Information Technology and the Labor-Market Value of Skills: Evidence from Europe*

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Abstract

This research investigates changes in the labor-market value of specific skills in Europe as a result of computerization. Applying a GLS estimator for random coefficient models, to deal with unbalanced panels and a mixture of fixed parameters and parameters systematically varying between regions, allows for investigating the extent to which the coefficients of the skill scores in the wage function depend on the regional use of information technology. The estimates, using the 1999 Higher Education and Graduate Employment in Europe Survey (CHEERS) and information technology use by region, suggest that the relationship between information technology and the value of skills is not equal for all skills. In particular, the estimates suggest information technology to decrease the marginal returns for skills such as cooperation and team working and to increase the value of analytical skills.

Keywords: Wage differentials by skill; Information technology; Skill-biased technological change
JEL Classification: J31; O15; O33

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1 Introduction

This research investigates changes in the labor-market value of specific skills in Europe as a result of computerization. Most research has focused on the complementarity between higher educational levels and computerization, because of data availability and the observation of rising wage inequality together the appearance of computers since the early 1980s.[1] It is likely that computerization has not only increased the demand for higher educated workers, but also the demand for some skills compared to others. We use the 1999 Higher Education and Graduate Employment in Europe Survey (CHEERS), which allows us to investigate the returns to skills taking advantage of differences in the use of information technology (IT) at work in 64 European regions. An advantage of using European regions is that there exists a substantial regional variation in IT use. Since an international comparison of different levels of education is often hampered by differences in educational systems and the level of skills experienced workers embodies are not only determined by educational levels, we use higher educated workers who recently entered the labor market. We use measures for a number of different skills to determine the relationship between wages and skills in each region and analyze whether the resulting estimates of the value of skills vary systematically with regional IT use.

To estimate the labor-market value of different skills the empirical strategy has a two step structure in which (1) wages depend on skills (and other covariates) at the individual level, and (2) the skill parameters, reflecting the labor-market value of skills, depend on the level of regional IT use. This strategy allows for systematically varying parameters to capture the effect of regional IT use on the coefficients in the wage equation.[2] More specifically, we apply the GLS estimator for random coefficient models to deal with unbalanced panels and a mixture of fixed and systematically varying parameters to investigate whether the estimates of the skill coefficients in the wage function depend on the degree of regional IT use.[3]

[1]In addition, most research has focused on explaining wage trends in the United States and United Kingdom. See e.g., Autor et al. (1998) and Borghans and ter Weel (2005) for overviews of the literature.

[2]Moulton (1986) shows that if the possible stochastic properties of the parameters at the regional level are not taken into account, the estimator could be very inefficient with misleading standard deviations.

[3]Harville (1976) provides the general GLS estimator for this class of models. Furthermore, see Swamy (1970; 1971) for the initial approach into the estimation of random coefficient models. See also Hildreth ad Houck (1968) and Hsiao (1975) for early contributions and Lindley and Smith (1972) for a Baysian interpretation of the model. Swamy and Tavlas (1995) provide a useful overview of the theory and applications of random coefficient models in economics. Raj et al. (1980) discuss the combination of random and fixed coefficients. In the economic literature systematically varying parameters have been studied in the debate on wage differentials across industries and firms (e.g., Dickens and Katz (1987), Dickens (1990), Cardoso (2000), and Gibbons et al. (2005)) and the analyzes of the wage curve (e.g., Blanchflower and Oswald (1994) and Bell et al. (2002)). In these models variations in the intercept of a wage equation are related to firm, industry or regional characteristics. Attention is paid to the impact of

In a two-step OLS analysis, the estimates suggest that the value of field-specific theoretical knowledge and analytical competencies is positively correlated with regional IT use, whereas learning abilities, the ability to work in a team, and leadership skills are negatively correlated with regional IT use. Accounting for possible differences in the variance of the error term in the regional wage equations shows that the major shift in the value of skills is in the increasing value of analytical skills, and the decreasing value of teamwork and leadership. Although the estimates are gross effects, the decreasing value of leadership skills is consistent with theories stressing the impact of IT on organizational structures.[4] The results suggest that IT adoption has not the same effect for all skills, since the value of some skills increases, whereas other skills are likely to become less valuable as a result of IT use. Overall, the estimates suggest that IT substitutes for tasks demanding cooperation and soft skills and complements tasks requiring hard analytical competencies.

Of course, the value of skills is influenced by others (labor-market) factors as well. To assess the robustness of the estimates, we analyze regional differences in occupational structures and supply of skills as alternative explanations for our findings, but do not find a large impact. Since regions within countries might experience similar shocks unrelated to IT use, we estimate the model at the national rather than the regional level. Again, the effect of IT use on the value of skills does not change significantly. Finally, institutional differences between European countries are also likely to affect labor-market outcomes. We therefore test the sensitivity of our results for institutional differences between countries. Here too the estimated effects of IT use are unaffected.

This research is related to the literature investigating the changing value of skills, including the work by Murnane et al. (1995), and Gould (2002; 2005). The former report findings suggesting that the mastery of basic mathematics is more important in predicting wages among 1980 U.S. high-school graduates than among 1972 graduates. Gould (2005) uses an IQ proxy to see whether cognitive skills become more important within occupations and finds an increasing role for IQ to explain wage inequality. Similarly, Gould (2002) shows that an increasing emphasis on general unobservable skills in the United States has diminished the role of comparative advantage in reducing the observed level

group effects on the estimator of the parameters and standard deviations. Amemiya (1978) proposes an estimator for models in which the coefficients of the explanatory variables vary systematically, introducing parameter variation at the individual level. In our approach, the parameters systematically vary at the regional level, introducing both group effects and heteroscedasticity.

[4]See e.g. Kremer and Maskin (1997), Bresnahan et al. (2002) and Borghans and ter Weel (2006) who present approaches in which computer technology leads to more decentralization as workers can deal with more tasks on their own. See also Caroli and Van Reenen (2001) assume that all organizational change is of a decentralizing nature.

of inequality from what would occur in a random assignment economy. However, these papers do not establish a direct link between the returns to skills and the use of IT and are not able to analyze the sources of technological change underlying changes in the value of skills. The research is also related to Autor et al. (2003) and Spitz (2006) who construct measures of occupational skill requirements based on the tasks workers perform. Their focus is primarily on the changing importance of tasks related to IT use in the United States and Germany, whereas our approach is broader allowing for all possible roles IT has played in the changing value of skills. Finally, our analysis is related to Fernandez (2001) who studies changes in the demand for labor after a retooling of a large chocolate factory in the United States. He finds that the retooling resulted in greater wage inequality and higher returns to cognitive skills, but also finds that organizational and human resource factors strongly mediated the impact of new technology. This stresses the importance of not restricting the analysis to the importance of changing tasks only, as in Autor et al. (2003) and Spitz (2006).

