AUTOMATION AND JOB POLARIZATION: ON THE DECLINE OF MIDDLING OCCUPATIONS IN EUROPE

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WORKING PAPER SERIES (ISSN 1211-3298)
Electronic Version

576

Working Paper Series 576
(ISSN 1211-3298)

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CERGE-EI
Prague, November 2016

ISBN 978-80-7343-383-3 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-399-3 (Národohospodářský ústav AV ČR, v. v. i.)

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Vahagn Jerbashian*

Abstract

Using data from 10 Western European countries, I provide evidence that the fall in prices of information technologies (IT) is associated with a lower share of employment in middle wage occupations and a higher share of employment in high wage occupations. The decline in IT prices has no robust effect on the share of employment in the lowest paid occupations. Similar results hold within gender, age and education-level groups, with notable differences in these groups. For instance, the share of employment in high wage occupations among females has increased more than among males with the fall in IT prices. This is consistent with arguments that women hold a comparative advantage in communication and social skills, which are complementary to IT and in demand in high wage occupations.

Keywords: Job Polarization; Information Technologies; Gender; Age; Education-Level

JEL classification: J23; J24; O33

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1 Introduction

For quite some time, the consensus has been that most of the recent technological changes have been skill-biased, complementing high-skill workers and substituting for low-skill workers (see, e.g., Katz and Autor, 1999). However, skill-biased technological change alone cannot explain a prominent and relatively recent phenomenon: the decline in the share of middle wage occupations relative to high and low wage occupations. Goos and Manning (2007) call this phenomenon "job polarization."

One of the main hypotheses put forward for job polarization is that recent technologies, such as the computers, substitute for routine tasks. These tasks tend to be readily automatable and are usually performed by middle wage occupations, such as office clerks. They complement nonroutine cognitive tasks, which are usually performed by high wage occupations, such as managers. In turn, the rise of employment in highly paid occupations increases the demand for nonroutine manual tasks, which are usually performed by low wage occupations, such as personal services (see, e.g., Autor, Levy, and Murnane, 2003, Autor and Dorn, 2013, Mazzolari and Ragusa, 2013).

In this paper, I empirically investigate the effect of the rapid fall in prices of information technologies (IT) on industries' demand for high, middle and low wage occupations using a difference-in-differences framework in the spirit of Rajan and Zingales (1998). More specifically, I ask whether the fall in prices of information technologies has affected the demand for high, middle and low wage occupations more in industries which depend more on IT compared to industries which depend less. I use industry- and country-level data from 10 Western European countries and 1993-2007 period to establish the results.

I find that the share of employment in middling occupations has declined and the share of employment in high wage occupations has increased with the fall in IT prices. I find no systematic evidence that the fall in IT prices affects the share of employment in the lowest paid occupations. Similar results hold within gender, age and education-level groups. These findings provide support for the hypothesis put forward for explaining job polarization. They are broadly in line with and complement the results of Autor et al. (2003), Autor and Dorn (2013), Goos, Manning, and Salomons (2014), and Michaels, Natraj, and van Reenen (2014), among others.

I also find that there are differences in gender, age and education-level groups, which is a novelty relative to these papers. The fall in IT prices has increased (reduced) the share of employment in high (medium) wage occupations among females more than among males. It has increased (reduced) the share of employment in high (medium) wage occupations among old workers less than among young and medium-age workers. It has increased (reduced) the share of employment in high (medium) wage occupations among medium-educated workers more than among highly educated and low-educated workers. These results are robust to a wide range of specification checks and alternative identifying assumptions.

A possible explanation for these results is that task content and the types of skills in occupations and occupation groups vary with gender, age and education-level. For example, a number of papers argue that women have a comparative advantage in communication and social skills, which have a growing importance in the labor market and tend to be more important in leadership in high wage occupations (e.g., Borghans, Weel, and Weinberg, 2014, Beaudry and Lewis, 2014, Deming, 2015). Information technologies can complement these skills helping to create and run networks, and to structure, process and disseminate data. The adoption and use of information technologies would then increase employment in high wage occupations among females more than among males. In turn, Autor and Dorn (2009) argue that workers in routine task intensive occupations accumulate occupation-specific skills and that switching the occupation is more costly for these workers when they are old compared to when they are young. This suggests that IT matters for the employment of old workers less than for the employment of young and medium-age workers. IT could also substitute medium-educated (medium-skill) workers in medium wage occupations more than highly educated and low-educated workers because tasks performed by medium-educated workers tend to be the most routine intensive (Michaels et al., 2014). I do not attempt to test these hypotheses in this paper given its scope and the available data. All in all, these results highlight the role of gender, age group and skill/education-level in job polarization and suggest a need for a more nuanced view on the labor market effects of recent technological changes.

