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The effect of computer use on work discretion and work intensity: evidence from Europe

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Abstract

This paper studies changes in computer use and work discretion and intensity in the EU-15 between 1995 and 2015. We document that while the proportion of workers using computers has increased from 40% to more than 60%, there remain significant differences between countries even within the same occupations. Several countries have seen a significant increase in computer use even in low-skilled occupations generally assumed to be less affected by technology. Overall, the great increase in computer use between 1995 and 2015 coincided with a period of modest deterioration of job quality in the EU-15 as whole, as work discretion declined for most occupational and educational groups while work intensity increased slightly for most of them. Our OLS results exploiting variation within country-occupation cells point to a sizeable positive effect of computer use on work discretion, but to no effect on work intensity. Our instrumental variable estimates point to an even more benign effect of computer use on job quality as measured by work discretion and work intensity. 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; work intensity.

JEL codes: J21, J23, J24, O33.

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 points to no overall effect on the quantity of jobs (D. Autor and Salomons 2017; OECD 2017; Flavio Calvino and Virgillito 2017; OECD 2016)[2], 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 degrees to which workers in different jobs can be substituted or complemented by technology (Maarten Goos, Manning, and Salomons 2014; Michaels, Natraj, and Van Reenen 2013; Marcolin, Miroudot, and Squicciarini 2016), while changes within jobs occur when the adoption of technology leads to changes in the organisation of work, the nature of the tasks performed and the skills required (F. Green, Felstead, and Gallie 2003; Spitz-Oener 2006; D. H. Autor 2013; F. Green 2012). A broad body of literature has focused on the implications of these changes for wages, but less attention has been given to their impact on non-monetary aspects of job quality.

This paper provides novel direct evidence on the impact of computer use on two aspects of job quality, namely work discretion (i.e. the extent to which workers have control over tasks, methods and speed at work) and work intensity (i.e. the extent to which a job involves working at high speeds or tight deadlines). While papers documenting overall trends typically use broader measures of job quality, we focus on these two aspects for ease of interpretation.[3] We choose work discretion and work intensity because they have featured prominently in the debate on the effects of technology on employment. As we detail below, this provides a useful intuitive background to think about how they might be affected by computer use. In addition, work discretion and work intensity are interesting outcomes per se since the literature has already established their link to workers' wellbeing. Work discretion is strongly correlated with employees' motivation (F. Green 2006) and with various measures of psychological wellbeing (Gallie 2013; Wheatley 2017)[4], while work intensity can lead to negative psychological outcomes, including stress (F. Green and McIntosh 2001).

We focus on computer use for both substantive and practical reasons. The substantive reason is that computers are the most widely used form of technology in the labour market that are already recognised in the literature to have played a central role in changing skill demands and job tasks (D. H. Autor, Levy, and Murnane 2003; Spitz-Oener 2006; F. Green 2012; Elsayed, de Grip, and Fouarge 2017). The practical reason is that reliable indicators of actual *use* of other forms of technology are not currently available.[5] In the concluding section we argue that, given

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[2] Recent papers have found a negative effect of robots on employment in the US (Acemoglu and Restrepo 2017), but not in Germany (Dauth et al. 2017). Graetz and Michaels (2015) do not find an effect of robots on overall employment exploiting variation over time within country and industries.

[3] Job satisfaction measures are often used in related literature. We acknowledge their importance and usefulness in general, but because they can vary for a number of different reasons other than actual changes in circumstances of work (including changes in workers' reference points and expectations (Kalleberg (2011))) they are not very useful for the exercise conducted in this paper.

[4] 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).

[5] Joling and Kraan (2008) propose an indicator of machine use at work based on the EWCS survey. However, these measures are constructed using questions which are not designed to directly measure the use of machines at work. For example, one of the questions used is whether the worker is exposed to vibrations from

how pervasive digital technologies are becoming in all aspects of life and work, there is an urgent need to verify the effectiveness of standard survey questions on computer use to measure the penetration of technology, particularly in low skill jobs.

Using data from the European Working Conditions Survey[6] (EWCS) covering the EU-15 countries between 1995 and 2015,[7] we provide direct evidence on the link between computer use and job quality, exploiting variations within occupations over time. Similar approaches have been used to study the link between computer adoption and changing skill requirements (F. Green 2012; Spitz-Oener 2006), but most of the literature on the effects of technology on other aspects of job quality has generally taken a more indirect approach.[8] In particular, researchers have interpreted common patterns in different countries as consistent with technology being a common driver[9] and have used the direction of aggregate changes in job quality to discriminate between different theories on the impact of technology on job quality. For example, Gallie (2013) concludes that the evidence of stable work discretion in several countries in recent decades is not consistent with theories that predict that new complex technologies raise work discretion. However, the overall trend can be the product of different forces and it is therefore not necessarily informative of the effect of technology on job quality. Indeed, the fact that computer adoption has counteracted (rather than contributed to) a modest negative trend in job quality is one of the main results of our analysis, to which we return below.

Isolating the causal effect of computer use on job quality remains a difficult task, even in models that focus on variation over time within occupations. To mitigate concerns that endogeneity might bias our estimates from the base model in first-differences, we resort to an instrumental variable approach 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. While we are not aware of other applications to study the effect of computer use[10], the approach of using changes in other countries as instruments to exploit common exogenous trends for identification is increasingly 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

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machines at work. It is perfectly plausible that by this indicator machine use appears to decline as the quality of the machines improve, resulting in a reduction of vibration. Other contributions have proposed industry-level indicators of adoption of other forms of technology. These indicators are informative of broad between-industry differences in technology adoption, but not of actual use by different types of workers within industries (F. Calvino et al. forthcoming)

[6] European Foundation for the Improvement of Living and Working Conditions. (2018). European Working Conditions Survey Integrated Data File, 1991-2015. [data collection]. 7th Edition. UK Data Service. SN: 7363, http://doi.org/10.5255/UKDA-SN-7363-7

[7] This appears to be one of the first studies to make use of the most recent wave of data released in 2017.

[8] (Joling and Kraan 2008) use data from the 2005 wave of the EWCS to provide a detailed picture of the profile of workers who use technology and those who do not.

[9] A recent example of a paper applying this logic is Green et al. (2013), but the same type of inference if often invoked well beyond the literature on job quality. See for example Card and Lemieux (2001), Dustmann et al. (2009) and Green and Sand (2015).

[10] Spitz-Oener (2006) and Green (2012) also exploit variation over time within occupations to study the effect of computer use on skill requirements and tasks, but neither uses an instrumental variable approach.

changes in robot penetration in US industries with those in other advanced countries and Dauth et al. (2017) apply the same strategy to German data.

To measure these two aspects of job quality we employ sub-components of the indexes proposed by Green et al. (2013) using earlier waves of the EWCS.[11] 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. Our measure of work intensity combines the answers to questions on whether a job involves working (i) at high speeds and (ii) to tight deadlines.

