Technology and the labour market: evidence on the effect of the spread of computers on job quality in Europe

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Abstract

This paper studies changes in computer use and job quality across different occupations using harmonised data on a large sample of employees from across the EU-15 over the period 1995-2015. We document that while the proportion of employees using computer has increased from 40% to over 60% over twenty years, there remains significant differences between countries even within the same occupations. Several countries have seen significant increase in computer use even in low-skill occupations generally assumed to be less affected by technology. Overall, the large increase in computer use between 1995 and 2015 has coincided with a period of modest deterioration of job quality in the EU-15 as whole, as discretion declined for most occupational and educational groups while intensity increased slightly for most of them. Our OLS results that exploit variation within country-occupation cells point to a sizeable positive effect of computer use on discretion, but to small or no effect on intensity at work. Our instrumental variable estimates point to an even more benign effect of computer use on job quality. Hence, the results suggest that the (moderate) deterioration in the quality of work observed in the EU-15 between 1995 and 2015 has occurred despite the spread of computers, rather than because of them.

Keywords: job polarisation; job quality; tasks; discretion; intensity.

JEL codes: J21, J23, J24, O33.

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[†] If you cannot click on the link, enter https://goo.gl/5j4jzQ into your browser.

1 Introduction

There is currently a lively debate both in academic and policy circles on the effect of technology on the labour market. While the bulk of the evidence point to no overall effect of technology on the quantity of jobs (D. Autor and Salomons 2017; OECD 2017), a number of studies have shown that technology changes the types of jobs in the economy both through compositional effects and through changes within existing jobs. The compositional effects arise because of the varying degree to which different jobs can be automated (Goos, Manning, and Salomons 2014), while changes within jobs occur when the adoption of technology leads to changes in the organisation of work and in the nature of the tasks performed (Spitz-Oener 2006; D. H. Autor 2013). A large literature has focused on the implications of these changes for wages, but little or no attention has been given to their impact on non-monetary aspects of job quality.

This paper contributes to the research on the effects of technology in the labour market by providing new evidence on the impact of arguably the most widely spread technology (computers) on two important aspects of job quality, namely job discretion and intensity. The focus on job quality is both useful and interesting for at least two reasons.

First, job quality is clearly important to people and increasingly recognised as such by a growing number of academics and policy makers (OECD 2014). The link between job quality and wellbeing has long been studied in the psychology literature (Warr 2007) and several papers have provided both descriptive and causal evidence of the link between wellbeing and productivity (Böckerman and Ilmakunnas 2012; Oswald, Proto, and Sgroi 2015; Bryson, Forth, and Stokes 2014). Secondly, studying its effect on job quality can provide new insights on how technology changes work which can help refine the theoretical frameworks used to study its impact on wages and employment. As recently discussed in Autor (2015), the current paradigm for thinking about the effect of technology in the labour market faces considerable puzzles. For example, the prediction that lower demand for routine jobs should lead to lower employment shares and wage growth has not be borne out by the data in most countries. This suggests that our understanding of how technology impacts these (and other) jobs might not be complete.[3] From this perspective, our approach of investigating changes in job quality can be seen as complementary to the standard approach of focusing on wages and employment.

We use data from the European Working Conditions Survey covering the EU-15 countries between 1995 and 2015. We begin by documenting recent changes in computer use and job quality with an emphasis on how differences between countries have evolved for similar occupations over time. To study the effect of computer use on job quality we then exploit variation

[3] See for example the discussion in Autor and Dorn (2013) who find that the wages of clerical workers increased robustly in the US between the 1990s and the 2000s in spite of the decline in their employment shares. They conjecture that this might be due to the fact that technology has two-fold effect on these jobs. On one hand, it reduces the demand for these jobs because the tasks involved are relatively easier to automate. On the other hand, it also changes the nature and organisation of the remaining jobs, possibly leading to an increase in the productivity of the remaining jobs in these occupations. By contrast, the recent literature tends to see technology as wither complementary or a substitute to workers in a given job.

over time within occupation-country pairs. Our OLS results from a model in stacked first-differences are complemented with IV results that exploits the secular declining trend in computing cost for identification (Acemoglu and Autor 2011; D. H. Autor and Dorn 2013; Nordhaus 2007). We instrument the change in computer use in one country-occupation cell with the average of the contemporaneous change in computer use in occupations involving similar tasks in other countries. The approach of using changes in other countries as instruments to exploit common exogenous trends for identification is commonly used in related literature. For example, Autor et al. (2013) use changes in Chinese imports to other high-income countries to instrument changes in import penetration to US local labour markets while Acemoglu and Restrepo (2017) instrument changes in robot penetration in US industries with changes in robot penetration in other advanced countries.

We focus on computer use for both substantive and practical reasons. The substantive reason is that computers are the most widely use form of technology in the labour market which have already been the subject of a large literature across disciplines. The practical reason is that while measures of computer use are readily available in existing surveys, reliable indicators of use or adoption of other forms of technology are not currently available. In fact, we argue in our conclusions that given how pervasive digital technologies are becoming in all aspects of life and work, there is an urgent need to develop new tools to measure their penetration in the workplace in more effective ways.

Our measure of work discretion reflects the extent to which individuals have control over (i) the order in which they perform their tasks, (ii) the methods of work, and (iii) the speed at which they work. The effect of computer use on discretion is a priori ambiguous. On the one hand, computers might provide workers with a higher degree of flexibility in the organisation of their work and increase the control they have over it. On the other hand, technology can be used to achieve higher standardisation of work and increased monitoring leading to a decline in the level of control individuals have over their work (Weil 2014). The net effect of computer use may differ across occupations. In fact, while technology might increase discretion for workers who mostly perform cognitive tasks, the negative effect might prevail in manual or service occupations if technology is mostly used to ensure that the workers follow precise procedures or work at a certain pace. For example, computers can be used to provide call centres operators with precise scripts to reduce the duration of calls, or to automate parts of the ordering and food-preparation processes in catering, or to shorten health care workers' visit time and to ensure more efficient transfers between visits. While the limited number of occupations available in our data provide little leverage to obtain precise estimates by occupations, we do investigate descriptively whether the effect of computer use appear to differ across different occupations.

Our measure of work intensity combines the answers to questions on whether a job involves (i) working at high speeds and (ii) to tight deadlines. Similarly to those on job discretion, the effects of technology on intensity might also differ across occupations. Technology might be "effort-biased" as it allows increased monitoring and rapid and efficient allocation of tasks to workers (Green 2006), but it might also allow greater flexibility in the organisation of work easing the pressure on workers. The net effect of technology on work intensity may differ depending on the type of tasks performed, as workers performing cognitive tasks that do not require their physical presence in a given workplace or direct contact with clients and customers might be better positioned to take advantage of the increased organisational flexibility allowed by technology.

Our results show computer use has grown substantially between 1995 and 2015 across Europe, with the share of workers who report using computers at work increasing from 40% to 60%. However, long after the onset of the PC revolution in the 1980s, countries continued to differn significantly in the extent to which they used computers in similar occupations. In particular, Nordic countries have seen large increases in computer use in occupations (such as "service and sales occupations" and "elementary occupations") that are typically thought to be less affected by this technology in the literature.