Job polarization is a global phenomenon. Goos and Manning (2007), Goos, Manning, and Salomons (2009) and Goos et al. (2014) provide comprehensive evidence for it for Western European countries and Autor, Katz, and Kearney (2006, 2008), Acemoglu and Autor (2011) and Autor and Dorn (2013) for the US. Recent technological changes are thought to be one of the primary causes of job polarization, and a growing number of papers offer evidence corroborating this view. Using US data, Autor et al. (2003) show that the use of IT is associated with reduced employment in middle wage (routine) occupations within industries, occupations, and education levels. Autor and Dorn (2013) show that, in the US, the growth of employment in low wage occupations and the growth of workplace computer use have been faster in areas which had initially high proportions of routine workers. Goos et al. (2014) show that during the period of 1993-2010 employment has declined in routine task intensive occupations in 16 Western European countries.

The polarization of employment is also mirrored in closely linked education-level groups. Acemoglu and Autor (2011) show that in the US the demand for workers with high- and low-levels of education has increased relative to the workers with a medium-level of education. Using data from 11 OECD countries, Michaels et al. (2014) provide evidence that industries with faster growth in information and communication technologies have increased the demand for highly educated workers at the expense of middle-educated, with almost no effect on low-educated workers.

A few recent papers explore the differences in the trends of polarization across genders using US data (e.g., Cerina, Moro, and Rendall, 2016, Cortes, Jaimovich, and Siu, 2016). Cerina et al. (2016) document that job polarization is more prevalent among females than among males. The results of the current study suggest that the fall in prices of information technologies can be one of the rationales of their finding.[1]

The findings of this study complement the results of these papers. An innovation of this study is that it utilizes the industry-level variation of dependence on IT, the variation

[1] Beaudry and Lewis (2014) show that the diffusion of IT has reduced the male-female wage gap in the US and conjecture that this is because female workers have a comparative advantage in skills that complement IT. The results of this paper support their conjecture and suggest that IT might have reduced the wage gap increasing the demand for female workers more than male workers in high wage occupations.

of IT prices over countries and time, and the assignment of occupations into task/wage groups by Goos et al. (2014) to compute employment in occupation groups with different task contents. It provides international evidence corroborating the hypothesis for job polarization. By exploring differences in gender, age and education-level groups, it also uncovers some more concealed features of the effects of recent technological changes on labor markets in Europe.

The next section describes a simple model to motivate the empirical test. The third section offers the empirical specification, and describes the data and its sources. The fourth section summarizes the results. The last section concludes.

2 Theoretical Background

A fall in IT prices would increase demand for nonroutine cognitive (abstract) task intensive occupations and reduce demand for routine task intensive occupations more in industries which depend more on information technologies. I present a simple model to show explicitly how such an inference can hold and to set the stage for the empirical analysis. The model bears a resemblance to the models of Autor and Dorn (2013) and Goos et al. (2014).

The producers use abstract and routine task inputs, T_A and T_R, and information technologies, IT, to produce homogenous goods, Y. They have a CES production technology, which is given by

$$Y = \left[\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_{T_R} T_R^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}\alpha} T_A^{1-\alpha}, \tag{1}$$

where $\alpha_{IT} > 0$, $\alpha_{T_R} > 0$, $\alpha \in (0,1)$, and $\varepsilon > 1$. In the production of Y, α_{IT} measures the relative importance of IT and a higher α_{IT} implies higher share of compensation for IT. In this sense, α_{IT} measures the technological dependence on IT. In turn, ε is the elasticity of substitution between routine tasks and information technologies, and the elasticity of substitution between abstract tasks and information technologies is equal to 1 by construction. Since $\varepsilon > 1$, information technologies are more complementary to abstract tasks than to routine tasks.

The usual profit maximization implies the following conditions

$$p_{IT}IT = \alpha \frac{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_{T_R} T_R^{\frac{\varepsilon-1}{\varepsilon}}} Y, \tag{2}$$

$$p_{T_R}T_R = \alpha \frac{\alpha_{T_R} T_R^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_{T_R} T_R^{\frac{\varepsilon-1}{\varepsilon}}} Y, \tag{3}$$

$$p_{T_A}T_A = (1-\alpha) Y, \tag{4}$$

where the price of Y is normilized to 1.