The effect of computer use on work discretion is a priori ambiguous. A positive effect might arise if computers provide workers with a higher degree of flexibility in the organisation of their work and increase the control they have over it. In particular, researchers have argued that the upskilling brought about by modern technologies is closely linked to a higher degree of control over one's work. However, evidence for the US indicates that the arrival of computers has led to only a modest increase in skill requirements (Handel 2016; Osterman 2013). In addition, even in countries like the UK where upskilling has been stronger (F. Green 2012; F. Green et al. 2016), work discretion has been relatively stable in recent decades suggesting, as pointed out by Gallie (2013), that this upskilling has not necessarily translated into increased work discretion.

The negative effect of computers on work discretion can arise if technology is used to achieve higher standardisation of work and monitoring (Weil 2014). The net effect of computer use may differ across occupations. New technologies might afford workers in cognitive occupations higher discretion and control over their work, but they can also enable monitoring and closer management of cognitive tasks, giving rise to a form of "digital Taylorism" in which employees enjoy very limited control over their work (Brown et al., 2010).[12] Mazmanian et al. (2013) find that interconnected devices do provide professionals with the possibility of a greater control over the pace and organisation of their work, but also create an expectation of constant availability by colleagues and clients that actually reduces their work discretion. Workers in more manual occupations might see a decline in work discretion if technology is mostly used to ensure that they follow precise procedures or work at a certain pace. For example, computers can be used to provide call centre 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' visiting time and to ensure more efficient transfers between visits. While we cannot obtain precise estimates by occupation due to the limited sample size and level of aggregation, we do investigate descriptively whether the effect of computer use appears to differ across different occupations.

The effect of computer use on work intensity is also ambiguous a priori. Technology might be "effort-biased" in the sense that it complements workers who are able and willing to increase their effort by making the allocation of tasks more rapid and efficient and by facilitating monitoring (Green 2006). On the other hand, technology might allow greater flexibility in the organisation of work, easing the pressure on workers. The net effect of technology on work

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[11] As far as we are aware, the EWCS is the only dataset to offer harmonised data on these variables over time for a number of countries. Recently, PIACC has asked similar questions, but these data are currently available only for a point in time in the early 2010s.

[12] For a discussion of different schools of thoughts on the implications of technology on intrinsic job quality see Gallie (2013).

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. While there is evidence from both the US and Europe of an increase in work intensity in recent decades (Kalleberg 2011; F. Green 2006; Clark 2005) and that work intensity is higher in jobs that use computers more frequently (F. Green and McIntosh 2001; Gallie 2005), we are not aware of studies that have attempted to isolate the causal effect of computer use on work intensity.

Computer use grew 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 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, in the literature, to be less affected by this technology.

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

2   Measuring technology, work discretion and work intensity

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), 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[13], 2005 and 2010 and 2015. We use the survey weights provided in the EWCS to account for differential probabilities of being selected in the EU15 countries in all descriptive results.

2.1 Measuring computer 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 the available information 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: PCs, 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.

In all waves, responses to the computer use question are coded on a scale with 7 categories ranging from *Never* to *All the time[14]*. 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. This means that we focus on the effect of the introduction of computer use in a given occupation. In section 0 we discuss the robustness of our main results to using alternative measures that also capture some variation along the intensive margin (and the results are reported in the appendix).

As we explain below, to be able to exploit variation over time in our dataset of repeated cross-sections, our analysis is entirely conducted at the occupation-country-year level and therefore, effectively, our computer use variable measures the proportion of workers in each cell that uses computers at least a quarter of the time. 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.

A possible limitation of this measure of computer use which is rarely recognised in the literature is that it might be more effective in capturing the adoption and use of digital technology in some occupations than in others. We return to this issue and its possible implications for our results in Section 0.

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 –

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[13] 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 the exclusion of the year 2000 and, reassuringly, find qualitatively similar results.

[14] The 7 categories are coded ordinally as 0 "Never", 1 "Almost never", 2 "Around 1/4th of the time", 3 "Around half of the time", 4 "Around 3/4th of the time", 5 "Almost all of the time" and 6 "All of the time"

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, in the economics literature, are generally thought to be less affected by this technology. 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 work discretion and work intensity

Job quality is a multi-dimensional concept which has been the subject of many studies both from a theoretical and empirical point of view. For recent in-depth discussions of this subject see, among others, Green (2006), Bustillo et al. (2011), Kalleberg (2011) and Green et al. (2013). Our aim is not to document broad trends in job quality in general, but to address the question as to how computer use affects two specific aspects of job quality that feature prominently in the debate on the effects of technology on work, namely work discretion and work intensity. The focus on particular aspects of job quality rather than an overall aggregate index (as, for example in Bustillo et al. (2011)) allows a more intuitive interpretation of the regression results.

As an indicator for work 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[15] of that in Green et al. (F. Green et al. 2013) and uses the answers to "*Does your job involve;*

1. *Working at very high speeds*

2. *Working to tight deadlines*"

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[15] 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.

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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. A possible limitation of these indicators is that they are measured binary and thereby likely include substantial measurement error. This may lead to our estimates of changes being more conservative as relatively small individual changes in work discretion or work intensity would not necessarily be reported. We choose these subcomponents as they are available for all years in our analysis and construct the job quality indicators using a principal component analysis with a polychoric correlation matrix. The indices are calculated by pooling the EU15 countries across years together and are standardised to have mean of 100 and a standard deviation of 10. The proportion of variance explained by the first component is 0.84 and 0.82 for the discretion and work intensity indicators respectively.

Figure 2 plots average work discretion 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 (except for managers) that have seen some convergence in computer use. The picture also shows that high-skilled cognitive occupations tend to have both higher average work discretion and lower variation across countries. Ranges across countries are generally around half of a standard deviation for managers, professionals and technicians, but closer to a full standard deviation for occupations such as crafts, machine operatives, and elementary occupations.[16]

Figure 3 shows that there are also sizeable differences in reported work intensity for a given occupation across countries. However, unlike work discretion, the dispersion in work intensity across countries does not appear to be systematically different for cognitive occupations. All occupations, except elementary occupations, saw a decline in the dispersion of work intensity across countries over the two decades. This is mostly because across all occupations work 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 also become smaller.

Hence, 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 increased homogeneity in terms of work 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 work intensity in countries with initial low levels of work intensity across the board.[17]

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

[17] 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.

3 Trends in work discretion, work intensity, and computer use across Europe

Figure 4 plots changes in our two measures of job quality and computer use between 1995 and 2015 in the EU-15. Computer use (on the right-hand side scale) increased considerably, rising from just above 40% to just above 60%. Work 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, work discretion was at a level just below that of 1995, having almost fully recovered the loss of 10% of a standard deviation that occurred in the first decade.