The large increase in computer use between 1995 and 2015 coincided with a period of modest deterioration in job quality in the EU-15 as whole, as intensity increased for all occupational and educational groups while discretion decreased slightly for most of them. Our OLS estimates point to a sizeable positive effect on discretion, but to small or no effect on intensity at work. Hence, this evidence suggests that the (moderate) deterioration in the quality of work observed in the EU-15 between 1995 and 2015 has happened despite the spread of computers, rather than because of them. Our IV estimates point to an even more benign effect of computer use on job quality, with larger positive effects estimated on discretion and negative but insignificant effects on intensity. Finally, our descriptive analysis finds little indication of differences in the effect of computer use on job quality across different occupations. In particular, we find no indication that computer use is associated with a decline in discretion in any occupation.

2 Measuring technology, tasks and job quality

The European Working Conditions Survey (EWCS) is a 5-yearly survey of workers in the European Union starting from the year 1990. It is funded, designed and coordinated by the European Foundation for the Improvement of Living Conditions (EUROFOUND), which is an agency of the European Union using face-to-face interviews of a randomized representative sample in each member state. The content of the survey is fairly comprehensive and includes themes such as employment status, work-life balance and worker participation which are relevant to our analysis. We use data from the second wave onwards of the EWCS; year 1995 as this is the first sample that includes all EU15 countries. We use data up to and including the latest survey which was conducted in 2015. Thus our analytical sample consists of data from the years 1995, 2000[4], 2005 and 2010 and 2015.

2.1 Measuring technology use at work

While the measurement of technology at work is by no means a straightforward task, we rely on previous literature as a reference to determine our definition of technology use at work, subject to data availability. We follow previous work by Dhondt et al. (2002) and Joling and Kraan (2008) and exploit information available in the EWCS. Specifically we use the responses to the question *"How often does your main paid job involve each of the following? Working with computers: PC's, network, mainframe".* This question was asked consistently from 1995 to 2010. However, in 2015 the question was framed as "*Please tell me, does your main paid job involve ...? working with computers, laptops, smartphones etc.?*" to include laptops and smartphones.

[4] In the survey for the year 2000, no questions regarding education levels were recorded. For our main analysis we construct a noisy measure of education by extrapolating data. We also check if our results are robust to th exclusion of the year 2000 and reassuringly find qualitatively similar results.

In all waves, responses to the computer use question are coded on a scale with 7 categories ranging from *Never* to *All the time*. We create a binary measure of computer use where 0 indicates respondents who never use computers and 1 indicates respondents who reported some use of computers. Inspection of the change over time of the variable does not reveal any suspicious differences between the values in 2010 and 2015 in spite of the change in the wording of the underlying question. In any case, we verify the robustness of our results to the exclusion of the 2015 data throughout the analysis.

It is important to note that other technological changes besides increased computer use can affect working conditions and job quality; and that computer use may particularly affect more cognitive tasks. The EWCS includes variables that allow for a partial measure of exposure to machines – namely whether the pace of work is determined by the pace of machines and whether respondents are exposed to vibrations from machines. The problem with these measures is that they only capture machine use in specific conditions which are likely not representative of the full range of situations in which machines are used but either do not vibrate or determine the speed of work. For this reason – as well as its increasing pervasiveness – we focus in this paper on the influence of working with computers in their different forms.

Figure 1 reports average computer use by occupation in all countries at the beginning and the end of our observation period. A clear contrast emerges between the occupations typically characterised by cognitive tasks (from managers to clerks) and others. Within this former group of occupations, differences in computer use across countries have shrunk substantially. Even Greece, which in 1995 stood out as a clear outlier with PC use below 50% in all cognitive occupations, had reached values above 70% in all of them (except managers) in 2015. In countries where the figure was high to start with – such as Denmark, Sweden, and Finland – computer use was approaching saturation by 2015, with figures above 90% in several occupations.

However, the convergence in computer use across countries is not seen in all the remaining occupations. To the contrary, for crafts, machine operatives and elementary occupations the range of values across countries increased. Hence, long after the onset of the PC revolution in the 1980s, countries continued to differ significantly in the extent to which they used computers in similar occupations.

Interestingly, Figure 1 also shows that in 2015 some countries were making extensive use of computers in occupations that are generally thought to be less affected by this technology in the economics literature. For example, in Denmark, Luxembourg, The Netherlands, Sweden, Finland, Belgium and Austria over 50% of sales and service workers were already using a computer in 2015 – a share similar or higher to that found in several countries in 1995 among professionals and technicians, i.e. occupations typically thought to benefit from strong complementarities with computers. Even for elementary occupations, the proportion using computers was at least 20% in 5 countries in 2015, with the highest value of just under 40% recorded in Denmark.

2.2 Measuring job discretion and intensity

As an indicator for job discretion, we use a subcomponent of the Work Quality indicator of Green et al. (2013) which uses the answers to the following questions: "*Are you able to choose or change;*

1. *Your order of tasks*

2. *Your methods of work*
3. *Your speed or rate of work"*

Our indicator of work intensity is also a subcomponent[5] of that in Green et al. (Green et al. 2013) and uses the answers to "*Does your job involve;*

1. *Working at very high speeds*

2. *Working to tight deadlines"*

For both of these indicators, the items are conceived as heterogeneous manifestations of the relevant aspect of job quality rather than as variables reflecting an underlying single construct. We choose these subcomponents as they are available for all years in our analysis and construct the job quality indicators using a principle component analysis with a polychoric correlation matrix. The indices are calculated by pooling the EU15 countries across years together. The proportion of variance explained by the first component is 0.84 and 0.82 for the discretion and intensity indicators respectively.

Figure 2 plots average autonomy by country for each occupation in 1995 and 2015. The graph shows no clear sign of decreasing dispersion across countries over time, even in cognitive occupations (with the exception of managers) that have seen some convergence in computer use. Noticeably, Greece remains a clear outlier in terms of autonomy in most cognitive occupations, despite the significant catch-up in computer use seen in Figure 1. Among clerks, the range of values reported has increased even once Greece is excluded. The picture also shows that high-skill cognitive occupations tend to have both higher average autonomy and lower variation across countries. Ranges across countries are generally around half of a standard deviation for managers, professional and technicians, but closer to a full standard deviation for occupations such as crafts, machine operatives, and elementary occupations.[6]

The higher cross-country dispersion of autonomy in lower-skill occupations is mostly due to the fact that these occupations have particularly low levels of autonomy in countries generally found at the lower end of the autonomy ranking. In other words, there is more inequality in autonomy within countries with generally lower levels of autonomy across occupations. In particular, Denmark, Sweden, Finland and the Netherlands have high average autonomy and lower dispersion across occupations[7], while Austria, Portugal, Greece and Germany have a relatively low average autonomy with larger differences between occupations[8].

[5] We exclude some subcomponents of the index of Green et al. (2013) that are often used as task indicators in related literature. For example, whether the pace of work depends on direct demands from people such as customers, passengers, pupils, patients etc.

[6] The differences in the range of average autonomy by country between the cognitive occupations and the others remain even if one ignores Greece which tends to have particularly low levels of autonomy in most occupations.

[7] Their average autonomy across occupations (unweighted) is between 101 and 103 and the standard deviation (across occupations) is always below 2.8.