The paper is organized as follows. Section 2 develops the model. Section 3 discusses the data and presents descriptive statistics. Section 4 reports the estimation results. Section 5 explores the robustness of the estimates. Section 6 concludes.

2 Strategy

The empirical strategy is to explain returns to skills by differences in regional IT use. In general, the production function of a region can be described by

$$Y_r = Y(\overline{S}_{1r}, \overline{S}_{2r}, \ldots \overline{S}_{K_1 r}, \overline{IT_r}), \tag{1}$$

for every region $r = 1, \ldots, R$, in which Y_r denotes regional output, $\overline{S}_{jr}$, $j = 1 \ldots K_1$, denote the stocks of K_1 different skills, and $\overline{IT}_r$ denotes the stock of IT capital in region r (see Heckman et al. (1996) for a similar exposition).

Individual workers can add to regional welfare by bringing in their individual skills S_{ij} (for every individual worker $i = 1, \ldots, n_r$) into the production process. Employers decide about IT investments and wages are determined by the marginal value of skills. Assume that log wages (W_{ir}) are a linear function of skills:

$$\begin{aligned} W_i \equiv \ln w_i = \quad & C(\overline{S}_{1r}, \overline{S}_{2r}, \ldots \overline{S}_{K_1 r}, \overline{IT}_r) + \\ & S_{i1} Y_1(\overline{S}_{1r}, \overline{S}_{2r}, \ldots \overline{S}_{K_1 r}, \overline{IT}_r) + \\ & S_{i2} Y_2(\overline{S}_{1r}, \overline{S}_{2r}, \ldots \overline{S}_{K_1 r}, \overline{IT}_r) + \\ & \ldots + S_{iK_1} Y_{K_1}(\overline{S}_{1r}, \overline{S}_{2r}, \ldots \overline{S}_{K_1 r}, \overline{IT}_r), \end{aligned} \tag{2}$$

where $Y_j = (\partial Y/\partial S_{ij})/Y$. Equation (2) implies that the wage of worker i depends on the skills he possesses and the derivative of the production function with respect to skill j, which depends on the aggregate stocks of skills and $\overline{IT}_r$. So, for each skill the contribution to the log wage depends on individual supply multiplied by the value, which depends on regional rather than individual characteristics.

In principle, the value of a skill depends on the stocks of all skills and the stock of IT capital. Since we distinguish 10 different skills, this would mean that 110 (10×11) parameters have to be estimated. Since the variation between the stock of skills is low compared to the variation in regional IT stocks, we initially neglect the influence of regional stocks of skills on the value of skills.[5]

To identify the impact of regional IT use on the value of skills, we estimate for each region wage equations including a vector of skills and the usual demographic variables, such as age, gender and secondary school grades, and job characteristics, such as whether or not the individual worker has a temporary or permanent job. Grouping individuals by region, the wage equation then looks as follows:

$$W_{ir} = S_{ir}\beta_r + X_{ir}\delta + \epsilon_{ir} \tag{3}$$

in which S_{ir} is a vector of skills and personal characteristics with varying effects also including a constant, and X_{ir} is a vector of personal characteristics of individual i in region r that have a fixed effect on wages, and ϵ_{ir} an error term with mean zero and a constant variance per region. Since we are interested in the way in which the extent of IT use in region r influences the returns to skills for worker i, β_r is written as an equation in which IT use in region r is included. More formally, the systematically varying parameter β_r equals $\beta_r^{(j)} = Z_r^{(j)}\gamma^{(j)} + \upsilon_r^{(j)}$, where $j = 1, \ldots, K_1$ is an index of the random variables, $Z_r^{(j)}$ contains a constant and the degree of computerization in region r, and $\upsilon_r^{(j)}$ is an error term with constant variance for each j. When we stack these data, the following expression for β_r results:

$$\beta_r = Z_r\gamma + \upsilon_r. \tag{4}$$

The estimation of wage equations by region presupposes that labor markets in each region are sufficiently separate markets in which prices are determined by regional supply and demand. In Section 4 we will provide evidence showing that labor mobility is not large enough to generate mobility to the extent that it would seriously affect our estimates. In addition, Acemoglu and Angrist (2000) have argued that trade could compensate for a

[5] The largest effect of the supply of skills on its value can be expected to come from the skill itself. In Section 5 we will add the skill stocks to the analysis when we explore the robustness of the estimates for a number of different specifications.

lack of labor mobility in equalizing wage differentials per skill between regions. Since the diffusion of IT is taking place in a relatively short period of time, we think that there is no short-run scope for a full industrial reorganization that would be required to equilibrate markets. Nevertheless, the existing labor mobility and regional trade patterns are likely to moderate the regional effects to some extent.

Without disturbance term υ_r the two equations could be merged and the model could be estimated by ordinary least squares (OLS) using interaction variables for each skill variable and the use of IT in the region. However, Moulton (1986) shows that neglecting the possible random variation of the parameters at the regional level is likely to lead to considerable inefficiency of the OLS estimators and a strong downward bias of the standard errors, leading to spurious regression results. This means that we have to deal with a model exhibiting not only a composite systematic part (A) but also a composite disturbance term (B):

$$W_{ir} = \underbrace{(S'_{ir}Z_r)\gamma + X'_{ir}\delta}_{A} + \underbrace{S'_{ir}\upsilon_r + \epsilon_{ir}}_{B}\,. \tag{5}$$

Equation (5) is different from ordinary random coefficient models in which β_r is random, whereas in the specification here it is systematically varying with regional IT use. In Appendix 1 we derive the general least squares (GLS) estimator applied to this problem.

3 Data

The data used to estimate the model are taken from the 1999 Higher Education and Graduate Employment in Europe Survey (CHEERS). The sample includes the results of a survey carried out in 11 European countries in 1999 and includes labor-market information on recently graduated people who attended either higher vocational schools or universities (n=21,518).[6] The survey has been conducted in Austria, the Czech Republic, Finland, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, and the United Kingdom. In 1999, the written survey has been sent to school leavers who left higher education in 1996. The respondents have, among others, been asked to assess their skills for a number of competencies at the moment of graduation. The number of higher educated workers as a percentage of the workforce is comparable between the 11 countries in our sample. For each country between 2,000 and 3,000 observations are available.