I assume that the prices of task inputs and of information technologies are determined at country level. This implies that the derivative of the demand for T_A relative to T_R with respect to p_{IT} and the change of the absolute value of that derivative with α_{IT} are given by

$$\frac{\partial T_A/T_R}{\partial p_{IT}} = \frac{\varepsilon-1}{\varepsilon} \frac{\partial \ln IT}{\partial p_{IT}} \frac{1-\alpha}{\alpha} \frac{p_{T_R}}{p_{T_A}} \frac{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{T_R} T_R^{\frac{\varepsilon-1}{\varepsilon}}}, \tag{5}$$

and

$$\frac{\partial}{\partial \alpha_{IT}} \left| \frac{\partial T_A/T_R}{\partial p_{IT}} \right| = \frac{1}{\alpha_{IT}} \left| \frac{\partial T_A/T_R}{\partial p_{IT}} \right|. \tag{6}$$

It is straightforward to show that $\partial \ln IT/\partial p_{IT}$ is negative. Therefore, the decline in p_{IT} increases the demand for T_A more than the demand for T_R when $\varepsilon > 1$, according to (5). According to (6), in a country, the demand for T_A relative to T_R would increase more in industries with higher α_{IT} than in industries with lower α_{IT} with the decline in p_{IT} in such a case. This means that T_A increases and T_R declines with the fall of p_{IT} if employment in Y is fixed and these changes are larger in industries with a larger α_{IT}.[2]

These differential changes in the demand for abstract and routine tasks should be observed in the data as differential changes in the demand for high and medium wage occupation groups which perform these tasks. I look exactly for such differential changes across industries in the empirical specification.

[2] I incorporate demand for nonroutine manual tasks and close the model in the Technical Appendix. I show that such an inference also holds in general equilibrium.

3 Empirical Methodology and Data

I start with estimating the effect of the rapid fall in IT prices on employment shares in high, middle, and low wage occupations. Let Employment Share$_{c,i,t}$ be the share of employment in one of the occupation groups, industry i, country c, and year t and IT Price be the measure for the price of information technologies (p_{IT}). Assuming that I have a measure of industries' technological dependence on IT, I estimate the following specification for each occupation group:

$$\begin{aligned}\text{Employment Share}_{c,i,t} &= \beta\left[\text{Industry i's Dependence on IT}_i \times (1/\text{IT Price})_{c,t}\right] \\ &+ \sum_c \sum_i \zeta_{c,i} + \sum_c \sum_t \xi_{c,t} + \eta_{c,i,t},\end{aligned} \tag{7}$$

where ζ and ξ are country-industry and country-year fixed effects, and η is an error term. The parameter of interest is β, and country-industry and country-year fixed effects capture regulatory differences across countries and industries and the trends in relative wage rates.

An advantage of this test is that it alleviates the potential endogeneity concerns because of omitted country- and industry-level variables. Admittedly, however, this test might not fully reveal the effects of the fall in the price of information technologies on employment shares if there are economy-wide changes that are not different across industries. In such a case, this test can be also viewed as a test of whether industry-level differences exist.

The data for employment in high, medium and low wage occupations in industries are from the harmonized individual-level EU Labour Force Survey (ELFS). Occupations have ISCO-88 coding and are at 2- and 3-digit aggregation levels in this database, and industries are 1-digit NACE Rev. 1. I use sample weights, and the assignment of occupations into high, medium and low wage groups by Goos et al. (2014), to compute the number of (usual) weekly hours worked in these occupation groups in each sample industry, country and year. I derive employment shares from the number of hours worked.[3]

[3] The results are robust to using the number of persons employed instead of the number of hours.

Goos et al. (2014) also use ELFS data and exclude from the sample some of the occupations and industries because of sample imperfections and potentially large state involvement. These occupations and industries are also excluded from the analysis in this paper. Moreover, similarly to Goos et al. (2014), I use 2-digit aggregation levels for occupations throughout the analysis.

Given data availability, the analysis of this paper focuses on 10 Western European countries and the period between 1993 and 2007. The list of sample countries and the sample period for each country are offered in Table 1. Table 2 offers the averages of employment shares in high, medium and low wage occupations in sample industries in Panel *A*.[4] Overall, services industries tend to have higher shares of employment in high and low wage occupations and a lower share of employment in middle wage occupations as compared to manufacturing industries.