The break down by three education levels in the top panel of Table 1 shows that the increase in work intensity took place within all education groups, but was larger for those with high and low education – exceeding 20% of a standard deviation. Work discretion decreased slightly for the two groups with lower education only.

Computer use increased within all education groups, but 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 work intensity and lower work discretion. Over the two successive decades, work intensity increased by 25% of a standard deviation for non-pc users, but remained substantially stable for PC-users. Hence, the aggregate increase in work intensity is driven by non-PC-users. Similarly, work discretion declined by 13% of a standard deviation for non-PC-users but by less than 5% of a standard deviation for PC-users, (both changes are statistically significant (p<0.01)). As a result, the gap in work intensity between users and non-users of PCs has all but closed, while that in work discretion has slightly increased.

The lower part of the table reveals that at a given point in time there are greater differences between occupations in terms of work discretion than work intensity. Discretion declines almost monotonically as one moves down the occupational classification, but work intensity exhibits a more complex pattern. In particular, throughout the period, crafts and machine operatives exhibit the highest levels of work intensity, but professionals and technicians report levels similar to those of workers in service and elementary occupations.

Work intensity increased in all occupations between 1995 and 2015, but not statistically significantly (p<0.1) so among managers and plant and machine workers. The greatest increase (30% of a standard deviation) is seen in elementary occupations.

Work discretion has decreased slightly in most occupations, but the decrease is only statistically significant (p<0.05) for technicians, those in service and sales occupations and plant and machine workers. Only crafts saw a statistically significant increase in work discretion which exceeded 10% of a standard deviation.

Computer use has increased significantly (p<0.01) 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 (pp) 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 5 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 great 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 work intensity increased for all occupational and educational groups while work discretion decreased slightly for most of them.

In Figure 5 shows a positive relationship between changes in computer use and changes in work discretion which is statistically significant at the 1% level, but a positive and statistically insignificant one between changes in computer use and changes in work intensity.[18] Taken at face value, these results suggest that computer use might have had no impact on work intensity while counteracting the decline in work discretion over our observation period in the EU-15. However, these simple bivariate correlations are likely to be affected by endogeneity. In the next section, we discuss the strategy we adopt to tackle this issue.

4 Empirical strategy

To move beyond the simple bivariate correlation of Figure 5, we estimate a model in first-differences including controls at the occupation-country level whose exclusion could bias the estimates of the effect of computer use. [19] In particular, we estimate the following model in stacked-differences:

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

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, the share of employment of a given occupation-country pair in three broadly defined industries (non-services, personal services, and other services), the share on temporary contracts and the share of self-employed.[20] We include these latter two controls because these groups might differ both in terms of job quality and computer use, but they will also help capture business cycles effects to some extent. Russel and McGinnity (2014) argue that organisational changes implemented during the recession in Ireland led to a higher work pressure. Since some of these changes might be correlated with computer adoption, we want to control for the business cycle to try and purge our estimates of these confounding effects. To this end, we also include the country-level unemployment rate and include time dummies (

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[18] 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.

[19] Similarly, when studying the impact of computer use on skill requirements and tasks, 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. We focus on the occupational level analysis as there is no gain in terms of identification of the effect of interest in using individual level data.

[20] The sample used throughout the analysis reported here includes the self-employed, but we obtain very similar results if we exclude them from the sample.

$\sum_{i=2}^{3} T_i$) that capture temporary deviations from the linear trends in levels implied by the inclusion of the constant in this model in first-differences.

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; F. 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 all other countries included in the sample.[21] [22]Here we define as similar those occupations that fall within the same group of the classification proposed by Acemoglu and Autor (Acemoglu and Autor 2011) (AA henceforth) based on the nature of the prevalent task in the occupation and widely used in subsequent literature.[23]

The rationale for our instrument is that (i) the major driver of the pervasive increase in computer use in recent decades is the secular decline in the price of computing and that (ii) the rates of computer adoption between occupations involving similar tasks in different countries will be correlated for purely technological reasons. Both parts of this argument are commonly made in related literature. Nordhaus (2007) finds that, during the 1980s and 1990s, the rate of decline of computing costs was on average 64% per year. A large body of literature spurred by Autor et al. (2003) argues that computer adoption occurs differentially across occupations depending on the extent to which they involve tasks that are easier to automate with the new technology (Acemoglu and Autor 2011; D. H. Autor and Dorn 2013).

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[21] 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. We prefer the version excluding the own-occupation from the instrument as we think it makes the assumption of no correlation across countries more plausible. As we discuss in the text, a possible threat to this assumption arises from common shocks to industries in which an occupation is concentrated in different countries. Using different occupations involving similar tasks reduces the chances of correlation due to common industry shocks and increases the chances that any correlation is driven by the common level of exposure to the effect of technology. We discuss possible threats to this assumptions in the main text.

[22] We have also considered a different instrument: we used measures of changes in information and communication technology (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 too weak in our first-stage regressions for changes in computer use to provide reliable IV estimates.

[23] 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.

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 into US industries driven by the arguably exogenous expansion of the Chinese economy by using changes in Chinese import penetration into the same industries in 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 the same industries 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 (occupation) 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 occupational 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 and country-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 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.[24] For this reason we do not report these results here, but they broadly align with the results of our other robustness checks.

5 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.[25] Panel A reports the results for work discretion. The first column includes only time dummies and implies that, between 1995 and 2015, work discretion decreased slightly across the EU-15 by 0.14 points – or just over 1% of a standard deviation.[26] The change conditional on observable characteristics implied by the estimates in column 2 is greater (-1.8 or 18% of a standard deviation). Hence, compositional changes have tended to counteract the decline in work 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[27], which implies an increase in the work discretion index for the average occupation of over 11% of a standard deviation.[28] This is a large effect when compared to the overall conditional *decline* in work discretion of 18% of a standard deviation: in the average occupation, the spread of computers is associated with a reduction in the decline in work discretion of over 60%.[29] To test whether the effect of computer use has changed over time (perhaps as consequence of the growth in computing power or the increase in interconnectivity), we also run separate regressions for each of the four time periods covered by our data. These results – not reported here – show stable coefficients over time.

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

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[24] 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 the 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 use them only in our robustness checks.

[25] 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 difference with aggregate data. When we do that, the statistical significance of all our estimates for work discretion improves, while the estimates remain statistically insignificant in the regressions for work intensity.

[26] Since this is a model in first difference, including a constant and a dummy for all but one changes, the total estimated change is the sum of each change, and each change is given as the constant (the change for the reference period of 1995 to 2000) and the difference of that change from the reference. The change from 1995 to 2015 is then given as the sum of all time dummies plus four times the constant (as there are four changes).

[27] This benign effect of computer use on job quality is supported by further analyses we carry out on wages, which is often used as an indicator of job quality. In results for 2005 to 2015, discussed in the appendix, we find a positive association of computer use and earnings. However, as these results are not available for the full period the instrument is weaker and the effect is less precisely estimated.