[8] For the first group of countries the (unweighted) average autonomy is between 101 and 103 and the standard deviation (across occupations) is always below 2.8, while for the second group the average is always below 100 (around 98 for Germany, and below that for Greece) and the standard deviation always in excess of 4.

Figure 3 shows that there are also sizeable differences in reported job intensity for a given occupation across countries. However, unlike autonomy, the dispersion in intensity across countries does not appear to be systematically different for cognitive occupations. All occupations except elementary ones saw a decline in the dispersion of intensity across countries over the two decades. This is mostly because across all occupations intensity has increased among the countries that reported the lowest levels in 1995. In some occupations – such as professionals and clerks – the highest values have become smaller as well.

Hence, overall, while the past twenty years have seen convergence among countries in the use of computers in some occupations (notably the ones involving more cognitive tasks), there is little indication that this has coincided with a period of increasing homogeneity in the quality of work. The increase homogeneity in terms of intensity that we find does not seem to be concentrated in occupations that have seen convergence in computer use and it is mostly driven by increasing intensity in countries with initial low levels of intensity across the board. The weak relation between dispersion in job quality and dispersion in computer use across countries is confirmed more formally when we run a regression (not reported here) of the variance across countries of the (occupation-level) job quality indicators on the variance of computer use. Overall these descriptive results are suggestive that technology is not a clearly dominating determinant of labour market conditions across countries, a result that might appear surprising given the central role that technology has played in the recent debates on the ongoing changes in the labour market. To gain further insights on the link between computer use and job quality in Europe, we now turn to the central question of this paper and exploit variation over time within country-occupation cells to estimate the effect of computer use on job quality at the mean.

3 Trends in job quality and computer use across Europe

Figure 4 plots changes in job quality and computer use between 1995 and 2015 in the EU-15. Computer use (on the right-hand side scale) increased dramatically, rising from just above 40% to just above 60%. Job intensity increased by 0.15 standard deviations, with most of this increase occurring in the first decade. At the end of the two decades under consideration, autonomy was at a level just below that of 1995, having almost fully recovered the loss of 10% of a standard deviation which occurred in the first decade.

The break down by three education levels in the top panel of Table 1 shows that the increase in intensity took place within all education groups, but was larger for those with high and low education – exceeding 20% of a standard deviation. Autonomy changed only slightly for all groups but in different directions, leading to a small widening in the gap between those with high education and the rest.

Computer use increased within all education groups. In fact, workers with the lowest level of education saw the largest proportional increase (+77%) as the share using computers increased from 0.18 to 0.32. Nevertheless, computer use remains much higher among workers with higher levels of education, having reached 0.54 among those with secondary education and 0.86 among those with tertiary education.

The break down by computer use shows that in 1995 workers who did not use computers had both lower intensity and lower autonomy at work. Over the two successive decades, intensity increased by 25% of a standard deviation but decreased slightly for pc-users. Hence, the aggregate increase in intensity is driven by non-pc-users. Similarly, autonomy declined by 13% of a standard deviation for non-PC-users but by less than 5% of a standard deviation for pc-users. As a result, the gap in intensity between users and non-users of PC has all but closed, while that in autonomy has slightly increased.

The lower part of the table reveals that at a given point in time there are larger differences between occupations in terms of autonomy than intensity. For example, in 2015 there is more than a standard deviation difference in discretion between managers and machine operatives, but for intensity the range is less than 40% of a standard deviation. Autonomy declines almost monotonically as one moves down the occupational classification, but intensity exhibits a more complex pattern. In particular, throughout the period, crafts and machine operatives exhibit the highest levels of intensity, but professionals and technicians report levels similar to those of workers in service and elementary occupations.

Intensity increased in all occupations between 1995 and 2015. The largest increase (30% of a standard deviation) is seen in elementary occupations, but some middle skill (such crafts) and high-skill (professionals and technicians) occupations also saw increases in excess of 20% of a standard deviation.

Autonomy has decreased slightly in most occupations, with the largest decline of 17% of a standard deviation recorded among service and sales occupations. Only elementary and crafts saw a slight increase in autonomy, and only for the latter group did the increase exceed 10% of a standard deviation.

Computer use has increased significantly across the board albeit at different rates. In 1995 the fraction using computers was above 75% only among clerks, with the second highest figure (found among professionals) a distant 20 percentage points lower. By 2015, the cognitive occupations (i.e. the first four occupations in the table) had computer use rates above 80% and spanning a range of only 5percentage points (pp). Computer use did grow significantly in all other occupations as well – including elementary occupations which saw a proportional increase of over 60%. Nevertheless, in 2015 the fraction using computers was generally 45pp lower in non-cognitive occupations than in cognitive ones.

Overall, therefore, the large increase in computer use between 1995 and 2015 coincided with a period of modest deterioration in job quality in the EU-15 as whole, as intensity increased for all occupational and educational groups while autonomy decreased slightly for most of them.

In Figure 5 we plot changes in job quality against changes in the proportion using computers for each country-occupation pair in our dataset, using all five waves available between 1995 and 2015. The regression lines fitted through the scatter plots (which are weighted by cell size) indicate a positive relationship between computer use and autonomy which is statistically significant at the 1% level, but a positive and statistically insignificant one between changes in computer use and changes in intensity.[9] Taken at fact value, these results suggest that computer use might have contributed to the increase in intensity but counteracted the decline in autonomy over our observation period in the EU-15. However, these simple bivariate correlations are likely

[9] We check if the results are consistent to the exclusion of 2015 data to ensure our estimates are not driven by the new wording of the question on computer use and find similar results.

to be affected by endogeneity. In the next section, we discuss the strategy we adopt to tackle this issue.

4 Empirical strategy

The first-difference transformation underlying these plots in Figure 5 accounts for any time-invariant omitted variables at the country-occupation level which might make computer use endogenous.[10] However, endogeneity could still arise if changes in computer use are correlated with occupation-country shocks. To address this concern, we first move beyond the simple bivariate correlation of Figure 5 to include controls at the occupation-country level which can capture some of the confounding changes. In particular, we estimate the following model in stacked-differences:

$$\Delta y_{oct} = \alpha + \beta_1 \Delta PC_{oct} + \beta_2 \Delta X_{oct} + \sum_{i=2}^{3} T_i + \Delta\epsilon_{oct} \quad (1)$$

Where Δ is the difference operator between t and t-1, and the subscripts o and c refer to (1-digit) occupations and countries respectively. PC is our binary computer use indicator and X is a vector of controls which includes the within-occupation share of education, gender and age groups and the share of employment of a given occupation-country pair in three broadly defined industries (non-services, personal services, and other services). The inclusion of the constant implies a linear trend in levels while the time dummies $\sum_{i=2}^{3} T_i$ capture temporary deviations from it.

The OLS estimates of equation 1 will still be biased if time-variant determinants of computer use and job quality are omitted. For example, a strand of literature emphasises that significant changes in the organization of work have taken place in recent decades which are often correlated with technology adoption but have effects on workers' outcomes over and above those of technology (Caroli and Reenen 2001; Green 2012, 2004). More generally, exogenous changes in the conditions (e.g. in wages) of labour markets can alter the incentives facing firms to adopt technology.