I also retrieve information from the ELFS database on the levels of education, age groups and gender. There are three levels of education in this database: pre-primary to lower-secondary (low; ISCED-97 0-2), secondary to post-secondary and non-tertiary (medium; ISCED-97 3-4) and tertiary (high; ISCED-97 5-6). The data for age are in five year bands, and the minimum age is 17. I restrict the maximum age to 62 and create three age groups: young (younger than 32), middle-age (between 32 and 47), and old (older than 47). I compute the number of hours worked in each of these categories for all occupation group-industry cells in sample countries and years. Table 3 offers basic statistics for the employment shares in high, medium and low wage occupations within each of these categories. The data reveal seemingly intuitive patterns. On average, men work more in high wage occupations and less in low wage occupations than women, which can contribute to the wage gap. The share of employment in high wage occupations is higher and the share of employment in low wage occupations is lower among medium-age and old workers than among young workers. In turn, the share of employment in high wage occupations is the highest among highly educated workers, and the share of

[4] Table 6 in the Data Appendix offers the assignment of occupations into high, medium and low wage groups. Table 14 in the Appendix - Tables and Figures offers the shares of employment in sample occupations and industries. Figure 5 in the Appendix - Tables and Figures illustrates the trends of employment shares in high, medium and low wage occupations.

employment in low wage occupations is the highest among low-educated workers.

The data for information technologies are from the EU KLEMS database (O'Mahony and Timmer, 2009). I use the share of IT capital compensation in industrial value added to construct a proxy for industries' dependence on information technologies. This proxy needs to identify the technological differences across industries (i.e., α_{IT}). To accomplish this, I follow Rajan and Zingales (1998) and use data from US industries.[5] The measure for industries' dependence on information technologies (IT Dependence) is defined as the share of IT capital compensation in industrial value added in US industries, averaged over the period of 1993-2007. The industry-level variation of the share of IT capital compensation in US industries accounts for more than 90 percent of the total variation. Moreover, this measure of industries' dependence on information technologies firmly correlates with the share of IT capital compensation in the industries of the sample European countries. These observations suggest that the dependence measure used in this paper is likely to identify the technological differences across industries but not the temporal variation because of changes in relative factor intensities.

I also need a measure for the price of information technologies, p_{IT}. To construct it, I obtain the price of investments in information technologies in industries of sample countries from the EU KLEMS database. Following the model, I normalize it with the price of value added in each industry. The price of investments in information technologies, as well as its normalized counterpart, display a large variation over time, relatively little country-level variation, and almost no industry-level variation. The over time variation can be largely attributed to the significant innovations in IT that occured over the sample years in the US and to the rise of IT production in Asia and, in particular, in China. The country-level variation is likely to be stemming from regulations that affect the access to and adoption of IT and from differences in the aggregate demand for IT. In turn, the near absence of industry-level variation suggests that the law of one price holds in sample countries. I average the price of investments in IT relative to the price of value added across industries, in sample countries and years, and use that average as the measure of

[5] Jerbashian and Kochanova (2016a,b) use similar measures and data from US industries to identify industries' dependence on information and communication technologies.

the price of information technologies, p_{IT}.

In the estimations of the baseline specification (7), I use the inverse of this measure. According to the theoretical model, β is then expected to be positive for high wage occupations and negative for medium wage occupations as p_{IT} declines and its inverse increases.

Table 1 offers basic statistics for the price of information technologies in Panel A. The price of information technologies has fallen everywhere.[6] Panel B of Table 1 reports the correlation of the measure of dependence with the share of IT capital compensation in industrial value added in the sample European countries. Panel B of Table 2 offers the values of the dependence measure in sample industries.

It is worth to outline the interpretation of the coefficient of interest, β. Roughly speaking, the difference-in-differences estimator in (7) splits the sample into four groups according to the magnitude of the fall in prices of information technologies and the dependence on these technologies. For each year, these four groups are composed of the industry-country pairs with high fall in prices and high dependence (HF&HD), industry-country pairs with high fall in prices and low dependence (HF&LD), pairs with low fall in prices and high dependence (LF&HD), and pairs with low fall in prices and low dependence (LF&LD). The coefficient β, in this respect, represents the difference in the trends of employment in occupation groups between HF&HD industry-country pairs relative to HF&LD industry-country pairs and LF&HD pairs relative to LF&LD pairs. It is positive (negative) for an occupation group if employment in that group grows at a higher (lower) rate in HF&HD industry-country pairs relative to HF&LD industry-country pairs than in LF&HD pairs relative to LF&LD pairs.[7]

I take the residuals from a regression of the share of employment in an occupation group on country-industry and country-year dummies to illustrate the existence of such differential trends. Panels A and B of Figure 1 show that there are such disparities

[6] I average the price of information technologies across sample countries and illustrate its trend over time in Figure 6 in the Appendix - Tables and Figures.