[28] Computer use increased by 20pp between 1995 and 2015. Multiplying this change by the coefficient on the PC variable yields: 0.20*6.065=1.14.

[29] Results obtained excluding controls for the share of temporary contracts and self-employed indicate even larger effects.

the bottom of the table.[30] The coefficient on PC decreases slightly in absolute value and retains statistical significance at the 10% level and the implied increase in work discretion for the average occupation (11%) is very similar to that found in column 3.

Column 4 adds occupation and country linear trends to our baseline IV specification. Neither sets of linear trends are jointly statistically significant as indicated by the tests reported at the bottom of the column, and here the instrument remains strong. The computer use variable now attracts a larger coefficient which is itself statistically significant at the 5% level. Its size implies an increase in work discretion in the average of occupation of 19% of a standard deviation which offsets just over 60% of the entire conditional decline implied by the coefficients on the time dummies in column 4. 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 is again statistically significant at the 5% level and implies an increase in work discretion in the average occupation of over 15% of a standard deviation.

Column 1 of Panel B shows that over the sample period work intensity increased across Europe by just over 17% of a standard deviation. The estimated increase is greater (at about 25% of a standard deviation) in column 2 where we condition on observable characteristics. Hence, as we have already seen for work 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, which implies a small effect of less than 1% of a standard deviation for the average occupation. In regressions not reported here we find similar results throughout the period covered by our data. The IV estimates in the remaining columns are negative and greater 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 that have tended to counteract this trend. As for computer use, the OLS estimates point to a sizeable positive effect on work discretion, but no effect on work intensity. 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 mostly greater positive effects estimated on discretion and negative but insignificant effects on work 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 work intensity regression, paint a consistent picture overall: they suggest more benign effects of computer use in the form of larger positive coefficients for work discretion and larger negative coefficients for work intensity.

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[30] 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.

In the appendix, we report the results obtained replacing our computer use variable with (i) the average of the computer use scale in an occupation; (ii) the proportion using computer more than 50% of the time and (iii) the proportion using computer more than 75% of the time. These results confirm the main conclusion that changes in computer use do not explain the observed trends in our indicators of job quality. In general, they also suggest that any effects of computer use on work discretion might be limited to low levels of computer use. Finally, we also report the results using wages as the dependent variable in the Appendix. These results confirm the conclusion of our main analysis that computer use tends to have benign effect on job quality.

5.1. 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). 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-skilled occupations involving non-routine manual tasks are generally thought to offer 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. Relatedly, the literature on 'digital Taylorism' proposes that technological change could induce a routinization of cognitive work through increased codification of tasks and oversight (e.g. Brown et al. 2010; Lauder, Brown & Cheung, 2018).

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.[31]

Panel A shows the results for two specifications for work discretion, one including only time dummies and the other additionally including the same controls used in the main analysis. The estimated constants and time dummies indicate that the change in work discretion has been small in all groups and negative in all except routine manual (+6% of a standard deviation). However, the conditional change was negative for all groups and larger than the unconditional one for all except routine cognitive occupations. There is no indication in these results that computer use reduces work discretion in any occupational group: the coefficient on computer use is positive for all occupations and is statistically significant at least the 10% level for all except the routine cognitive group.

The large positive coefficients found for manual occupations are somewhat surprising. In existing studies, non-routine manual occupations , are generally assumed not to be affected in substantial ways by existing technologies. By contrast, the coefficients in Table 3 imply that a 10

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[31] For the exact grouping of ISCO codes see footnote 23.

percentage point increase in computer use is associated with an increase in work discretion of 9% of a standard deviation in non-routine manual occupations, and only of 4% of a standard deviation in routine cognitive jobs. Such a great 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 work discretion. Nevertheless, the finding of a strong association between computer use and work discretion in lower-skilled 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 not easily substitute or 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 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 a higher degree of discretion to the employee.

The results from the work intensity regressions by occupational groups are reported in Panel B of Table 3. The estimated time dummies and constant imply that work intensity has increased over the period in our sample, albeit it not statistically significantly for non-routine occupations, and that compositional changes have partially counteracted the increasing trend in routine cognitive and non-routine manual occupations. 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 work intensity of just 7% of a standard deviation. In non-routine manual occupations, on the other hand, computer use attracts a negative and statistically insignificant coefficient.

6 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 work discretion and work intensity. The paper has two main empirical findings concerning (I) diffusion of computers across occupations in Europe and (II) the effect of computer use on work discretion and work intensity.

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 great 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).

The finding of differences in computer use in similar occupations across countries calls 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 analyses for different countries.[32]

In addition, these findings show that computer use is increasingly reaching into segments of the labour markets that have so far widely been considered exempt from a direct impact in the economics literature (M. Goos and Manning 2007; Acemoglu and Autor 2011; D. H. Autor 2015). Other studies have provided evidence in line with this result for the UK (Cortes and Salvatori 2019) and the US (Kulkarni et al. 2017) and Weil (2014) discusses cases that illustrate that technology has the potential to significantly impact the organisation and the content of low-skilled occupations. This evidence points to the need to develop 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 our measures of job quality in the EU-15 as whole, [33] as work intensity increased for all occupational and educational groups while work discretion decreased slightly for most of them. Our main empirical results suggest that the modest deterioration in job quality has occurred in spite of the spread of computers rather than because of it. Our OLS estimates suggest a sizeable positive effect of computer use on work discretion, but small or no effect on work intensity. Our IV estimates point to an even more benign effect of computer use on job quality, with greater positive effects estimated on work discretion and negative but insignificant effects on work intensity. These results might reflect changes in job quality of existing jobs, but also changes in the composition of jobs within the broad occupational categories used in the analysis. In addition, we find little indication of differences in the effect of computer use on job quality across different occupations and no indication that computer use is associated with a decline in work 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, rather than a stricter control over work processes driven by digital technologies. In addition, they also illustrate that computer adoption has not been the dominant driver of the evolution of working conditions within occupations. This is a somewhat surprising result, given that technology has taken the centre-stage in the policy debate on the ongoing changes in the labour market. While our data do not allow us to investigate this hypothesis directly, a number of earlier studies have argued that organisational change plays an important role affecting job quality over and above technology (F. Green 2012; Caroli and Reenen 2001). In their review of the UK literature, Green et al. (2016) refer to changes in "management culture" as their preferred explanation for the decline in work discretion over the past 10-15 years. Bryson et al. (2016) show that job quality is affected by managerial practices (and other workplace characteristics) over and above individual and job characteristics. Understanding the relative importance of these factors vis-à-vis technology in driving aggregate trends in job quality remains an important challenge for future research, with significant policy implications.

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

[33] Other studies that have used earlier data have also reported limited time variation in job quality in Europe (F. Green et al. 2013; Eurofound 2007).