To mitigate these remaining concerns, we instrument ΔPC_{oct} with the average of the contemporaneous change in computer use in occupations involving similar tasks in other countries.[11] Here we define as similar those occupations that fall within the same group of the

[10] Similarly, when studying the impact of computer use on skill requirements and takss, Spitz-Oener (2006) uses first-differences at the occupational level with German data and Green (2012) uses a fixed-effect model at the occupational level with British data.

[11] In the construction of the instrument, we weight each occupation-country cell by its size. We also use the average change in computer use in the same occupation in other countries and obtained very similar results which are not reported here. Furthermore, we considered a different instrument: we used measures of changes in ICT intensity at the country-industry level from the EUKLEMS dataset and apportion that to our occupation-country level observations using the proportion of occupational employment found in a given industry at the beginning of our sample period (1995) within each country. This method is similar to that in Ebenstein et al. (2014), and measures the exposure of an occupation to changes in ICT intensity at the industry level. As we are interested in isolating exogenous variations driven by the secular decline in computing prices, we use variation in ICT intensity in countries not included in our sample, namely US, Australia and Japan. This approach is similar to that followed by Bloom et al. (2015) to instrument import penetration. However, we find that this instrument is always too weak in our first-stage regressions for changes in computer use to provide reliable IV estimates.

classification proposed by Acemoglu and Autor (2011) (AA henceforth) and widely used in subsequent literature.[12]

The rationale for our instrument is that the major driver of the pervasive increase in computer use in recent decades is the secular decline in the price of computing. This is an argument often made in related literature (Acemoglu and Autor 2011; D. H. Autor and Dorn 2013) and supported by the observation that, during the 1980s and 1990s, the rate of decline of computing costs was on average 64% per year (Nordhaus 2007). Our IV strategy aims at isolating the exogenous variation in computer adoption driven by the secular decline in computing costs and uncorrelated with the occupation-country specific shocks. This approach is conceptually similar to that of Autor et al. (2013) who attempts to isolate the increase in import penetration to US local labour markets driven by the arguably exogenous expansion of the Chinese economy by using changes in Chinese imports to other high-income countries. More recently, Acemoglu and Restrepo (2017) have instrumented changes in robot penetration in US industries with changes in robot penetration in other advanced countries. As these authors point out, while not a panacea against all sources of endogeneity, this strategy enables the researcher to focus on the variation that results solely from industries (or occupations in our case) in which the change in the potential endogenous variable has been concurrent in most advanced economies, attenuating endogeneity concerns arising from potential unobserved country-industry shocks.

A threat to the exogeneity of the instrument arises from the possible cross-country correlation in shocks to job quality between occupations in the same AA group. The time trend and dummies will capture changes that affect job quality in all occupations and countries. Nevertheless, correlation in shocks to similar occupations could arise from global shocks to industries in which such occupations are concentrated across countries. Plausible sources of international industry-level changes over our sample period are the growth in international trade (D. H. Autor, Dorn, and Hanson 2013) and changes in output demand due to demographic changes or wealth effects (Mazzolari and Ragusa 2013; Moreno-Galbis and Sopraseuth 2014).

All our specifications control for the share of employment of a given occupation-country in broadly-defined industries. To the extent that industry shocks lead to changes in the distribution of occupational employment across such industries (for example a shift away from manufacturing and towards personal services), this will help address the issue. Similarly, the controls for demographics should alleviate the concerns relating to the growth in the number of graduates and older workers. We further investigate the robustness of our results in three different ways.

First, we verify the robustness of our results to the inclusion of EU-wide occupation-specific trends. This is a demanding specification which effectively assumes that only deviations from these linear trends can be attributed to the secular decline in computing costs which our instrument exploits. Second, we consider a different version of the instrument which for any occupation-country pair excludes the data from bordering countries. This is a useful approach if

[12] We map the ISCO88 1-digit codes available in the data as follow: legislators (1), professionals (2) and technicians and associate professionals (3) are non-routine cognitive; clerks (4) are routine cognitive; service workers and shop and market sales workers (5) and elementary occupations (9) are non-routine manual; craft and related trade workers (7) and plant and machine operators and assemblers (8) are routine manual.

the correlation between different spatial units is weaker the further apart they are, as commonly assumed in spatial econometrics (Gibbons and Overman 2012).

Finally, we use data from a different dataset to control for changes in wages at the occupation-country level in our IV models. In this approach, changes in wages are treated as a proxy for shocks affecting different occupations across countries since the significant increase in international trade over our sample period has been documented to affect wages differentially across industries (D. H. Autor, Dorn, and Hanson 2013). Unfortunately, the data we need to perform this check are only available to us for the period up to 2010 and not for every country in every year.[13] For this reason we do not report these results here, but they broadly align with the results of the other robustness checks we report.

4.1 Results

In Table 2 we report our OLS and IV estimates from models in first-difference in which each country-occupation observation is weighted by their average size between t and t-1.[14] Panel A reports the results for job discretion. The first column only includes time dummies and implies that, between 1995 and 2015, job discretion decreased slightly across the EU-15 by 0.14 points – or just over 1% of a standard deviation.[15] However, the change conditional on observable characteristics implied by the estimates in column 2 is larger (-2.2 or 22% of a standard deviation). Hence, compositional changes have tended to counteract the decline in discretion over the sample period. Computer use appears to have played a significant role in this sense: the variable attracts a positive and statistically significant coefficient which implies an increase in the discretion index for the average occupation of over 11% of a standard deviation.[16] This is a large effect when compared to the overall conditional *decline* in discretion of 22% of a standard deviation: in the average occupation, the spread of computers is associated with the halving of the decline in discretion.

Column 3 presents our IV estimates using our baseline specification from column 2. The instrument is strongly correlated with computer use, as shown by the test statistic reported at the bottom of the table.[17] The coefficient on PC increases slightly in absolute value and retains

[13] The wage data come from the ECHP and EU-SILC and are not available for all observations in our sample. In particular, we do not have Finland 1995; Sweden and Netherlands 1995-2000; Luxembourg 2000; Greece 2010; and half of occupations are missing in France 2000. Due to these issues and the fact that it is unclear whether wages are a "good" control (Angrist and Pischke 2009) in our main regressions since they might be one of the channels through which computer adoption affects job quality, we do not control for wages in our preferred specifications but only use them in our robustness checks.

[14] We note that as a default STATA uses weights from time t in first difference models. This is also the approach taken in other related papers using models in first differences with aggregate data. When we do that, the statistical significance of all our estimates for job discretion improves, while the estimates remain statistically insignificant in the regressions for job intensity.

[15] Since this is a model in first difference including a constant and a dummy for all but one changes, the total estimated change is computed as the sum of 3 times the constant and the two coefficients on the time dummies.

[16] Computer use increased by 20pp between 1995 and 2015. Multiplying this change by the coefficient on the PC variable yields: 0.20*5.827=1.17.

[17] We use the command xtivreg2 (Schaffer 2010) in STATA to compute our IV estimates which provides the Kleibergen-Paap rk Wald F statistic for weak identification when using robust standard errors. Critical values for such statistics are not available but the software reports those for the Cragg-Donald F statistic with i.i.d. errors for different levels of tolerated relative bias above 10%. In all cases in which we refer to our IV as strong, the reported (robust) test statistic is above each of those critical values.

statistical significance at the 5% level. The implied increase in discretion for the average occupation is now about 17% of a standard deviation, which amounts to almost two thirds of the overall conditional decline in discretion of 27% of standard deviation implied by the estimates in column 3.