[7] The coefficient of interest β is identified from the temporal and country-level variation of IT prices and the variation of technological dependence on IT across industries. Utilizing the temporal variation of IT prices allows this study to focus on significant and omnipresent advances of IT.

in employment trends for high and medium wage occupations. These panels show that employment has increased (declined) more rapidly in high (medium) wage occupations in industries with high IT dependence relative to industries with low IT dependence, with the fall in IT prices. Panel C of Figure 1 shows that there are no distinguishable differential trends in low wage occupations. Moreover, there seem to be no trends at all for low wage occupations, which suggests that, on average, employment in low wage occupations is likely to be not affected by the fall in IT prices, at least directly.[8]

4 Results

Panel A of Table 4 presents the results from the estimation of the specification (7) for the shares of employment in high, medium and low wage occupations. The estimates of the coefficient β are significant and positive for the share of high wage occupations and negative for the share of medium wage occupations. These estimates imply that the fall in the price of information technologies is associated with higher demand for high wage occupations and lower demand for medium wage occupations. Conversely, the estimate of the coefficient β is not significant for the share of employment in low wage occupations. This suggests that, on average, information technologies are not likely to have direct effects on the share of employment in low wage occupations.

One way to compute the magnitude of these results is as follows. I take the countries and years where IT prices are the lowest and the highest and compute the difference between the levels of the inverse of IT prices for them. Further, I take the industries that rank the lowest and the highest in terms of the level of dependence on IT and compute the difference between dependence levels. Finally, I compute

$$\hat{\beta} \times \Delta 1/\text{IT Price} \times \Delta \text{IT Dependence},$$

where Δ stands for the difference operator between the lowest and the highest levels.

[8] Figures 2-4 in the Appendix - Tables and Figures offer similar evidence for employment shares in high, medium and low wage occupations in gender, age and education-level groups.

Focusing on statistically significant estimates of β, the computed effect for the share of high wage occupations is 0.183 and -0.179 for medium wage occupations. These numbers correspond to the effect of moving from the pair of country-year with the highest IT price to the pair with the lowest IT price in the highest dependence industry relative to the lowest dependence industry. They suggest that the fall in IT price has economically large and significant effect on employment shares in high and medium wage occupations, at least relative to the means of these shares, which are 0.389 and 0.387. These are of course the largest effects of the fall in IT prices according to the estimations.

I also estimate the specification (7) for the shares of employment in high, medium and low wage occupations within each gender, age and education-level group. The results are reported in Panels *B*-*I* of Table 4. They are broadly consistent with the results for the shares of employment in occupation groups in Panel *A*, with some notable differences. The fall in IT prices has increased (reduced) the share of employment in high (medium) wage occupations among women by about 50 percent more than among men according to Panels *B* and *C* of Table 4. It has increased (reduced) the share of employment in high (medium) wage occupations among old workers by about 50 percent less than among young and among medium-age workers, according to Panels *D*-*F*. The fall in IT prices has also increased (reduced) the share of employment in high (medium) wage occupations among medium-educated workers by about twice as much as among highly educated and low-educated workers according to Panels *G*-*I*.[9] These differences are economically large and statistically significant at least at the 10% level according to the standard t-test.

One possible interpretation of these results is that the levels of abstract and routine intensity of tasks performed in high, medium and low wage occupations, as well as the types of skills used in these occupations, vary with the gender, age and education-level group. For example, it is often argued that women have a comparative advantage in interpersonal communication and social skills, which tend to be prevalent in leadership tasks within high wage occupations (e.g., Borghans et al., 2014, Deming, 2015). The adoption and use of IT would then increase employment in high wage occupations among females

[9] The fall in IT prices has reduced the share of employment in low wage occupations among medium-educated workers according to Panel *H* of Table 4. However, this effect is relatively negligible.

more than among males because IT can complement these skills helping to structure, analyze and disseminate data.[10] In turn, workers in routine task intensive occupations are argued to accumulate occupation-specific skills and thus switching the occupation is more costly for these workers when they are old than when they are young (Autor and Dorn, 2009). The adoption and use of IT would then matter for the employment of old workers less than for the employment of young and medium-age workers. IT could also substitute medium-educated (medium-skill) workers in medium wage occupations more than highly educated and low-educated workers because tasks performed at this level of skill tend to be the most routine intensive (Michaels et al., 2014).