The 11 countries have been split into 64 regions. For most EU member states (all countries, except the Czech Republic and Norway) the NUTS-1 classification has been

[6] More information about the data and the means of collection can be obtained from http://www.uni-kassel.de/wz1/tseregs.htm.

used. However, Sweden is defined as one region at the NUTS-1 level and has been analyzed at the NUTS-2 level, which results in 8 Swedish regions. For some regions there are too little observations in the sample, so these regions have been merged with neighboring ones. The data for Spain do not contain regional information and Spain is therefore analyzed as a single region. In Finland the population is so strongly concentrated around its capital Helsinki that it is impossible to analyze separate Finnish regions. Hence, Finland is also put in the data set for estimation as a single region. For the Czech Republic and Norway a comparable regional division has been applied, resulting in 3 regions in the Czech Republic and 7 regions in Norway. Table A1 in the Appendix reports the 64 regions, the country they belong to, the NUTS-1 (NUTS-2) codes, and the number of observations.

Table 1 reports a number of regional statistics. The top panel of the table reports the mean, standard deviation, and minimum and maximum of the regional use of IT, the log gross monthly wages, hours worked on a weekly basis, whether or not the workers in a particular region occupy a temporary job (1=yes, 0=no), the fraction of female workers, the age of the respondents, and whether they have children or not. Finally, the top panel reports the share of workers employed in the computer sector. The use of IT at work is 85.9 percent on average with a standard deviation of 4.3 percent.[7] The use of IT is lowest in Bassin Parisien and Nord-pas-de-Calais (71.7 percent) and highest in Norra Mellansverige in Sweden (96.3 percent). There is a relatively large dispersion in wages, taking into account that the sample only consists of higher educated workers with similar years of working experience. However, this might be due to part-time employment. The minimum log gross annual wages in euros$\times 1,000$ equal 1.46 and the maximum 3.74; the average equals 3.09. On average 18.9 percent of the workers occupies a temporary job, and 49.9 percent of the workers is female. The average age equals 30.7 with a standard deviation of the means per region of only 1.83, which is what we expected since the group of workers under consideration is a relatively homogenous one with respect to the development of their working careers. We also included a variable assessing a worker's scores in secondary school, as a measure for worker quality. The information available assesses whether a worker obtained above average school grades (2), average school grades (1) or below average school grades (0). It turns out that on average, they obtained

[7]This level of use is rather high compared to previous studies (e.g., Autor et al., 1998 for the United States and Entorf et al., 1999 for France), but one has to keep in mind that we only investigate graduates from higher vocational education and universities. Using the 1997 CPS information, it turns out that 72.6 percent of all (i.e., young and old) U.S. college graduates uses a computer at work and Weinberg (2002) shows that computer use at work among young U.S. college graduates with less than 10 years of working experience is between 74 and 86 percent in the late 1990s, figures well comparable to the figures reported in the first row of Table 1. See also Borghans and ter Weel (2005) for computer use at work among different demographic groups in the United States, the United Kingdom and Germany.

slightly higher than average scores in secondary school (1.226). It is important to note that the educational systems in Europe are different from the ones in the United States. In Europe there are several levels of secondary education whereas in the United States most pupils go to high school. Hence, the secondary school scores that we apply here are measured relative to the scores of pupils within the same level of secondary education. Approximately 23 percent of the sample population has children. More male workers than female workers have children (12.3 compared to 10.7 percent). Finally, the number of workers in the computer sector equals 5.4 percent.

Age, gender and temporary job, which are assumed to have the same impact on wages in every single region, are included in the analyzes as fixed parameters. The systematically varying parameters are the constant and dummy variables for female and female*child, and secondary school grades. We allow the returns to specific job skills to differ between regions depending on the degree of IT use in that region. Except for the constant and the gender dummy, the estimation results turn out to be very insensitive to the choice of covariates to be either fixed or systematically varying.

The 10 skills included in the empirical analysis are (1) field- specific theoretical knowledge, (2) planning, coordinating and organizing, (3) analytical competencies, (4) learning abilities, (5) accuracy, attention to detail, (6) manual skills, (7) working in a team, (8) oral communication skills, (9) leadership, and (10) taking responsibility, making decisions. These 10 skills reflect a great many aspects of the average higher educated job ranging from relatively hard analytical skills to relatively soft skills such as working in a team, and from routine skills such as accuracy, and attention to detail to non-routine leadership skills. The question asked was the following: "Please state the extent to which you had the following competencies at the time of graduation."

The bottom panel of Table 1 reports the self-assessed scores of the respondents on a scale from 1-5; 1 being "not at all", and 5 being "to a very high extent". The average highest scores by region are obtained for learning abilities (4.16) and field-specific theoretical knowledge (3.80), which are typically skills embodied by recently graduated workers. The lowest average scores are obtained for leadership (2.85), and manual skill (2.96); the former is most likely to be acquired by working experience, and the latter is a job item not often demanded in jobs at the high end of the labor market. Furthermore, accuracy, attention to detail (3.69), analytical competencies (3.67), working in a team (3.66) and oral communication skills (3.61) are also skills that seem to be possessed at a relatively high level by the workers in the sample, whereas the taking responsibility, making decisions (3.38) and planning, coordinating and organizing (3.13) scores are comparatively low. Of course there might be cultural differences in the way graduates evaluate their own abilities. Since in the analyzes we investigate the variation of these self-assessed measures within each region, such differences between countries do not bias our results.

4 Estimation Results

4.1 Basic Results

We start by reporting estimates for simple OLS wage regressions including standard demographic controls, regional dummies or country dummies and the 10 skill variables. The results of these regressions are reported in Table 2. In the first column of Table 2 we report the results of a regression of the log of the monthly wages depending on a number of usual demographic covariates. The regression coefficients reveal that there is a significant gender wage gap: women earn on average 22.9 percent less than men (exp(.206)−1). Our proxy for unobserved ability (secondary school grades) reveals that workers with higher grades in secondary school earn significantly higher wages compared to the control group of workers with below average secondary school scores. In addition, women with children earn lower wages, temporary jobs pay less, and there is a significant effect of age on wages, which is likely to reveal institutional influences of age on wages because years of working experience are essentially the same in the sample.[8] Finally, men with children earn somewhat higher wages.