A possible limitation of our study is that our computer use variable might be more effective in capturing the adoption and use of digital technology in some occupations than in others.[34] Dhondt et al. (2002) raise concerns that standard computer use questions might not effectively capture the use of digital technologies in lower-skilled manual occupations. 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 (some of) 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 computers 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, the growth in computer use in low-skilled occupations that we have reported might be an underestimate, while our estimates of the effect of computer use on job quality might disproportionally reflect the effect for workers who perform more cognitive tasks (within occupations). We are not aware of any discussion of these issues in the literature, but they would have implications for any of the many studies that use standard questions to look at the impact of computers on a broad variety of outcomes. 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 to measure the use of technology in the workplace and to develop new and improved ones if necessary.

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[34] A similar concern may be raised within occupations, as workers who perform more cognitive tasks that are typically associated with the use of standard computers might be more likely to report using a computer at work.

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8 Tables

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

	Work Intensity			Work Discretion			Computer Use		
	1995	2015	% change	1995	2015	% change	1995	2015	change
Lower Secondary Qualifications	98.19	100.4	2.25***	98.38	97.83	-0.56**	0.18	0.32	0.14***
Upper Secondary Qualifications	99.61	100.53	0.92***	99.78	99.41	-0.37**	0.41	0.54	0.13***
Tertiary Qualifications	98.55	100.6	2.08***	102.5	102.63	0.13	0.56	0.86	0.30***
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	0.56	0.81	0.25***
Professionals	97.72	100.09	2.43***	103.19	102.96	-0.22	0.57	0.89	0.32***
Technicians	97.68	99.96	2.33***	102.28	101.75	-0.52**	0.52	0.86	0.34***
Clerks	99.18	100.24	1.07***	100.37	100.2	-0.17	0.76	0.86	0.10***
Service/Sales	97.71	99.56	1.89***	100.13	98.39	-1.74***	0.33	0.41	0.08***
Craft/Trade	100.69	103.26	2.55***	98.77	99.78	1.02***	0.15	0.30	0.15***
Plant/Machine	101.57	102.12	0.54	94.26	93.55	-0.75*	0.19	0.33	0.14***
Elementary	97.31	100.28	3.05***	97.45	98.02	0.58	0.10	0.16	0.06***

*** p<0.01, ** p<0.05, * p<0.1, weighted estimates and changes over waves. Significance of the difference is tested in bivariate regression of the difference from 1995 to 2015 within each category.

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

	(1) OLS	(2) OLS	(3) IV 1	(4) IV 1	(5) IV 2
Panel A – Dependent Variable - Work Discretion					
D.Computer Use		6.065***	5.705*	9.389**	7.313**
		(1.172)	(3.305)	(3.907)	(3.445)
D.2005	0.308	-0.105	-0.0901	-0.262	-0.158
	(0.368)	(0.315)	(0.324)	(0.341)	(0.327)
D.2010	1.076***	0.828**	0.825**	0.757**	0.838**
	(0.384)	(0.401)	(0.399)	(0.375)	(0.398)
D.2015	1.575***	1.037***	1.036***	1.047***	1.039***
	(0.338)	(0.333)	(0.329)	(0.319)	(0.325)
Constant	-0.775***	-0.911***	-0.896***	-1.153**	-0.962***
	(0.247)	(0.254)	(0.297)	(0.563)	(0.298)
Composition controls (a)	No	Yes	Yes	Yes	Yes
F-Test of joint significant of time trends	No	No	No	Yes	No
	0.000	0.000	0.000	0.000	0.001
F-Test of joint significant of country trends (df=13)				0.531	
F-Test of joint significant of occupational trends (df=6)				0.758	
Observations	480	480	480	480	480
R-squared	0.087	0.338	0.338	0.351	0.334
Kleibergen-Paap rk Wald F from first-stage			26.68	22.23	25.54
Panel B: Dependent Variable – Work Intensity					
D.Computer Use		0.335	-3.809	-5.724	-3.418
		(1.691)	(3.794)	(4.393)	(4.073)
D.2005	0.700	0.763	0.937*	1.042**	0.920*
	(0.468)	(0.469)	(0.495)	(0.462)	(0.493)
D.2010	-0.931**	-1.021**	-1.053**	-0.988**	-1.050**
	(0.426)	(0.483)	(0.482)	(0.441)	(0.483)
D.2015	-0.116	0.118	0.111	0.184	0.112
	(0.460)	(0.460)	(0.463)	(0.434)	(0.462)
Constant	0.526	0.670*	0.840**	1.241*	0.824**
	(0.341)	(0.350)	(0.367)	(0.683)	(0.372)
Composition controls (a)	No	Yes	Yes	Yes	Yes
Occupational and country trends	No	No	No	Yes	No
F-Test of joint significant of time trends	0.001	0.001	0.000	0.000	0.000
F-Test of joint significant of country trends (df=13)				0.000	

	(1)	(2)	(3)	(4)	(5)
F-Test of joint significant of occupational trends (df=6)				0.289	
Observations	480	480	480	480	480
R-squared	0.055	0.164	0.132	0.182	0.138
Kleibergen-Paap rk Wald F from first-stage			26.68	22.23	25.54

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, share of self-employed, share of those in temporary contracts, and overall unemployment rate by country-year.

All regressions use data from five waves of the EWCS (1995, 2000, 2005, 2010 and 2015) and include data on employees and self-employed workers. 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 for all employed.

	Non Routine Cognitive		Routine Cognitive		Routine Manual		Non Routine Manual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent Variable: Work Discretion								
D.Computer Use		4.622*		3.817		4.302*		9.407***
		(2.645)		(3.104)		(2.400)		(1.796)
D.2005	-0.710*	-0.326	-0.817	-0.310	-0.186	-0.168	2.975***	0.483
	(0.387)	(0.381)	(0.639)	(0.715)	(0.633)	(0.761)	(1.000)	(0.902)
D.2010	0.392	0.563	0.285	0.518	1.517**	1.265*	2.244**	2.091**
	(0.534)	(0.607)	(0.492)	(0.653)	(0.764)	(0.695)	(0.960)	(0.859)
D.2015	0.232	1.081**	1.965***	1.250**	2.353***	1.488**	3.055***	1.129
	(0.411)	(0.481)	(0.520)	(0.556)	(0.659)	(0.683)	(0.806)	(0.822)
Constant	0.0105	-0.747*	-0.400*	-0.763	-0.769*	-1.027*	-2.293***	-1.549**
	(0.225)	(0.417)	(0.237)	(0.597)	(0.402)	(0.594)	(0.697)	(0.747)
Controls (a)	No	Yes	No	Yes	No	Yes	No	Yes
F-Test of joint significant of time trends	0.123	0.025	0.001	0.006	0.000	0.029	0.003	0.270
Observations	180	180	60	60	120	120	120	120
R-squared	0.050	0.307	0.306	0.702	0.199	0.485	0.209	0.566
Panel B: Dependent Variable: Work Intensity								
Computer Use		4.255		7.170**		3.150		-2.551
		(3.663)		(3.217)		(3.055)		(2.667)
D.2005	-0.149	-0.335	2.397***	2.057**	1.075	1.887**	0.870	1.022
	(0.771)	(0.802)	(0.850)	(0.770)	(0.886)	(0.721)	(1.014)	(1.130)
D.2010	-1.138	-1.119	0.362	-1.311	-1.937***	-1.710**	-0.424	-0.939
	(0.726)	(0.825)	(0.867)	(0.871)	(0.714)	(0.799)	(0.942)	(0.925)
D.2015	-0.362	0.0966	0.772	1.100	-0.898	-0.010	0.395	0.430