4.1 Further Results and Robustness Checks

The demand for IT is a potential source of reverse causality if industries' employment of different tasks affect it. Country-industry and country-year fixed effects in the specification (7) are likely to alleviate such reverse causality concerns given the sources of variation in IT prices. Nevertheless, I attempt to further circumvent the reverse causality concerns in two ways. Industries with the heaviest use of information technologies are the plausible candidates that affect prices of information technologies. In Panel C of Table 5, I exclude industries which have expenditures on IT higher than the 75 percentile of the distribution of IT expenditures across industries in each country and year. I also attempt to circumvent the reverse causality problem using the prices of communication technologies (CT Price), such as telephones and other communication infrastructure, as an instrumental variable. The prices of communication technologies have fallen in recent decades similarly to IT prices. This fall is mainly driven by the same technological change and growth of production in Asia as for information technologies. Communication technologies, however, are not likely to be directly related to employment in abstract and routine task requiring occupations because communication technologies are not evident complements or substitutes for these tasks. The data for the prices of communication

[10] The differences between results for women and men can also stem from differences in preferences. Women tend to favor flexible work more than men (Goldin, 2014). IT can make the work more flexible. Its adoption and use would then increase female employment, particularly in high wage occupations.

technologies are from the EU KLEMS database. Panel D of Table 5 presents the results when I instrument IT Price using the prices of communication technologies. In both cases, the estimated coefficients are close to those in Panel A of Table 4.

Omitted variables can be another source of endogeneity. It could be that the effects that the estimates in Panel A of Table 4 identify are not because of the fall in IT prices, but rather because of changes in the prices of new physical capital goods (see, e.g., Krusell, Ohanian, Ríos-Rull, and Violante, 2000). The movements in the prices of new physical capital goods could be the result of an ongoing investment specific technological change and could cause changes in the demand for physical capital and employment.

To test this hypothesis, I construct an industry-level measure for dependence on physical capital (net of information technology capital) and a country-year-level measure for the price of physical capital. The data for these measures are from the EU KLEMS database, and these measures are constructed in much similar way as the measures of dependence on IT and the price of IT. I add to the specification (7) an interaction term between the measure of dependence of industries on physical capital and the inverse of the price of physical capital. Panel E of Table 5 reports the results. The coefficient on the interaction term between IT Dependence and 1/IT Price is very close to the coefficient reported in Panel A of Table 4. The coefficient on the interaction term between dependence on physical capital and the price of physical capital is significant for the shares of employment in high and medium wage occupations and has the same sign as the coefficient on the main interaction term. These results suggest that more ubiquitous processes, such as changes in the prices of physical capital, affect the share of employment in high and medium wage occupations and this is over and above the effects of information technologies.[11]

According to the theoretical model, the parameter which measures the relative importance of routine tasks in value added, α_{T_R}, should be important for the analysis similarly to α_{IT}. It can be easily shown that the fall in IT prices increases (reduces) the demand

[11]The changes in the prices of physical capital, while affecting the demand for capital and labor, can lead to a structural change in the economy. In this respect, these results provide supporting evidence to several recent papers, which link job polarization and structural changes in the economy (e.g., Bárány and Siegel, 2015).

for abstract (routine) tasks more in industries with a low α_{T_R} than in industries with a high α_{T_R} [see equation (15) in the Technical Appendix]. A supplementary test of whether the fall in IT prices has affected employment in high, medium and low wage occupations utilizes this variation. The proxy for α_{T_R} can be constructed similarly to the proxy for α_{IT}. Ideally, I need data for wages in routine intensive occupations in order to construct such a proxy. However, there are no data for wages in the ELFS database.

I use wage compensation of medium education-level (skill) employees obtained from the EU KLEMS database as a proxy for the wages in routine intensive occupations. This can be a valid proxy because routine intensive occupations are the middle wage occupations and medium skill/education-level employment has the highest percentage within these occupations.[12] I measure α_{T_R} using the share of compensation of medium education-level employees out of value added in US industries, averaged over the period of 1993-2007. I add the interaction of this share with the inverse of IT Price to the specification (7). Panel *D* of Table 5 reports the results from this exercise. The results for the main interaction term are close to the main results in each regression. In turn, as expected, the estimated coefficient on this additional interaction term has a sign opposite to the sign of the main interaction term.

It could also be that the interaction term in the specification (7) simply identifies the effects of relative wage changes within industries. In order to alleviate such concerns, I include in the specification (7) industry group-year dummies and present the results in Panel *E* of Table 5. I also add to the specification (7) the shares of wage compensation of medium- and low-skill employees out of value added. The data for these variables are from the EU KLEMS database. Panel *F* of Table 5 reports the results. In both cases, the results are very similar to the main results suggesting that this is not likely to be a major concern.

The Appendix - Further Robustness Checks and Results provides additional robustness check exercises and results. I also perform all of these robustness checks for the shares

[12] Table 13 reports the pairwise correlations between wage compensations of high-, medium- and low-skill (education-level) employees relative to value added and employment shares in high, medium and low wage occupations. These correlations suggest that there is an intuitive correspondence between the wages of these skill and wage groups.

of employment in high, medium and low wage occupations among gender, education-level and age groups. The main results for these shares stay unaffected. For brevity, these robustness check results are not reported.

