0.051	0.021	0.037	0.000	0.000	0.000	0.004	0.003
AR2	0.738	0.697	0.760	0.160	0.156	0.771	0.773	0.780	0.466	0.700
Hansen	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Notes: All variables reflect exponential growth rates. IS is a dummy with 1 for ICT-skill intensive industries and 0 otherwise. Time dummies included. Outliers excluded. AR1, AR2 and Hansen indicate p-values. Robust standard errors in brackets allow for intra-industry correlation. Significance levels: * significant at 10, ** significant at 5, *** significant at 1 percent. *Sources:* EUKLEMS (2008) and IIGAD (2008).

Appendix

Table A1: ISIC Classification

		Industry Abbreviations	ISIC Classification Revision 3.0
1	Agriculture, Hunting and Forestry	AHF	A: 01 to 02, B: 05
2	Mining and Quarrying	MQ	C: 10 to 14
3	Food and Tobacco	FT	D: 15 to 16
4	Textiles, Apparel, and Leather	TAL	D: 17 to 19
5	Wood Products	WP	D: 20
6	Paper, Pulp, Publishing, Printing	PP	D: 21 to 22
7	Coke, Petroleum, Nuclear Fuels	CPF	D: 23
8	Chemicals	CH	D: 24
9	Rubber and Plastics	RP	D: 25
10	Other Non-metallic Mineral Products	ONM	D: 26
11	Basic and Fabricated Metals	BFM	D: 27 to 28
12	Machinery	M	D: 29
13	Office Machinery and Electronic Equipment	OE	D: 30 to 33
14	Motor Vehicles and Other Transport	MO	D: 34 to 35
15	Manufacturing n.e.c.[a)]	MN	D: 36 to 37
16	Electricity, Gas & Water Supply	EGW	E: 40 to 41
17	Construction	CO	F: 45

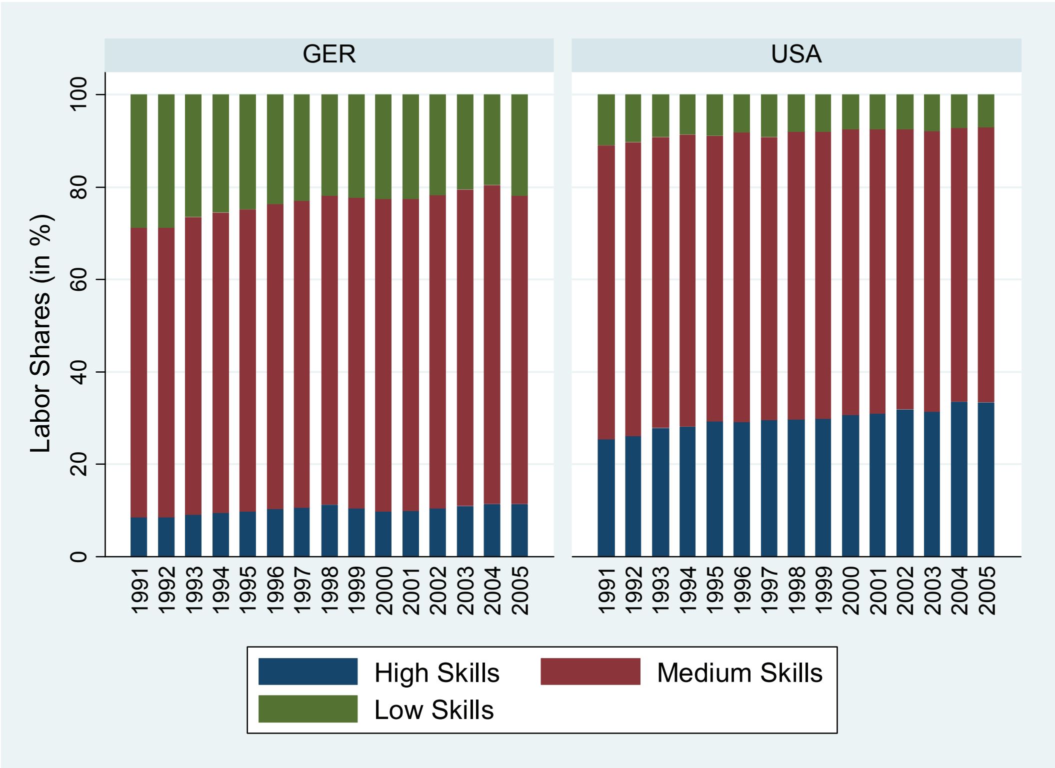
Note: a) consists of the sectors Furniture, Recycling, and Manufacturing n.e.c.