Column 4 adds occupation-specific linear trends to our baseline IV specification. The linear trends appear jointly statistically insignificant as indicated by the test reported at the bottom of the column, but the instrument remains strongly correlated with the computer use variable which now attracts a much larger coefficient. Its size implies an increase in discretion in the average of occupation of 25% of a standard deviation. Finally, column 5 reports the estimates obtained excluding bordering countries from the computation of the instrument. The instrument performs well in the first stage and returns a coefficient for computer use which again implies an increase in discretion in the average occupation of over 20% of standard deviation.

Column 1 of Panel B shows that over the sample period work intensity increased across Europe by just over 17% a standard deviation. The estimated increase is larger (at about 25% of a standard deviation) in column 2 where we condition on observable characteristics. Hence, as we have already seen for discretion, compositional changes in general appear to have counteracted the underlying trend in work intensity. Computer use, however, attracts a positive and statistically insignificant coefficient (at the 10% level) which implies a small effect of about 1% of a standard deviation for the average occupation. The IV estimates in the remaining columns are negative and larger in absolute value but are also statistically insignificant.

To summarise, we find that the overall modest decline in job quality has occurred in spite of compositional changes which have tended to counteract this trend. As for computer use, the OLS estimates point to a sizeable positive effect on discretion, but to small or no effect on intensity at work. Hence, this evidence suggests that the (moderate) deterioration in the quality of work observed in the EU-15 between 1995 and 2015 has happened despite the spread of computers, rather than because of them.

Our IV estimates point to an even more benign effect of PC on job quality, with larger positive effects estimated on discretion and negative but insignificant effectson intensity. These estimates are conditional on changes in demographics and in the distribution of occupational employment across industries which, as we discussed above, should capture some of the potential correlation across countries that might confound the instrument. Moreover, our attempts to increase the plausibility of the exogeneity of the instrument, while again resulting in statistically insignificant estimates in the intensity regression, paint a consistent picture overall: they suggest more benign effects of computer use in the form of larger positive coefficients for job discretion and increasingly larger negative ones for intensity.

4.1.1 Regressions by occupation groups

Recent contributions emphasise that the effect of computers on jobs depends on the type of tasks they involve (D. H. Autor, Levy, and Murnane 2003; D. H. Autor 2015). In particular, this literature argues that workers performing cognitive tasks benefit from strong complementarities with computers while those performing more routine tasks are more likely to be substituted by current technology. Furthermore, low-skill occupations involving non-routine manual tasks are generally thought as offering little scope for either complementarity or substitution with technology. This argument suggests that the effect of computer use on job quality might also differ across occupations, perhaps being more pronounced in occupations involving cognitive tasks.

To investigate differences in the effect of computer use across occupations, in Table 3 we present OLS estimates obtained separately for different types of occupations. This is a simple exploratory analysis as the small samples used in each regression make it difficult to obtain statistically precise estimates. Moreover, our instrument does not offer enough variability to be applied in this context. As in our main analysis, we stack the five-year differences between 1995 and 2015 together and include a constant and a full set of time dummies in all specifications. Each observation is again weighted by the average cell size for each difference.

Following several previous studies, we group occupations as in Acemoglu and Autor (2011) based on their task content. The tasks are classified along two dimensions: routine vs. non-routine, and cognitive vs manual. Non-routine cognitive occupations are high-skill managerial, professional and technical occupations requiring problem-solving, intuition and creativity. Routine cognitive occupations include clerical jobs and involve tasks including organising, storing, retrieving and manipulating information. Routine manual occupations are those involving repetitive production work. Finally, non-routine manual occupations include personal service jobs and typically require situational adaptability, visual and language recognition and in-person interactions.[18]

Panel A shows the results for two specifications for job discretion, one including only time dummies and the other including the same controls used in the main analysis. The estimated constants and time dummies indicate that discretion has declined in all groups of occupations and that for all except the non-routine cognitive occupations, the conditional decline was larger than the unconditional one. There is no indication in these results that computer use reduces job discretion in any occupational group: the coefficient on computer use is positive for all occupations, but is statistically significant only for the (routine and non-routine) manual ones.

The large positive coefficients found for manual occupations are somewhat surprising. In existing studies, non-routine manual occupations, in particular, are generally assumed not to be affected in substantial ways by existing technologies. By contrast, the coefficients in Table 3 imply that a 10pp increase in computer use is associated with an increase in job discretion of a full standard deviation in non-routine manual occupations, but only of 20% of a standard deviation in routine cognitive jobs. Such a large difference might in part be due to the fact that technology might have less of an impact in occupations (such as the cognitive ones) that enjoy higher initial levels of discretion. Nevertheless, the finding of a strong association between computer use and discretion in lower skill occupations is an interesting one which warrants a more careful consideration of the relationship between technology and employment at the lower end of the skill spectrum.

The standard argument in the existing literature is that computers do no easily substitute nor complement workers in performing the main tasks that characterised non-routine manual occupations. But even if computers do not lead to substantial changes in the type of tasks

[18] We map the ISCO88 1-digit codes available in the data as follow: legislators (1), professionals (2) and technicians and associate professionals (3) are non-routine cognitive; clerks (4) are routine cognitive; service workers and shop and market sales workers (5) and elementary occupations (9) are non-routine manual; craft and related trade workers (7) and plant and machine operators and assemblers (8) are routine manual.

performed by workers – they could lead to changes in the organisation of work that affect the management and organisation of tasks -rather than the nature of the tasks themselves – in a way that attributes employee a higher degree of discretion.

The results from the intensity regressions by occupational groups are reported in Panel B of Table 3. The estimated time dummies and constant imply that intensity has increased across the board and that compositional changes have partially counteracted the increasing trend in all occupational groups except the routine manual one. Computer use has a positive and significant coefficient only in the regression for routine cognitive occupations. The estimated coefficient means that a 10pp increase in computer use is associated with an increase in intensity of just under 80% of a standard deviation. In non-routine manual occupations, on the other hand, computer use attracts a negative and statistically insignificant coefficient.

5 Discussion and conclusions

This paper uses harmonised data from across the EU-15 spanning the period 1995-2015 to study the relationship between computer use and two aspects of job quality, namely discretion and intensity. The main empirical contributions of the paper are two-fold. First, the analysis provides an up-to-date picture of differences in computer use and job quality in the same occupations across different countries. Secondly, the paper investigates directly the impact of computer use on job quality, using an identification strategy that exploits variation over time within occupation-country cells. The analysis complements OLS estimates from a model in stacked first-differences with those obtained using an instrumental variable approach that exploits the variation in computer adoption generated by the arguably exogenous secular decline in computing cost.

Our results show computer use has grown substantially between 1995 and 2015 across Europe, with the share of workers who report using computers at work increasing from 40% to 60%. However, long after the onset of the PC revolution in the 1980s, countries continued to differ significantly in the extent to which they used computers in some occupations. In particular, Nordic countries have seen large increases in computer use in occupations (such as “service and sales occupations” and “elementary occupations”) that are typically thought to offer little scope for either complementarity or substitution with technology (D. H. Autor 2015).