5 Conclusions

I use evidence from 10 Western European countries and the assignment of occupations into high, medium and low wage groups by Goos et al. (2014) and find that the share of employment in high wage occupations has increased with the fall in IT prices. The share of employment in middle wage occupations has declined with the fall in IT prices. In turn, I find no systematic evidence that the fall in IT prices affects the share of employment in the lowest paid occupations and that similar results hold within age, gender, and education-level groups. These results corroborate the polarization hypothesis.

I find certain important differences in gender, age and education-level groups, however. The fall in IT prices has increased (reduced) the share of employment in high (medium) wage occupations among females by about 50 percent more than among males. It has increased (reduced) the share of employment in high (medium) wage occupations among old workers by about 50 percent less than among young and medium-age workers. It has increased (reduced) the share of employment in high (medium) wage occupations among medium-educated workers by about twice as much as among highly educated and low-educated workers. All in all, these results suggest a need for a more nuanced view on the labor market effects of recent technological changes.

A possible reason for such differences is that the levels of abstract and routine intensity of tasks performed in high, medium and low wage occupations, as well as the types of skills used in these occupations, vary with gender, age and education-level groups. This then creates differences in the levels of complementarity between information technologies and tasks performed in high, medium and low wage occupations by workers of different gender, age and education-level.

6 Tables and Figures

Table 1: Sample Countries, IT Price and Correlations of IT Dependence

		A. *Basic Statistics for IT Price*					B. *Correlations*
Country	Sample Period	Mean	SD	Min	Max	Δ IT Price	IT Dependence
Austria	1995-2007	0.350	0.276	0.102	1.000	-0.087	0.617
Denmark	1993-2007	0.453	0.444	0.083	1.435	-0.114	0.595
Finland	1997-2007	0.218	0.149	0.077	0.562	-0.061	0.921
Germany	1993-2007	0.538	0.411	0.094	1.376	-0.094	0.786
Italy	1993-2007	0.451	0.438	0.083	1.404	-0.107	0.936
Netherlands	1993-2007	0.464	0.438	0.102	1.430	-0.107	0.975
Portugal	1993-2007	0.358	0.286	0.120	1.000	-0.088	0.609
Spain	1993-2007	0.496	0.385	0.127	1.280	-0.090	0.914
Sweden	1997-2007	0.545	0.230	0.228	0.849	-0.059	0.909
UK	1993-2007	0.490	0.408	0.105	1.249	-0.091	0.916

Note: Columns 1-2 of this table list sample countries and period. Panel *A* offers basic statistics for the price of information technologies (IT Price). Column 5 of Panel *A* offers the average change in IT Price over the sample period in each country (Δ IT Price). Panel *B* offers the pairwise correlations of the measure of dependence on information technologies (IT Dependence) and the shares of IT capital compensation in the industries of the sample of European countries. All correlations are significant at least at the 10% level. See Table 6 in the Data Appendix for complete descriptions and sources of variables.

Table 2: Average Employment Shares in Sample Industries and IT Dependence

		A. Average Employment Shares				*B. IT Dependence*
Industry Name	Industry Code	Obs	High Wage	Medium Wage	Low Wage	Value of IT Dependence
Manufacturing	D	140	0.274	0.639	0.087	0.012
Electricity, Gas and Water Supply	E	140	0.390	0.549	0.061	0.010
Construction	F	140	0.176	0.736	0.088	0.004
Wholesale and Retail Trade; Repair of Goods	G	140	0.368	0.289	0.343	0.018
Hotels and Restaurants	H	140	0.279	0.071	0.650	0.004
Transport, Storage, and Communication	I	140	0.234	0.659	0.107	0.019
Financial Intermediation	J	140	0.567	0.414	0.020	0.057
Real Estate, Renting, and Business Activities	K	140	0.639	0.201	0.160	0.016
Health and Social Work	N	140	0.538	0.096	0.366	0.007
Other Community and Personal Service Activities	O	140	0.427	0.211	0.362	0.006

Note: Panel *A* of this table offers the averages of employment shares in high, medium and low wage occupations in sample industries. Averages are taken across sample countries and period. Panel *B* offers the values of the measure of dependence on information technologies (IT Dependence) in sample industries. Similarly to Goos et al. (2014), industries Agriculture, Hunting, and Fishing (NACE A-B), Mining and Quarrying (NACE C), Public Administration; Social Security (NACE L), Education (NACE M), and Extra-territorial Organizations and Bodies (NACE Q) are excluded from the analysis. I also exclude from the analysis Households with Employed Persons (NACE P) industry because there is no data for it in the EU KLEMS database. See Table 6 in the Data Appendix for complete descriptions and sources of variables.