The second column of Table 2 reports the results of the same regression but now also including country dummies to control for country-specific effects on wages. All unreported dummies are significant at the 1 percent level. The F-test of the joint significance of these country dummies equals $F[16,\ 21{,}501] = 2830.999$, which suggests a high significance of country differences in explaining wages. The results from the previous regression equation remain, although the gender wage gap falls somewhat, the effect of higher secondary school grades is also smaller, and the effect of age on pay is reduced. On the other hand, the negative wage effect for women with children and temporary jobs is larger; the same holds for the positive returns for men with children. The third column in Table 2 reports the results of including regional dummies instead of country dummies to see whether there exist regional labor markets. Comparing these regional dummies with the country dummies results in $F[66,\ 21{,}451] = 5.021$. Although the regional differentials within countries are much smaller than the country differentials themselves, this test is also significant at the 1 percent level, suggesting a relative independence of regional wages and labor markets in determining wages. We view this latter result as support for our

[8] As is usually found, the age pattern turns out to be concave, when including a squared term.

analysis of estimating wage equations at the regional level.

The results of a second set of three regressions are reported in Table 3. In these regressions we have included the 10 skill variables besides the standard demographic covariates. 7 skills yield significant effects with manual skills negatively so. Leadership and analytical competencies yield the highest labor market returns and the returns to learning abilities and teamwork are also relatively high. The coefficients on the demographic variables are comparable to the ones reported in Table 2. The next two columns report estimates including country dummies (column (2)) and regional dummies (column (3)). Both including country dummies ($F[26, 21{,}491] = 2616.686$) and including regional dummies (compared to a specification with country dummies, $F[76, 21{,}441] = 3.681$) improves the model significantly. The returns to analytical competencies remain positive and significant in both specifications but the positive returns to leadership skills disappear; the returns to learning abilities remain constant in all specifications and the ability to work in teams still yields positive labor market returns.

Not only wage differentials, but also patterns of regional mobility indicate that NUTS1 regions can be treated as separate labor markets. On average 22.4 percent of the sample population is working in a different region compared to the one in which they received higher education. These percentages are substantially higher for the United Kingdom (51.9 percent) and France (38.3 percent). In both cases this reflects a large flow of graduates from different regions to the London and Paris areas. Mobility between others regions in the United Kingdom and France is − consistent with mobility figures in the other countries − about 10 percent only. Only .9 percent of the population has moved to another country after completing their studies.

4.2 Model Estimation

4.2.1 OLS Estimates

Before estimating the full model, Table 4 reports estimates of equation (4) using OLS to estimate both equations, using the estimated parameters from equation (3) to estimate equation (4). This approach requires the assumption that the variance of the error term in the wage equation is equal in all regions. Positive (negative) coefficients should be interpreted as an increasing (decreasing) return to skill j when regional IT use is higher. The first column in Table 4 reports the constant effects and the second column the systematically varying coefficients. The coefficients of the constant effect should be read as the return to skills in a region with average IT use. The results of the systematically varying effect of regional IT use on the returns to skills suggest that with the increasing use of IT in European regions the returns to 6 skills are rising (not necessarily significantly rising). These are field-specific knowledge, analytical competencies, accuracy and attention to detail, manual skills, oral communication skills, and taking responsibility, decision making. The returns to planning, coordinating and organizing, learning abilities, working in a team, and leadership are declining when the use of IT in the region is increasing. However, only 5 skills show significant returns. It seems to be the case that field-specific theoretical knowledge and analytical competencies become more valued when the use of IT is rising. This result is consistent with studies revealing increasing returns to (non-routine) cognitive skills for higher educated workers (e.g., Autor et al., 2003 and Spitz, 2003). What is interesting to observe is that learning abilities, the ability to work in teams and leadership are becoming less valued when computer use is increasing.[9] These coefficients are inconsistent with claims that working in a team becomes more important in organizations employing a comparatively large fraction of higher educated workers, but consistent with the same studies showing that at the same time firms become organized in a less hierarchical way (e.g., Kremer and Maskin, 1997 and Garicano and Rossi-Hansberg, 2003). If IT reduces the number of hierarchical levels and workers become more responsible for their own tasks, leadership is a less important requirement. The importance of team working might both increase and decrease depending on whether or not IT leads to more generic or specialist jobs. These estimates are consistent with jobs becoming more generic leading workers to carry out more tasks themselves, which attaches less value to leadership skills and more value to taking responsibility for one's own actions, but also the removal of clerical and secretarial jobs (e.g., Autor et al., 1998 and Acemoglu, 1999).

4.2.2 EGLS Estimates

Table 5 reports the regression results from estimating the EGLS model in which we allow the variance of the error terms in the wage equation to vary per region. Of course, this more flexible specification will affect the power of the tests. As a first step, the 10 skills have been included separately. The reason for doing so is that correlations between the individual skills might make it difficult to find effects in a model in which all skills are entered simultaneously. Next to the skill variables three unreported systematically varying control variables and three fixed control variables have been included. The three systematically varying control variables are female, secondary school grades and female*child. The reason for making these three control variables systematically varying with computer

[9] The fact that learning abilities show a negative coefficient might also be due to the fact that most respondents embodied this skill at a relatively high level (score of 4.16 on a scale of 1-5), and that the variation in terms of the standard deviation is relatively low (.14).

technology use is that women and workers with higher unmeasured abilities tend to use computer technology more often (e.g., Entorf and Kramarz, 1997 and Weinberg, 2000). The three fixed control variables are temporary job, age and male*child. The results from the EGLS model reported in Table 5 are less strong than the ones from the two step OLS model presented in Table 4. Nevertheless, the overall picture that becomes apparent from this analysis remains similar. The returns to skills such as analytical competencies and field-specific theoretical knowledge seem to increase when IT use is higher, and there seems to exist a negative correlation between softer skills − such as working in a team of people and leadership − and regional IT use.

Next, all 10 skill variables have been included simultaneously in the regression equation. The results reported in Table 6 also reveal a less strong relationship between the returns to skill varying with regional IT use than the results from the two step OLS model reported in Table 4. However, the signs of the coefficients remain the same and the largest effects found in the OLS estimates are still present in the GLS estimation of the full model. In addition, the results are very comparable to the ones presented in Table 5 from estimating the model including one skill each time. Again, it turns out that hard skills, such as analytical competencies become more valued as IT use becomes more common. At the same time, the regression results suggest that relatively soft skills, or people skills, such as the ability to work in teams and exhibiting leadership become less valued. In all three regression analyzes this conclusion stands out relatively clearly.

5 Robustness

We have performed a number of robustness checks to investigate the sensitivity of our results. The results of these analyzes are presented in Table 7.

5.1 Regional Variation in Skill Demand and Supply

A first criticism concerning our results might be that, besides differences in IT, regions differ by other factors as well. In particular, occupational structure, the level of education, and the number of female workers (or the attitude towards female labor market participation) is likely to differ between different European regions. Since within some occupations IT use is higher than within others, the value of skills might be different as well (Berman et al., 1994). Secondly, it is well known that higher educated workers use IT more often than lower educated workers (e.g, Autor et al., 1998). Finally, women are more likely to use computers than men because computer technology has reduced the comparative advantage of men in many jobs (e.g., Weinberg, 2000).