						7		
	(0.778)	(0.775)	(1.069)	(0.773)	(0.892)	(0.767)	(0.924)	(0.860)
Constant	0.787	0.656	-0.578	0.379	0.873	0.122	0.389	0.715
	(0.588)	(0.658)	(0.643)	(0.593)	(0.679)	(0.615)	(0.696)	(0.672)
Controls (a)	No	Yes	No	Yes	No	Yes	No	Yes
F-Test of joint significant of time trends	0.321	0.353	0.026	0.010	0.000	0.000	0.580	0.664
Observations	180	180	60	60	120	120	120	120
R-squared	0.037	0.249	0.158	0.543	0.209	0.442	0.032	0.211

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, share of self-employed, share of workers on a temporary contract, and the overall unemployment rate by country-year.

All regressions use data from five waves of the EWCS (1995, 2000, 2005, 2010, and 2015) and include data on employees and self-employed workers..

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

9 Appendix

9.1 Wage regressions

We believe work discretion and intensity are particularly relevant indicators of job quality regarding technological change, which is thought to lead to more controllable and intensive work. While very relevant, these indicators are self-reported and can be subjective. As an extension to study how technological change may have impacted job quality we therefore re-estimate our main specifications on the net hourly wages within each occupation-country-year cell. The wage data is available in detail in 2015 and for some countries in 2010, but only in categories in 2005 and some countries in 2010 – in which case we took the midpoint.

Table A1 shows the results, indicating that a change in computer use is associated with an increase in wages on average. While this positive effect remains in the IV specifications, the smaller sample and especially the shorter time period means the identification is weaker and the estimates are less precise. This then supports the previous findings that technological change did not adversely affect job quality.

Table A1 - First-difference net hourly wages and number of hours usually worked regression using occupation-country observations from the EU-15, 2005-2015.

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	IV 1	IV 1	IV 2
Dependent Variable – Net hourly wages					
D.Computer Use		4.966*	40.25	22.24	30.39
		(2.970)	(28.98)	(31.09)	(22.78)
D.2010	-6.508***	-6.205***	-6.114***	6.083***	-6.139***
	(0.588)	(0.585)	(0.725)	(0.616)	(0.638)
Constant	0.819***	-0.135	-1.306	1.422	-0.979
	(0.271)	(0.447)	(1.121)	(1.785)	(0.901)
Composition controls (a)	No	Yes	Yes	Yes	Yes
Occupational and country trends	No	No	No	Yes	No
F-Test of joint significant of country trends (df=13)				0.005	
F-Test of joint significant of occupational trends (df=6)				0.559	
Observations	240	240	240	240	240
R-squared	0.371	0.494	0.193	0.484	0.338
Kleibergen-Paap rk Wald F from first-stage			3.484	1.923	4.312

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, share of self-employed, share of those in temporary contracts, and overall unemployment rate by country-year.

These regressions use data from three waves of the EWCS (2005, 2010 and 2015) and include data on employees and self-employed workers. 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

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9.2 Different indicators of computer use

While we believe that the most relevant measure of computer use is one that measures whether computers are being used at work, the question formulation in the EWCS allows us to measure the intensity of computer use. We re-estimate the models using three different specifications: one where computer use is estimated as the average of a 7-point scale indicating the intensity of use; one indicating the share of employees using a computer more than 50% of the time in a work day; and one indicating the share of employees using a computer more than 75% of the time in a work day.

Table A2 shows the coefficient of computer use on work discretion and work intensity in the OLS and main IV specification. The OLS results support our main findings of increasing discretion and no real change on intensity, while the IV estimates go in the same direction but are no longer statistically significant. This could indicate that the introduction of computer use is the main driver of change, rather than an increasing intensity of use.

Table A2 - First-difference job quality regression using occupation-country observations from the EU-15, 1995-2015 using different specifications of computer use
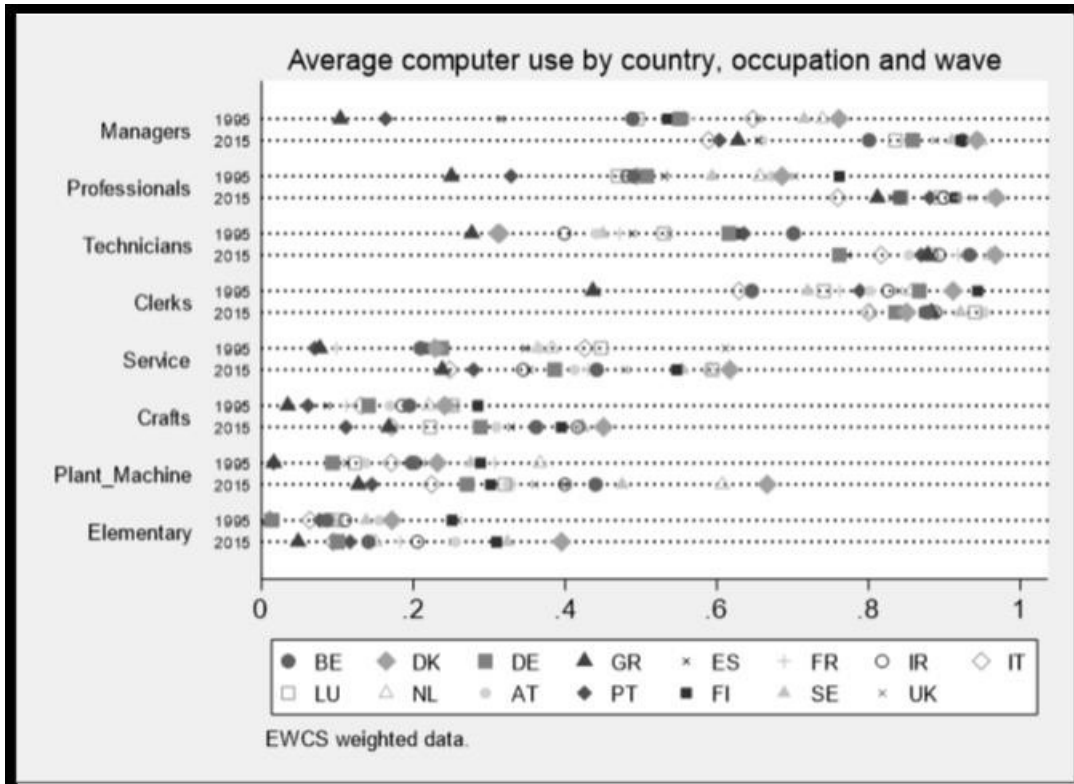
		Average intensity of computer use	Share using computer more than 50%	Share using computer more than 75%
Work Discretion	OLS	1.1777***	5.187***	4.730***
		(0.254)	(1.352)	(1.455)
	IV1	0.713	3.411	1.345
		(0.708)	(3.547)	(4.562)
Work Intensity	OLS	0.004	0.205	-0.195
		(0.339)	(1.670)	(1.735)
	IV1	-0.874	-3.923	-4.146
		(0.778)	(3.854)	(4.961)