When considered in relation to the recent literature in economics on the effects of technology in the labour market, these results lend themselves to two considerations. First, the finding the differences in computer use in similar occupations across countries – which are particularly large for some occupations – call into question the common assumption that occupations are homogenous across countries in terms of their task content and organisation. This assumption is often explicitly or implicitly made in the literature on the effects of technology on the occupational structure and underlies the use of task measures built from one country in the analysis for a different country.[19]

The second consideration is that these findings suggest that technology is increasingly reaching into segments of the labour markets that have so far widely been considered exempt from a direct impact. For example, in Autor and Dorn (2013)’s paper on the rise of low-skilled occupations in

[19] For example, task measures constructed for the US are often used in the analysis for European countries (Goos, Manning, and Salomons 2014). See Salvatori (2015) for further discussion of these issues in the context of the UK.

the US, technology only affects service occupations indirectly through complementarities in consumption with goods produced by occupations that are directly affected by automation. Other contributions have highlighted that technology has the potential to impact significantly the organisation and the content of low-skill occupations, but while useful and insightful these discussions have mostly been limited to anecdotical evidence or case studies (Weil 2014). Cortes and Salvatori (2016) have also provided evidence that the use of computer in firms that employ low-skill workers grew significantly in the UK over the 2000s. This evidence points to the need of developing a better understanding of what technology does at the lower end of the skill spectrum in future research.

The large increase in computer use between 1995 and 2015 coincided with a period of modest deterioration in job quality in the EU-15 as whole, as intensity increased for all occupational and educational groups while discretion decreased slightly for most of them. However, our main empirical results suggest that this modest deterioration in job quality has occurred in spite of the spread of computers rather than because of it. In particular, our OLS estimates suggest a sizeable positive effect of computer use on discretion, but small or no effect on intensity at work. Our IV estimates point to an even more benign effect of computer use on job quality, with larger positive effects estimated on discretion and negative but insignificant effects on intensity. In addition, we find little indication of differences in the effect of computer use on job quality across different occupations. In particular, we find no indication that computer use is associated with a decline in discretion in any occupation.

Hence, our results lend support to the theories that emphasise the potential positive effects of computer use on job quality through increased flexibility and control over one's work. In addition, they also illustrate that computer adoption is not the main or dominant driver of the evolution of working conditions within occupations. Understanding the causes of the negative trend in job quality documented in this paper is an important task for future research.

Finally, we acknowledge that some of our results might be influenced by the different degrees to which our computer use variable captures the adoption and use of digital technology across different occupations. In particular, concerns have been raised that computer use questions might not effectively capture the use of digital technologies in lower-skill manual occupations (Dhondt, Kraan, and Sloten 2002). For example, it is not obvious that workers at a fast-food restaurant who execute orders displayed on a monitor would report using a computer at work. Yet, the pace and content of the job for these workers is largely determined (if not entirely driven) by digital machines (Fitzgerald 2007; Orleck 2017). More generally, workers might be less likely to report the use of technology if this is confined to peripheral tasks relating to organisational and monitoring aspects of their jobs (as in the case of a cook receiving orders through digital devices).

If these reporting biases do exist, they clearly hinder the ability of researchers to effectively study the impact of technology across the occupational skill distribution. We would argue that, given how pervasive digital technologies are becoming in all aspects of life and work, there is an urgent need to verify the effectiveness of the survey instruments currently available in measuring technology use in the workplace and to develop new and better ones if necessary.

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Tables

Table 1 - **Job quality and computer use by education, technology use and occupations over time.**

	Intensity			Autonomy			
	1995	**2015**	**% change**	**1995**	**2015**	**% change**	**199**
Lower Secondary Qualifications	98.19	100.4	2.25	98.38	97.83	-0.56	0.
Upper Secondary Qualifications	99.61	100.53	0.92	99.78	99.41	-0.37	0.
Tertiary Qualifications	98.55	100.6	2.08	102.5	102.63	0.13	0.
No PC	97.59	100.12	2.59	98.85	97.51	-1.36	
PC	101.02	100.79	-0.23	102.45	101.97	-0.47	
Managers	100.61	100.63	0.02	104.88	104.85	-0.03	0.
Professionals	97.72	100.09	2.43	103.19	102.96	-0.22	0.
Technicians	97.68	99.96	2.33	102.28	101.75	-0.52	0.
Clerks	99.18	100.24	1.07	100.37	100.2	-0.17	0.
Service/Sales	97.71	99.56	1.89	100.13	98.39	-1.74	0.
Craft/Trade	100.69	103.26	2.55	98.77	99.78	1.02	0.
Plant/Machine	101.57	102.12	0.54	94.26	93.55	-0.75	0.
Elementary	97.31	100.28	3.05	97.45	98.02	0.58	0.

Table 2 - First-difference job quality regression using occupation-country observations from the EU-15, 1995-2015

	(1) OLS	(2) OLS	(4) IV 1	(5) IV 1	(6) IV 2
Panel A – Dependent Variable - Job Discretion					
D.Computer Use		5.827***	8.792**	12.60***	10.95***
		(1.278)	(3.654)	(4.385)	(4.106)
D.2005	0.308	-0.0974	-0.231	-0.394	-0.328
	(0.368)	(0.330)	(0.341)	(0.382)	(0.361)
D.2010	1.076***	0.816**	0.789**	0.746**	0.770**
	(0.384)	(0.374)	(0.364)	(0.373)	(0.365)
D.2015	1.575***	1.114***	1.078***	1.074***	1.052***
	(0.338)	(0.310)	(0.303)	(0.321)	(0.303)
Constant	-0.775***	-1.008***	-1.097***	-0.915*	-0.775***
	(0.247)	(0.227)	(0.252)	(0.484)	(0.247)
Composition controls (a)	No	Yes	Yes	Yes	Yes
Occupational trend	No	No	No	Yes	No
F-Test of joint significant of occupational effects				0.512	
Observations	480	480	480	480	480
R-squared	0.087	0.248	0.227	0.165	0.186
Kleibergen-Paap rk Wald F from first-stage			20.54	16.84	18.11
Panel B: Dependent Variable – Job Intensity					
D.Computer Use		0.592	-4.307	-7.014	-4.309
		(1.643)	(4.261)	(5.079)	(4.752)
D.2005	0.700	0.699	0.920*	1.011**	0.920*
	(0.468)	(0.442)	(0.474)	(0.476)	(0.479)

D.2010	-0.931**	-0.999**	-0.954**	-0.948**	-0.954**
	(0.426)	(0.423)	(0.430)	(0.432)	(0.429)
D.2015	-0.116	0.129	0.188	0.155	0.188
	(0.460)	(0.425)	(0.446)	(0.440)	(0.448)
Constant	0.526	0.667**	0.814**	0.401	0.814**
	(0.341)	(0.307)	(0.335)	(0.601)	(0.340)
Composition controls (a)	No	Yes	Yes	Yes	Yes
Occupational trend	No	No	No	Yes	No
F-Test of joint significant of occupational effects				0.413	
Observations	480	480	480	480	480
R-squared	0.055	0.160	0.113	0.073	0.113
Kleibergen-Paap rk Wald F from first-stage			20.54	16.84	18.11

First difference models with country-occupations weighted by average cell size.