To capture such possible effects, we regression adjust IT use by these three factors. The results for the EGLS estimator are reported in the first column of Table 7. The estimates reveal that the coefficients on the skill variables remain intact, except for the coefficient for analytical skills, which now becomes insignificant; however, field-specific theoretical knowledge now becomes significant. Our reading of these estimates is that the main results remain comparatively similar and that assuming regions to be different by IT use is perhaps a crude but justified assumption to estimate the returns to different skills.

Furthermore, not only the structure of demand might vary between region, but also the supply of skills is likely to differ between regions in Europe. Equation (2) shows that the value of a skill depends on the stock of IT and the stocks of all skills in a region. The main effect of skill supply on the value of a certain skill can be expected to come from the supply of this specific skill itself. We therefore expanded equation (4) by including an additional term for the average skill score. It turns out that all the effects of IT on the value of skills remain similar and significant.

5.2 Country Level Estimates and Institutions

A second important issue that could influence our results is that there are country specific influences on the wage structure that affect all regions in a country in a similar way. Due to such a correlation within countries the standard deviations could be underestimated. To investigate whether or not we pick up country specific effects we ran the analysis for the 11 countries instead of 64 regions.

The results of the systematically varying effects of this analysis are reported in the second column of Table 7. The estimates reveal that, even when we use the variation in 11 countries instead of the variation in IT use in 64 regions, the coefficients on the skill variables remain reasonably comparable. The returns to analytical skills are positive and also the negative returns to team working and leadership remain present. Our reading of these estimates is that our model is relatively well able to predict the value of skills on the basis of regional variation in IT use. The fact that the model performs only reasonably well is likely to be due to the fact that we now only use the variation in IT use between 11 observations instead of 64. This reduction can in all likelihood be expected to reduce the significance of the estimates. Linking these estimates to the ones in Tables 2 and 3 leads to the conclusion that regional variation in IT use is a justifiable way to identify our model upon.

A related potential concern is that country specific institutions might affect both the adoption of IT and the wage structure. It is well known that institutions play an important role in European wage determination. So, we want to make sure that IT use does not proxy for institutional differences between countries. To do so, we added the "industrial laws index" from Botero et al. (2004) as a second variable to equation (4). All effects of IT use on the value of skills remain similar, while this index turns out to have no significant relationship with the value of skills.

5.3 Excluding the Computer Industry

High levels of IT use might indicate a large computer sector and a large computer sector is likely to be focused on designing IT and not on applying IT in daily work. Since we are primarily interested in effects of the general purpose technology on the wage structure in the economy as a whole and since the computer sector might pay higher wages and require specific skills, we ran the model without including those workers employed in the computer industry. This concern seems to be justified when investigating the relatively high standard deviation (.030) compared to the mean (.054) of workers being employed in the computer sector reported in Table 1.

The results of the systematically varying part of this regression are reported in the final column of Table 7. The estimates reveal that controlling for workers occupied in the computer sector does not significantly change the estimates.

6 Conclusion

The wages of higher educated workers relative to lower educated workers increased dramatically over the past decades. To many, this is a direct consequence of the rapid diffusion of IT, which complemented higher educated workers. Since there is ample empirical evidence now that this increased the demand for skilled workers, it is likely that the type of skill demand has changed in this period.[10] It is therefore necessary to analyze the skills experiencing increasing (or decreasing) returns as a result of the computer revolution. To do so, we have estimated the returns to skills in relation to the use of IT making use of regional variation in IT use to identify the model. The estimation results in this paper suggest that the value of analytical competencies and theoretical knowledge increases when IT becomes more important, while skills such as team working, learning abilities, accuracy and leadership seem to become less valuable. These results suggest that the effects of IT on the value of skills within a relatively homogenous group of work-

[10] See Acemoglu (2002, p. 13 and Section 7.4) who argues that there is a need for this research.

ers is not straightforward, but that IT generally substitutes for tasks requiring soft skills such as cooperation and social abilities and complements tasks requiring relatively hard analytical skills.

Appendix 1: Econometric Model

We estimate a wage equation for every individual worker $i = 1, \ldots, n_r$ who works in region $r = 1, \ldots, R$, in which the log of the gross wage (W_{ir}) depends on fixed and systematically varying parameters. The fixed covariates are personal characteristics such as age and gender, and job characteristics such as whether the job is a permanent one or not, which are assumed to have the same impact on wages in every single region. The systematically varying parameters are the skill measures (see Section 3 of the paper and Appendix 2 for more details); they are allowed to differ between regions. More specifically, these covariates are assumed to depend on the level of use of IT in the region the individual worker resides. The wage equation then looks as follows:

$$W_{ir} = S'_{ir}\beta_r + X'_{ir}\delta + \epsilon_{ir} \tag{A1}$$

in which W_{ir} is the log of the gross annual wage of individual i in region r, S_{ir} is a vector of skills and systematically varying control variables, X_{ir} a vector of personal characteristics, and ϵ_{ir} an error term with a constant variance per region. Since we are interested in the way in which the extent of computerization of a region influences the returns to skills, β has to be written as an equation in which the use of IT in region r is included. The systematically varying parameter β_r is then:

$$\beta_r^{(j)} = Z_r^{(j)}\gamma^{(j)} + \upsilon_r^{(j)} \tag{A2}$$

where $r = 1, \ldots, R$, $j = 1, \ldots, K_1$, $\gamma^{(j)}$ is a vector of the skill variables, $Z_r^{(j)}$ contains a constant and the degree of computerization of region r, and $\upsilon_r^{(j)}$ an error term with a constant variance per skill. Equation (A2) can be written as

$$\begin{bmatrix} \beta_t^{(j)} \\ \vdots \\ \beta_t^{(K_1)} \end{bmatrix} = \begin{bmatrix} Z_t^1 & & 0 \\ & \ddots & \\ 0 & & Z_t^{K_1} \end{bmatrix} \begin{bmatrix} \gamma^{(1)} \\ \vdots \\ \gamma^{(K_1)} \end{bmatrix} + \begin{bmatrix} \upsilon_t^{(1)} \\ \vdots \\ \upsilon_t^{(K_1)} \end{bmatrix}, \tag{A3}$$

which results in equation (2) in the main text:

$$\beta_r = Z_r\gamma + \upsilon_r. \tag{A4}$$

The model with a composite systematic part and a composite disturbance term looks as follows:

$$W_{ir} = (S'_{ir}Z_r)\gamma + X'_{ir}\delta + S'_{ir}\upsilon_r + \epsilon_{ir}, \tag{A5}$$

where $(S'_{ir}Z_r)\gamma + X'_{ir}\delta$ is the composite systematic part and $S'_{ir}\upsilon_r + \epsilon_{ir}$ the composite disturbance term.