Table A2: Industry Clustering

		K-Means		K-Median		ICT-Skill Taxonomy	
		GER	US	GER	US	GER	US
1	Agriculture, Hunting and Forestry	C1-4	C2-2	C3-4	C4-2	OTHER	OTHER
2	Mining and Quarrying	C1-2	C2-1	C3-1	C4-1	IS	IS
3	Food and Tobacco	C1-4	C2-2	C3-4	C4-2	OTHER	OTHER
4	Textiles, Apparel, and Leather	C1-4	C2-4	C3-4	C4-3	OTHER	OTHER
5	Wood Products	C1-3	C2-4	C3-3	C4-4	OTHER	OTHER
6	Paper, Pulp, Publishing, Printing	C1-3	C2-1	C3-2	C4-1	OTHER	IS
7	Chemicals	C1-3	C2-1	C3-2	C4-1	OTHER	IS
8	Rubber and Plastics	C1-3	C2-2	C3-3	C4-2	OTHER	OTHER
9	Other Non-metallic Mineral Products	C1-3	C2-3	C3-3	C4-3	OTHER	OTHER
10	Basic and Fabricated Metals	C1-3	C2-3	C3-3	C4-3	OTHER	OTHER
11	Machinery	C1-3	C2-2	C3-3	C4-2	OTHER	OTHER
12	Office Machinery and Electronic Equipment	C1-1	C2-1	C3-1	C4-1	IS	IS
13	Motor Vehicles and Other Transport	C1-1	C2-1	C3-1	C4-1	IS	IS
14	Manufacturing n.e.c.[a)]	C1-2	C2-2	C3-1	C4-2	IS	OTHER
15	Electricity, Gas & Water Supply	C1-2	C2-1	C3-1	C4-1	IS	IS
16	Construction	C1-4	C2-4	C3-4	C4-3	OTHER	OTHER

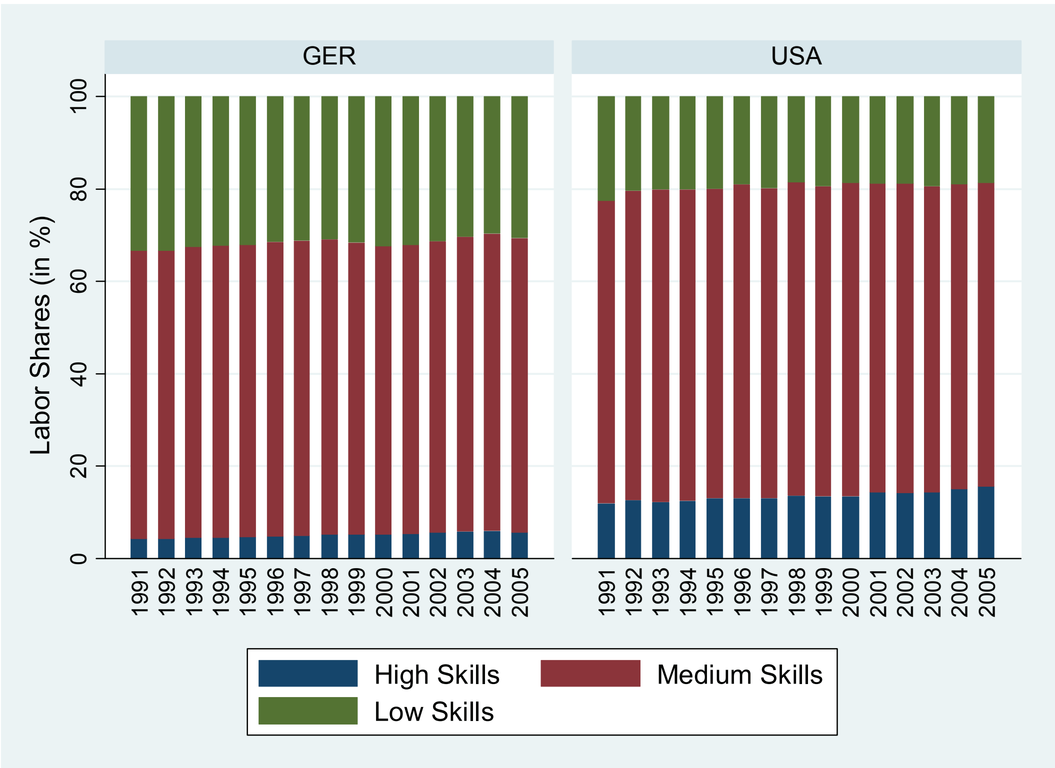
Notes: a) consists of the sectors Furniture, Recycling, and Manufacturing n.e.c. Outliers excluded. IS = ICT-skill intensive industries, OTHERS = non-ICT-skill intensive industries.

Table A3a: Average Labor Composition of Hours Worked, ICT-Skill Intensive Industries