(a): share of education, gender and age groups within each occupation-country cell; share of employment of a given occupation-country pair in non-services, personal services, and other services.

All regressions use data from five waves of the EWCS (1995, 2000, 2005, 2010 and 2015). IV 1 uses change in PC use in similar occupations in all other countries as instrument. IV 2 excludes bordering countries from the computation of the instrument.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3 - OLS estimates of first-difference models by occupational group.

	Non Routine Cognitive		Routine Cognitive		Routine Manual		Non Routine Manual	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A: Dependent Variable: Job Discretion								
D.Computer Use		0.579		2.048		5.722**		9.609***
		(2.710)		(2.349)		(2.342)		(1.712)
D.2005	-0.710*	-0.657	-0.817	-0.804	-0.186	0.0115	2.975***	0.774
	(0.387)	(0.447)	(0.639)	(0.645)	(0.633)	(0.643)	(1.000)	(0.883)
D.2010	0.392	0.0578	0.285	0.588	1.517**	1.483**	2.244**	1.953***
	(0.534)	(0.619)	(0.492)	(0.495)	(0.764)	(0.617)	(0.960)	(0.737)
D.2015	0.232	0.494	1.965***	0.980**	2.353***	1.877***	3.055***	1.182
	(0.411)	(0.508)	(0.520)	(0.478)	(0.659)	(0.590)	(0.806)	(0.727)
Constant	0.0105	0.0154	-0.400*	-0.589	-0.769*	-1.401***	-2.293***	-1.694***
	(0.225)	(0.375)	(0.237)	(0.431)	(0.402)	(0.485)	(0.697)	(0.613)
Controls (a)	No	Yes	No	Yes	No	Yes	No	Yes
Observations	180	180	60	60	120	120	120	120
R-squared	0.050	0.150	0.306	0.668	0.199	0.441	0.209	0.513
Panel B: Dependent Variable: Job Intensity								
Computer Use		3.531		7.973**		4.336		-2.404
		(3.575)		(3.216)		(3.108)		(2.636)
D.2005	-0.149	-0.553	2.397***	2.765***	1.075	1.630**	0.870	1.063
	(0.771)	(0.714)	(0.850)	(0.787)	(0.886)	(0.741)	(1.014)	(0.985)
D.2010	-1.138	-1.323*	0.362	-0.396	-1.937***	-1.653**	-0.424	-0.578
	(0.726)	(0.682)	(0.867)	(0.962)	(0.714)	(0.672)	(0.942)	(0.808)
D.2015	-0.362	-0.123	0.772	1.582	-0.898	-0.397	0.395	0.635
	(0.778)	(0.677)	(1.069)	(1.012)	(0.892)	(0.747)	(0.924)	(0.748)
Constant	0.787	0.908*	-0.578	-0.294	0.873	0.344	0.389	0.548
	(0.588)	(0.530)	(0.643)	(0.713)	(0.679)	(0.542)	(0.696)	(0.533)
Controls (a)	No	Yes	No	Yes	No	Yes	No	Yes
Observations	180	180	60	60	120	120	120	120
R-squared	0.037	0.234	0.158	0.487	0.209	0.393	0.032	0.191

First difference models with country-occupations weighted by average cellsize.

(a): share of education, gender and age groups within each occupation-country cell; share of employment of a given occupation-country pair in non-services, personal services, and other services.

All regressions use data from five waves of the EWCS (1995, 2000, 2005, 2010, and 2015).

Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

7 Figures

Figure 1 - Average computer use by country, occupation and wave. 1995-2015

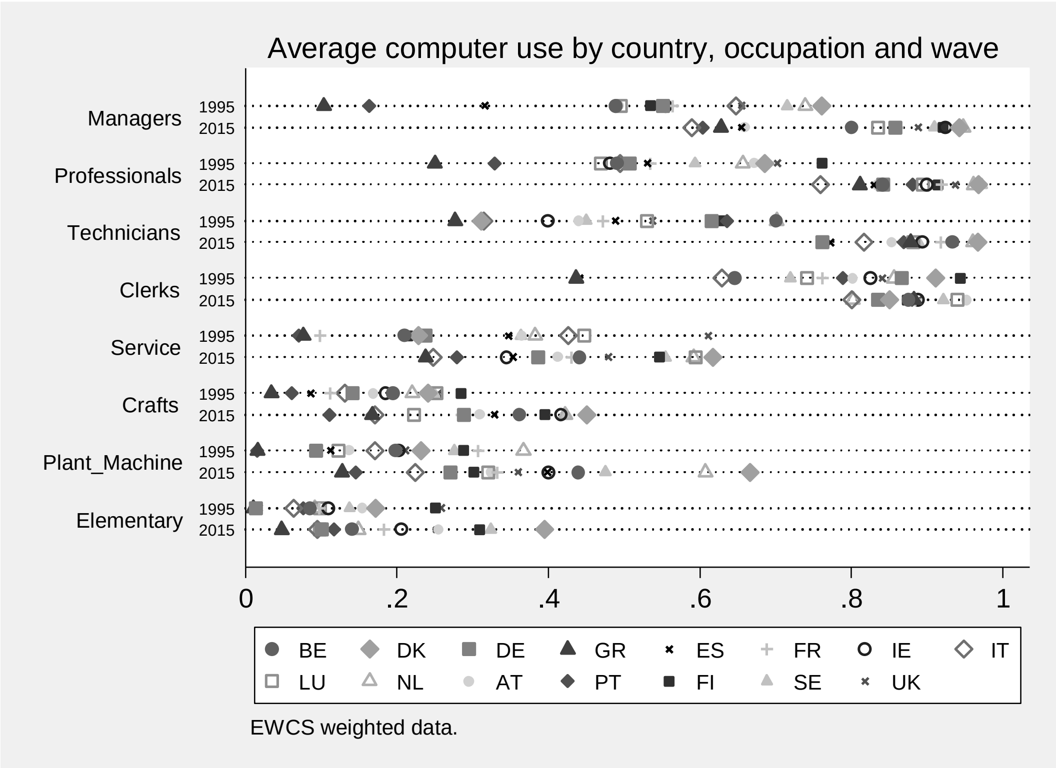

Figure 2 - Average autonomy by country, occupation and wave

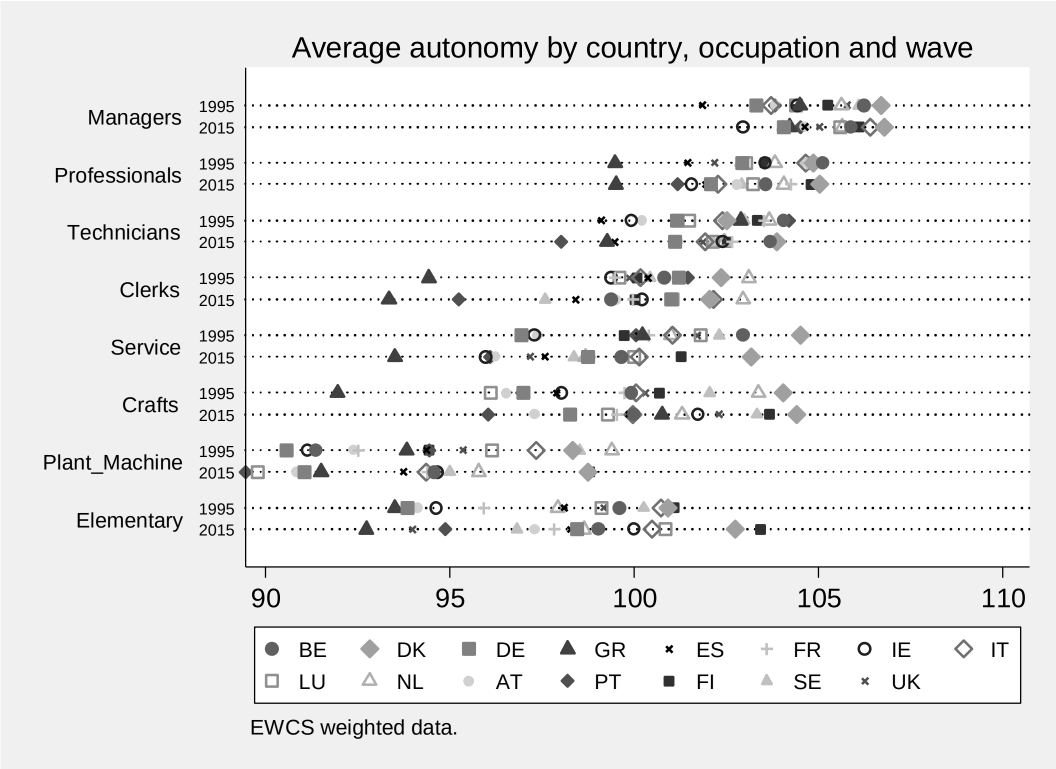

Figure 3 - Average intensity by country, occupation and wave

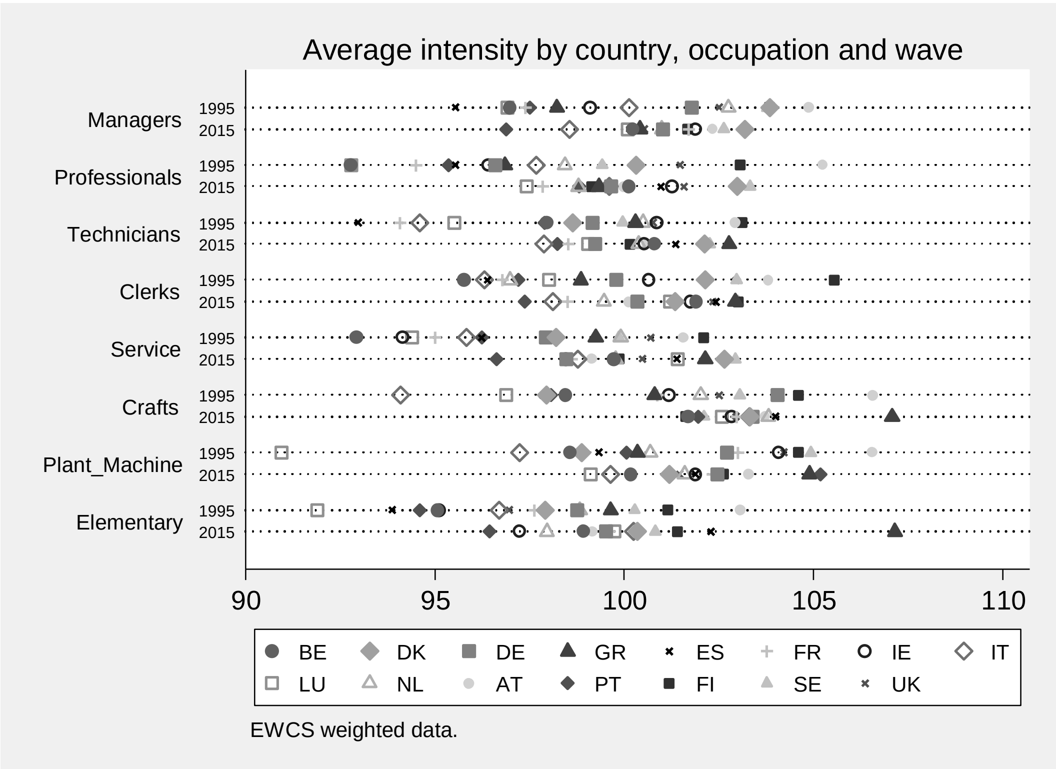

Figure 4 - Job quality and computer use in the EU-15 between 1995 and 2015

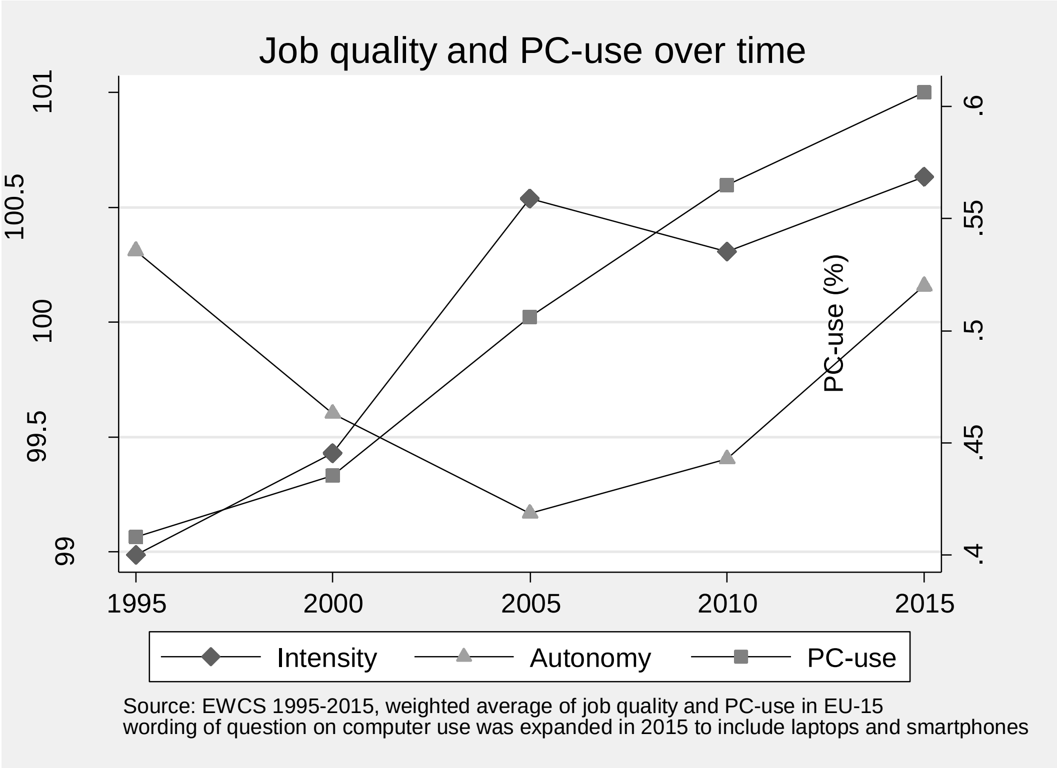

Figure 5 - Correlation between changes in job quality and computer use at the country-occupation level.