First difference models with country-occupations weighted by average cell size.
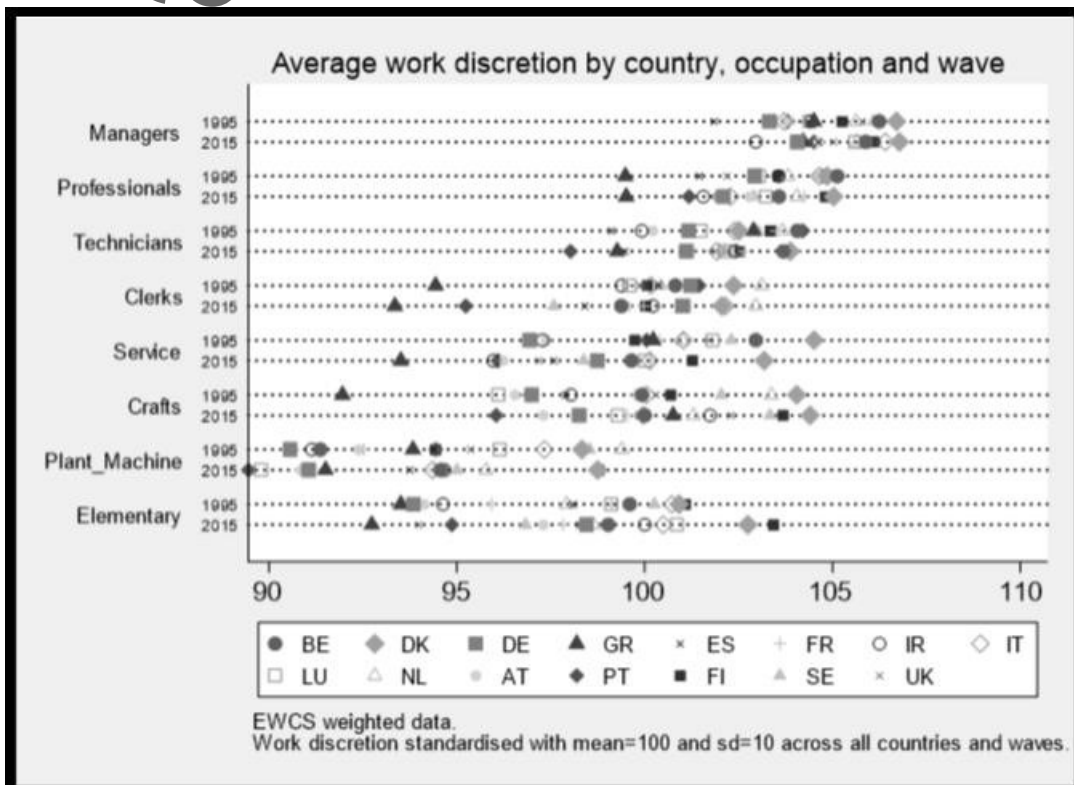*Controlling for share of education, gender and age groups within each occupation-country cell; share of employment of a given occupation-country pair in non-services, personal services, and other services, share of self-employed, share of those in temporary contracts, and overall unemployment rate by country-year.*
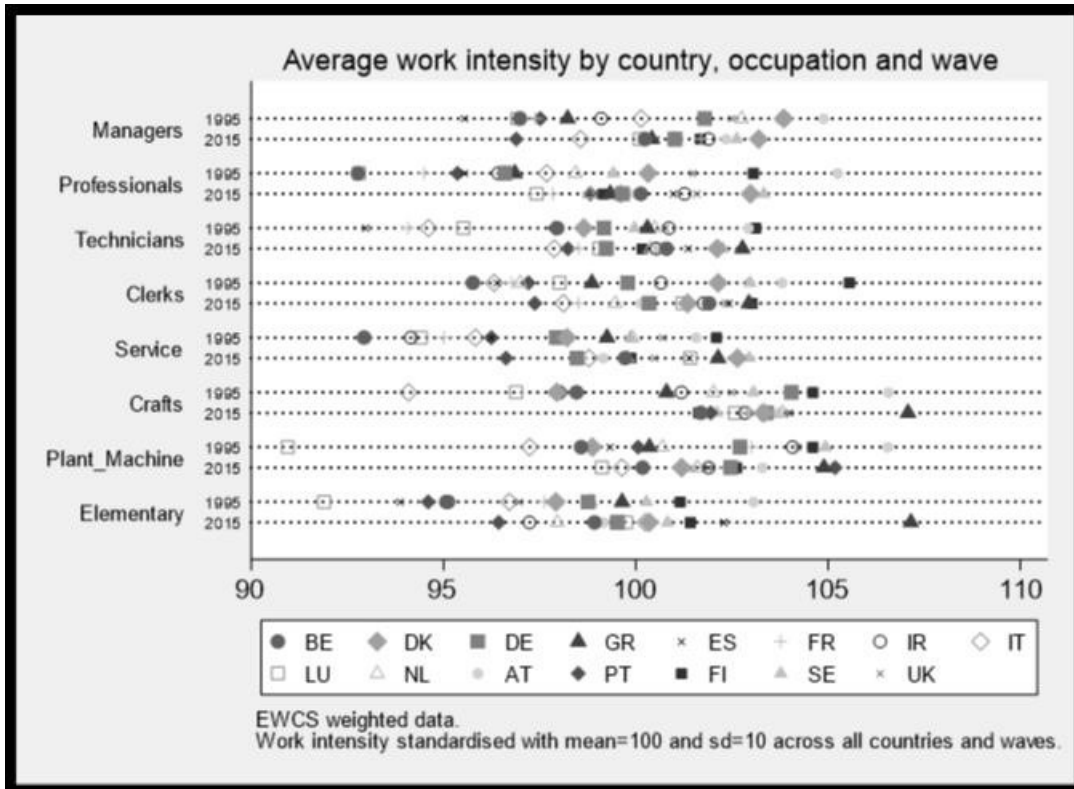*All regressions use data from five waves of the EWCS (1995, 2000, 2005, 2010 and 2015) and include data on employees and self-employed workers. IV 1 uses change in PC use in similar occupations in all other countries as instrument.*
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