This model is still in elementary form. In order to obtain the matrix form, we collect all data on individuals by region and stack the regional data. For each region r we can now write

$$\begin{bmatrix} W_{1,r} \\ \vdots \\ W_{n_r,r} \end{bmatrix} = \begin{bmatrix} S'_{1,r} Z_r \\ \vdots \\ S'_{n_r,r} Z_r \end{bmatrix} \gamma + \begin{bmatrix} X'_{1,r} \\ \vdots \\ X'_{n_r,r} \end{bmatrix} \delta + \begin{bmatrix} S'_{1,r} \\ \vdots \\ S'_{n_r,r} \end{bmatrix} \upsilon_r + \begin{bmatrix} \epsilon_{1,r} \\ \vdots \\ \epsilon_{n_r,r} \end{bmatrix} \tag{A6}$$

and the model looks like

$$W_r = \begin{bmatrix} S'_{1,r} Z_r & X'_{1,r} \\ \vdots & \vdots \\ S'_{n_r,r} Z_r & X'_{n_r,r} \end{bmatrix} \begin{bmatrix} \gamma \\ \\ \delta \end{bmatrix} + S_r \upsilon_r + \epsilon_r, \tag{A7}$$

where we define $A_r = \begin{bmatrix} S'_{1,r} Z_r & X'_{1,r} \\ \vdots & \vdots \\ S'_{n_r,r} Z_r & X'_{n_r,r} \end{bmatrix}$ and $\overline{\beta} = \begin{bmatrix} \gamma \\ \\ \delta \end{bmatrix}$

Now stack the regional data:

$$\begin{bmatrix} W_1 \\ \vdots \\ W_R \end{bmatrix} = \begin{bmatrix} A_1 \\ \vdots \\ A_R \end{bmatrix} \overline{\beta} + \begin{bmatrix} S_1 & & 0 \\ & \ddots & \\ 0 & & S_R \end{bmatrix} \begin{bmatrix} \upsilon_1 \\ \vdots \\ \upsilon_R \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_R \end{bmatrix}, \tag{A8}$$

which is equal to $W = A\overline{\beta} + S\upsilon + \epsilon$, where the first term on the right-hand side is the systematic varying part and the second term the composite disturbance term. This composite disturbance term equals $S\upsilon + \epsilon \sim N(0, \Phi)$.

The covariance matrix of the composite disturbance term, Φ, can be derived as follows:

$$\Phi = E[(S\upsilon + \epsilon)(S\upsilon + \epsilon)'] = E[S\upsilon\upsilon' S'] + E[\epsilon\epsilon'] = SE[\upsilon\upsilon']S' + E[\epsilon\epsilon']. \tag{A9}$$

In this equation

$$E[\upsilon\upsilon'] = E \begin{bmatrix} \upsilon_1\upsilon'_1 & & 0 \\ & \ddots & \\ 0 & & \upsilon_R\upsilon'_R \end{bmatrix} = \begin{bmatrix} \Delta & & 0 \\ & \ddots & \\ 0 & & \Delta \end{bmatrix}, \tag{A10}$$

$$E[\epsilon\epsilon'] = E \begin{bmatrix} \epsilon_1\epsilon'_1 & & 0 \\ & \ddots & \\ 0 & & \epsilon_R\epsilon'_R \end{bmatrix} = \begin{bmatrix} \sigma_{11} I_{n_1 \times n_1} & & 0 \\ & \ddots & \\ 0 & & \sigma_{RR} I_{n_R \times n_R} \end{bmatrix} \tag{A11}$$

and

$$SE[\upsilon\upsilon']S' = \begin{bmatrix} S_1 \Delta S'_1 & & 0 \\ & \ddots & \\ 0 & & S_R \Delta S'_R \end{bmatrix}. \tag{A12}$$

This implies that

$$\Phi = \begin{bmatrix} S_1 \Delta S'_1 + \sigma_{11} I_{n_1 \times n_1} & & 0 \\ & \ddots & \\ 0 & & S_R \Delta S'_R + \sigma_{RR} I_{n_R \times n_R} \end{bmatrix}. \tag{A13}$$

Now define $\Phi_{rr} = S_r \Delta S_r' + \sigma_{rr} I_{n_r \times n_r}$. Then, $\Phi = diag\{\Phi_{11}, \ldots, \Phi_{RR}\}$, which implies $\Phi^{-1} = diag\{\Phi_{11}^{-1}, \ldots, \Phi_{RR}^{-1}\}$.

The model for estimation then looks like $W = A\overline{\beta} + (Sv + \epsilon)$ with $Sv + \epsilon \sim N(0, \Phi)$. The general least squares (GLS) estimator for $\overline{\beta}$ equals:

$$\widehat{\overline{\beta}} = (\sum_{r=1}^{R} A_r' \Phi_{rr}^{-1} A_r)^{-1} \sum_{r=1}^{R} A_r' \Phi_{rr}^{-1} W_r. \tag{A14}$$

To implement feasible or estimated GLS (EGLS), we have to obtain estimates for Δ, and σ_{rr}. The estimated Δ, $\widehat{\Delta}$, is derived using the OLS estimate $\widetilde{\beta_r}$ from equation (A1) and the OLS estimate $\widetilde{\gamma}$, from equation (A4). The EGLS estimator for $\widehat{\Delta}$ then equals

$$\widehat{\Delta} = \frac{\sum_{r=1}^{R} (\widetilde{\beta}_r - Z_r \widetilde{\gamma})(\widetilde{\beta}_r - Z_r \widetilde{\gamma})'}{R - K_3}. \tag{A15}$$

Similarly, $\widehat{\sigma}$ equals

$$\widehat{\sigma}_{rr} = \frac{\widetilde{\epsilon_r'} \widetilde{\epsilon_r}}{n_r - K_1 - K_2}, \tag{A16}$$

where $\widetilde{\epsilon_r}$ is obtained from equation (A1) for $i = 1, \ldots, n_r$.

Appendix 2: Data Appendix

Table A1 provides an overview of all 64 regions used. Finland (n=2,058) and Spain (n=1,409) have been included as one region. For Germany 10 regions have been included (n=2,331), for France we have defined 7 regions (n=1,819), Italy is in the sample with 9 regions (n=1,594), the Netherlands have been split up into 4 regions (n=2,200), Austria has 3 regions (n=1,487), for Sweden 8 regions at the NUTS-2 level have been defined (n=1,764), the United Kingdom is included with 11 regions (n=2,260), Norway has 7 regions (n=2,640), and finally the Czech Republic is split into 3 regions (n=1,901).