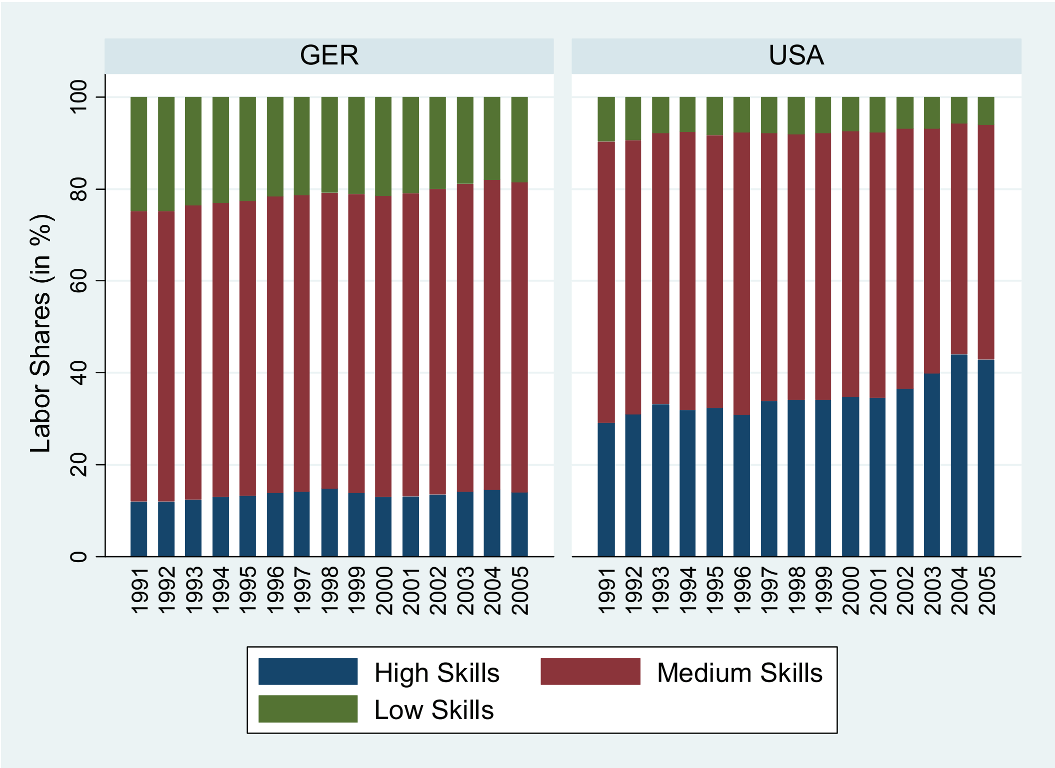
Notes: Figures represent industry averages. Outliers excluded. *Source:* EUKLEMS (2008).

Table A3b: Average Labor Composition of Hours Worked, Other Industries



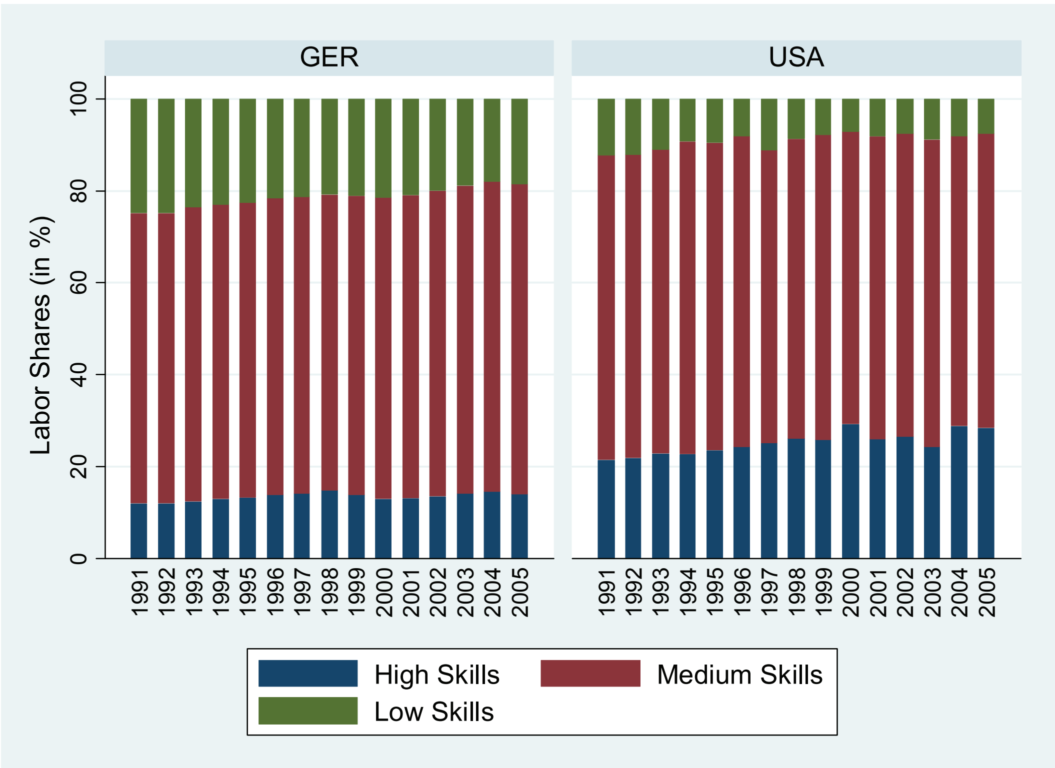
Notes: Figures represent industry averages. Outliers excluded. *Source:* EUKLEMS (2008).

Table A4: Labor Composition of Hours Worked, Office Machinery and Electronic Equipment (OE)



Source: EUKLEMS (2008).

Table A5: Labor Composition of Hours Worked, Motor Vehicles and Other Transport (MO)



Source: EUKLEMS (2008).

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