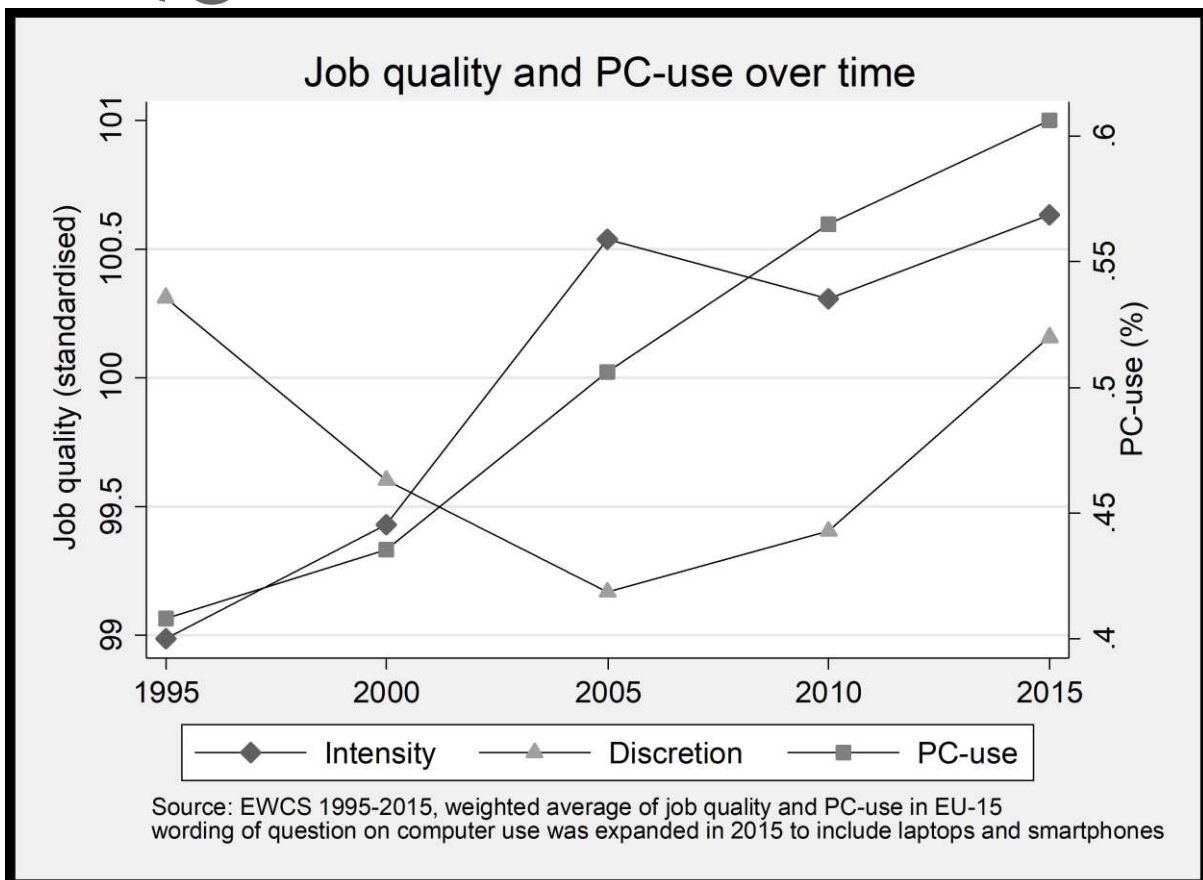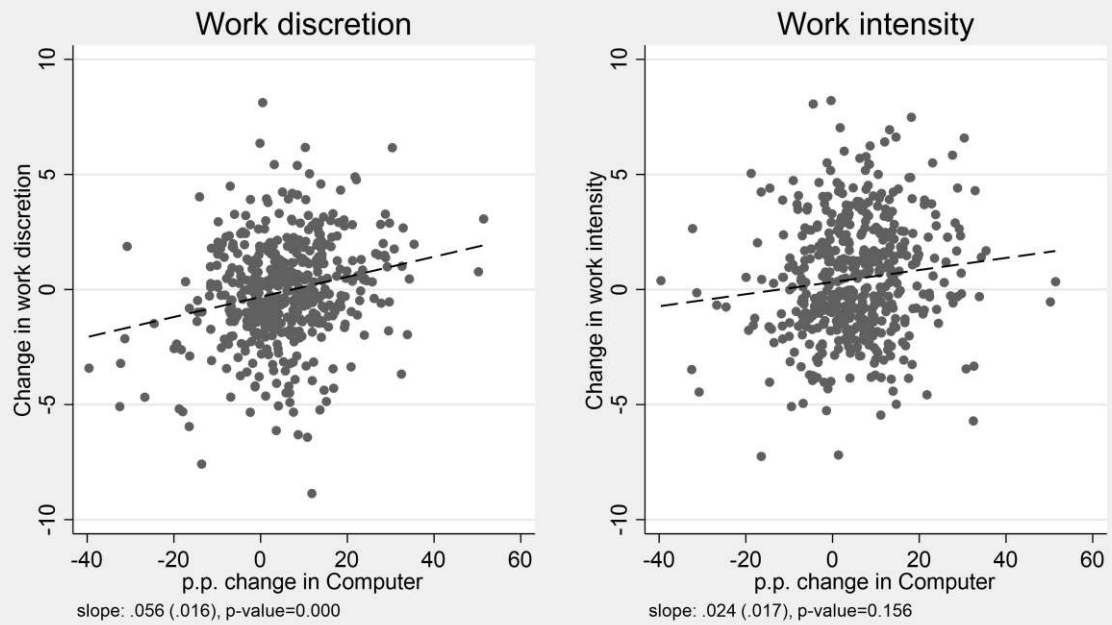Average computer use by country, occupation and wave

EWCS weighted data.

a

Average work discretion by country, occupation and wave

EWCS weighted data.
Work discretion standardised with mean=100 and sd=10 across all countries and waves.

Average work intensity by country, occupation and wave

EWCS weighted data.
Work intensity standardised with mean=100 and sd=10 across all countries and waves.

Job quality and PC-use over time

Source: EWCS 1995-2015, weighted average of job quality and PC-use in EU-15
wording of question on computer use was expanded in 2015 to include laptops and smartphones

Changes in job quality and technology use, '95-'15

Work discretion

slope: .056 (.016), p-value=0.000

Work intensity

slope: .024 (.017), p-value=0.156

Source: EWCS for EU-15, changes 1995-2000; 2000-2005; 2005-2010; 2010-2015 by occupation-country
relation between standardised job quality (mean=100, sd=10) and p.p. of change in technology use
slope and standard error from regression clustered by country and weighted by cell size
wording of question on computer use was expanded in 2015 to include laptops and smartphones