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Table 1

Data Description: The Means and Standard Deviations of the Variables and the Minimum and Maximum Average by Region

Variable	Mean	St.dev.	Min.	Max.
Information technology use	.859	.043	.717	.936
Log monthly wages (1,000 Euros)	3.098	0.551	1.46	3.74
Hours worked (weekly)	37.419	1.097	34.8	39.4
Temporary job	.189	.074	.052	.333
Female	.499	.078	.256	.709
Age	30.7	1.83	27.4	33.3
Secondary school scores	1.226	.361	.538	1.847
Individuals with children	.231	.141	.025	.587
Females with children	.108	.093	.013	.376
Males with children	.123	.062	.003	.266
Employed in computer sector	.054	.030	.000	.151
Field-specific theoretical knowledge	3.80	.20	3.42	4.19
Planning, coordinating and organizing	3.13	.27	2.46	3.65
Analytical competencies	3.67	.18	3.28	4.12
Learning abilities	4.16	.14	3.74	4.47
Accuracy, attention to detail	3.69	.16	3.44	4.04
Manual skills	2.96	.32	2.43	3.74
Working in a team	3.66	.26	3.22	4.38
Oral communication skills	3.61	.18	3.15	4.04
Leadership	2.85	.28	2.14	3.55
Taking responsibility, making decisions	3.38	.19	2.96	3.90
n = 21,518				

Table 2

Estimating Wage Equations[a]

Variable	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Female	−.206	.011***	−.197	.007***	−.193	.007***
HS grades	.108	.007***	.070	.005***	.073	.005***
Female*child	−.073	.017***	−.096	.012***	−.081	.012***
Temp	−.133	.012***	−.142	.008***	−.134	.008***
Age	.024	.001***	.007	.001***	.008	.001***
Male*child	.027	.016*	.042	.011***	.061	.011***
Country dum.	no		yes		no	
Regional dum.	no		no		yes	
Adj. R^2	.070		.598		.602	
n	21,518		21,518		21,518	

[a]Dependent variable log gross monthly wages; all regressions include an unreported constant.
* = significant at 10 percent confidence level
** = significant at 5 percent confidence level
*** = significant at 1 percent confidence level

Table 3

Estimating Wage Equations Including Skill Variables[a]

Variable	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Female	−.221	.011***	−.188	.007***	−.185	.007***
HS grades	.091	.007***	.064	.005***	.068	.005***
Female*child	−.058	.017***	−.093	.012***	−.079	.012***
Temp	−.122	.012***	−.139	.008***	−.132	.008***
Age	.023	.001***	.008	.001***	.008	.001***
Male*child	.036	.016**	.046	.011***	.064	.011***
Skill 1	.019	.005***	−.010	.004**	−.006	.004*
Skill 2	.009	.005*	−.005	.004	−.003	.004
Skill 3	.077	.006***	.026	.005***	.023	.004***
Skill 4	.030	.007***	.032	.004***	.030	.005***
Skill 5	−.007	.005	−.019	.004***	−.017	.004***
Skill 6	−.055	.004***	−.022	.003***	−.019	.003***
Skill 7	.037	.005***	.006	.004*	.008	.004**
Skill 8	−.001	.005	−.015	.004***	−.017	.004***
Skill 9	.079	.006***	.003	.004	.002	.004
Skill 10	.005	.006	.001	.004	.001	.004
Country dum.	no		yes		no	
Regional dum.	no		no		yes	
Adj. R^2	.118		.602		.605	
n	21,518		21,518		21,518	

[a]Dependent variable log gross monthly wages; all regressions include an unreported constant.
Skill 1: Field-specific theoretical knowledge; Skill 2: Planning, coordinating, and organizing; Skill 3: Analytical competencies; Skill 4: Learning abilities; Skill 5: Accuracy, attention to detail; Skill 6: Manual skill; Skill 7: Working in a team; Skill 8: Oral communication skill; Skill 9: Leadership; Skill 10: Taking responsibilities, making decisions
* = significant at 10 percent confidence level
** = significant at 5 percent confidence level
*** = significant at 1 percent confidence level

Table 4

Two Step OLS Estimates of the Systematically Varying Effect of Information Technology Use by Region on the Relationship between Skills and Wages[a]

Variable	Const. eff.		Varying eff.	
	Coef.	S.E.	Coef.	S.E.
Field-specific knowledge	.003	.005	.273	.119**
Planning, coordinating	−.012	.007	−.001	.141
Analytical competencies	.024	.006***	.476	.140***
Learning abilities	.021	.012*	−.443	.259*
Accuracy, attention to detail	−.013	.005**	.140	.111
Manual skills	−.015	.005***	.131	.103
Working in a team	.010	.007	−.457	.142***
Oral communication skills	−.012	.009	.146	.194
Leadership	.005	.008	−.504	.167***
Taking responsibility	−.009	.008	.111	.183

[a]Dependent variable log gross monthly wages. The regression includes an unreported constant

* = significant at 10 percent confidence level

** = significant at 5 percent confidence level

*** = significant at 1 percent confidence level

Table 5

EGLS Estimates of the Systematically Varying Effect of Information Technology Use by Region on the Relationship between Skills and Wages Including One Skill Each Time[a]

Variable	Const. eff.		Varying eff.	
	Coef.	S.E.	Coef.	S.E.
Field-specific knowledge	.003	.007	.203	.159
Planning, coordinating	−.004	.008	.014	.172
Analytical competencies	.025	.007***	.272	.169
Learning abilities	.024	.011**	.018	.247
Accuracy, attention to detail	−.009	.007	.104	.153
Manual skills	−.017	.007**	−.091	.151
Working in a team	.002	.007	−.432	.170**
Oral communication skills	−.009	.008	−.139	.190
Leadership	−.000	.008	−.491	.187***
Taking responsibility	.001	.009	−.181	.192

[a]Dependent variable log gross monthly wages;. The regression includes an unreported constant for each of the 10 regressions, fixed parameters for temporary job, age and male*child, and systematically varying parameters for female, secondary school grades and female*child. The first column reports the constant effect and the second column the estimate for the systematically varying part of the regression equation.
* = significant at 10 percent confidence level
** = significant at 5 percent confidence level
*** = significant at 1 percent confidence level

Table 6
EGLS Estimates of the Systematically Varying Effect of Information Technology Use by Region on the Relationship between Skills and Wages Including the 10 Skills Simultaneously[a]

Variable	Const. eff.		Varying eff.	
	Coef.	S.E.	Coef.	S.E.
Field-specific knowledge	−.003	.007	.151	.165
Planning, coordinating	−.007	.008	.107	.185
Analytical competencies	.024	.008***	.340	.196*
Learning abilities	.024	.014*	−.167	.307
Accuracy, attention to detail	−.012	.007*	.091	.157
Manual skills	−.018	.006***	.053	.140
Working in a team	.007	.008	−.383	.186**
Oral communication skills	−.013	.010	.064	.232
Leadership	.006	.009	−.590	.218***
Taking responsibility	−.003	.010	.177	.235
Female	−.187	.023***	−.090	.385
HS grades	.058	.013***	−.412	.283
Female*child	−.100	.040**	−.219	.785

[a]Dependent variable log gross monthly wages. The regression includes an unreported constant. The first column reports the constant effect and the second column the estimate for the systematically varying part of the regression equation. Female, Secondary school grades and female*child are assumed to be systematically varying with IT use, whereas Temporary job, Age and Male*child are assumed to have a constant effect only.
* = significant at 10 percent confidence level
** = significant at 5 percent confidence level
*** = significant at 1 percent confidence level

Table 7
Robustness of the Results[a]

	Reg. adj.		Country		Comp. sec.	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Skill 1	.214	.109**	.175	.218	.184	.165
Skill 2	.059	.125	.201	.250	.091	.195
Skill 3	.168	.135	.222	.174	.363	.216*
Skill 4	−.066	.205	−.109	.195	−.189	.317
Skill 5	.022	.107	−.155	.189	.126	.162
Skill 6	−.050	.098	.071	.114	.049	.147
Skill 7	−.267	.132**	−.288	.233	−.363	.205*
Skill 8	.178	.149	.283	.175	.064	.239
Skill 9	−.391	.144***	−.720	.300**	−.581	.222***
Skill 10	.067	.157	.281	.263	.145	.246
Female	−.276	.258	−.108	.542	−.176	.416
HS grades	−.095	.202	−.555	.342	−.426	.302
Female*child	.060	.482	−1.471	1.096	−.109	.802
Temporary job	−.071	.063	−.089	.106	−.056	.065
Age	.006	.004	.005	.006	.007	.004*
Male*child	.017	.063	−.015	.082	.010	.066

[a]Dependent variable log gross monthly wages. The regression includes an unreported constant. Only the systematically varying coefficients are reported in this table. The first column reports regression results from using regression adjusted computer technology use by region. The second column reports estimates from using the variation in IT use by country (11 countries) instead of region (64 regions). The final column reports regression results from excluding workers occupied in the computer sector.
Skill 1: Field-specific theoretical knowledge; Skill 2: Planning, coordinating, and organizing; Skill 3: Analytical competencies; Skill 4: Learning abilities; Skill 5: Accuracy, attention to detail; Skill 6: Manual skill; Skill 7: Working in a team; Skill 8: Oral communication skill; Skill 9: Leadership; Skill 10: Taking responsibilities, making decisions
* = significant at 10 percent confidence level
** = significant at 5 percent confidence level
*** = significant at 1 percent confidence level

Table A1
Overview of the Regions Used, with NUTS Classification Codes, and Number of Observations[a]

Region	Country	NUTS	n
Baden-Württemberg	GER	DE1	125
Bayern	GER	DE2	510
Berlin, Brandenburg, Mecklenburg-Vorpommern	GER	DE3,4,8	97
Hessen	GER	DE7	287
Niedersachsen, Bremen	GER	DE9, 5	197
Nordrhein-Westfalen	GER	DEA	863
Rheinland-Pfalz, Saarland	GER	DEB, C	66
Sachsen	GER	DED	61
Sachsen-Anhalt, Thueringen	GER	DEE, G	80
Schleswig-Holstein, Hamburg	GER	DEF, 6	105
Spain	ESP	ES	1,409
Ile De France	FRA	FR1	770
Bassin Parisien, Nord-pas-de-Calais	FRA	FR2, 3	413
Est	FRA	FR4	136
Ouest	FRA	FR5	209
Sud-Ouest	FRA	FR6	49
Centre-Est	FRA	FR7	160
Mediterranee	FRA	FR8	82
Nord Ovest	ITA	IT1	167
Lombardia	ITA	IT2	445
Nord Est	ITA	IT3	244
Emilia-Romagna	ITA	IT4	104
Centro	ITA	IT5	207
Lazio, Abruzzo-Molise	ITA	IT6, 7	172
Campania	ITA	IT8	119
Sud	ITA	IT9	61
Sicilia, Sardegna	ITA	ITA, B	75
Noord-Nederland	NLD	NL1	270
Oost-Nederland	NLD	NL2	454
West-Nederland	NLD	NL3	894
Zuid-Nederland	NLD	NL4	582

[a]GER: Germany, ESP: Spain, FRA: France, ITA: Italy, and NLD: The Netherlands

Table A1
(*Continued from previous page*)[a]

Region	Country	NUTS	n
Ost-Österreich	AUT	AT1	781
Süd-Österreich	AUT	AT2	299
West-Österreich	AUT	AT3	407
Finland	FIN	FI	2,058
Stockholm	SWE	SE01	367
Oestra Mellansverige	SWE	SE02	420
Sydsverige	SWE	SE04	255
Norra Mellansverige	SWE	SE06	96
Mellersta Norrland	SWE	SE07	55
Oevre Norrland	SWE	SE08	164
Smaaland Med Oearna	SWE	SE09	100
Vaestsverige	SWE	SE0A	307
North West (incl. Merseyside)	UK	UKD	204
Yorkshire & The Humber, North East	UK	UKE, C	126
East Midlands	UK	UKF	124
West Midlands	UK	UKG	144
Eastern	UK	UKH	227
London	UK	UKI	318
South East	UK	UKJ	412
South West	UK	UKK	118
Wales	UK	UKL	59
Scotland	UK	UKM	385
Northern Ireland	UK	UKN	143
Oslo, Akerhus	NOR	N1	1,020
Hedmark og Oppland	NOR	N2	101
Sør-Østland	NOR	N3	304
Agder og Rogaland	NOR	N4	293
Vestlandet	NOR	N5	416
Tøndelag	NOR	N6	242
Nord-Norge	NOR	N7	264
Prague	CZE	C1	652
Bohemia (excl. Prague)	CZE	C2	529
Moravia	CZE	C3	720

[a]AUT: Austria, FIN: Finland, SWE: Sweden, UK: United Kingdom, NOR: Norway, and CZE: Czech Republic