Table 3: Shares of Employment in High, Medium and Low Wage Occupations within Gender, Age and Education-Level Groups

	A. Share within Genders						*B. Share within Age Groups*						*C. Share within Education-Levels*					
Occupation Group	Gender	Obs	Mean	SD	Min	Max	Age Group	Obs	Mean	SD	Min	Max	Education Level	Obs	Mean	SD	Min	Max
High Wage	Male	1392	0.440	0.212	0.038	0.954	Young	1359	0.295	0.182	0.013	0.899	High	1200	0.735	0.166	0.075	0.994
Medium Wage		1392	0.381	0.255	0.002	0.838		1359	0.421	0.265	0.017	0.936		1200	0.172	0.132	0.002	0.616
Low Wage		1392	0.179	0.171	0.000	0.907		1359	0.284	0.248	0.001	0.929		1200	0.093	0.129	0.000	0.911
High Wage	Female	1386	0.355	0.145	0.033	0.846	Medium	1383	0.422	0.188	0.040	0.941	Medium	1333	0.348	0.158	0.059	0.897
Medium Wage		1386	0.371	0.225	0.015	0.863	Age	1383	0.373	0.246	0.009	0.844		1333	0.424	0.239	0.017	0.888
Low Wage		1386	0.274	0.231	0.002	0.937		1383	0.205	0.192	0.002	0.919		1333	0.228	0.221	0.001	0.876
High Wage							Old	1396	0.423	0.172	0.045	0.906	Low	1333	0.191	0.126	0.000	0.858
Medium Wage								1396	0.372	0.241	0.008	0.830		1333	0.452	0.279	0.007	0.939
Low Wage								1396	0.206	0.181	0.002	0.920		1333	0.357	0.256	0.005	0.967

Note: This table offers basic statistics for the shares of employment in high, medium and low wage occupations within gender, age and education-level groups in sample industries, countries and time. There are three age groups: young (between 17 and 32), medium-age (between 32 and 47) and old (between 47 and 62). Education levels are low (ISCED-97 0-2), medium (ISCED-97 3-4) and high (ISCED-97 5-6). Panel *A* offers basic statistics for the share of employment in high, medium and low wage occupations within each gender. Panel *B* offers basic statistics for the share of employment in high, medium and low wage occupations within each age group. Panel *C* offers basic statistics for the share of employment in high, medium and low wage occupations within each education-level. See Table 6 in the Data Appendix for complete descriptions and sources of variables.

Table 4: Results for Employment Shares in High, Medium and Low Wage Occupations and within Genders, Age and Education-Level Groups

	(1) High Wage	(2) Medium Wage	(3) Low Wage	(1) High Wage	(2) Medium Wage	(3) Low Wage	(1) High Wage	(2) Medium Wage	(3) Low Wage
	A. All			*B. Within Males*			*C. Within Females*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
IT Dependence	0.217***	-0.212***	-0.005	0.156***	-0.152***	-0.004	0.235***	-0.237***	0.001
× 1/IT Price	(0.026)	(0.022)	(0.017)	(0.028)	(0.028)	(0.020)	(0.034)	(0.033)	(0.019)
Obs	1,360	1,360	1,360	1,352	1,352	1,352	1,347	1,347	1,347
R2 (Partial)	0.083	0.122	0.000	0.040	0.054	0.000	0.050	0.062	0.000
	D. Within Young			*E. Within Medium-Age*			*F. Within Old*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
IT Dependence	0.219***	-0.220***	0.000	0.235***	-0.232***	-0.004	0.160***	-0.133***	-0.028
× 1/IT Price	(0.038)	(0.042)	(0.020)	(0.034)	(0.031)	(0.019)	(0.034)	(0.026)	(0.025)
Obs	1,319	1,319	1,319	1,343	1,343	1,343	1,356	1,356	1,356
R2 (Partial)	0.051	0.059	0.000	0.061	0.088	0.000	0.030	0.037	0.001
	G. Within Highly Educated			*H. Within Medium Educated*			*I. Within Low Educated*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
IT Dependence	0.147***	-0.108***	-0.038	0.294***	-0.222***	-0.071***	0.152***	-0.134***	-0.018
× 1/IT Price	(0.043)	(0.034)	(0.027)	(0.035)	(0.031)	(0.025)	(0.056)	(0.050)	(0.026)
Obs	1,172	1,172	1,172	1,297	1,297	1,297	1,293	1,293	1,293
R2 (Partial)	0.019	0.018	0.002	0.089	0.083	0.007	0.028	0.022	0.000

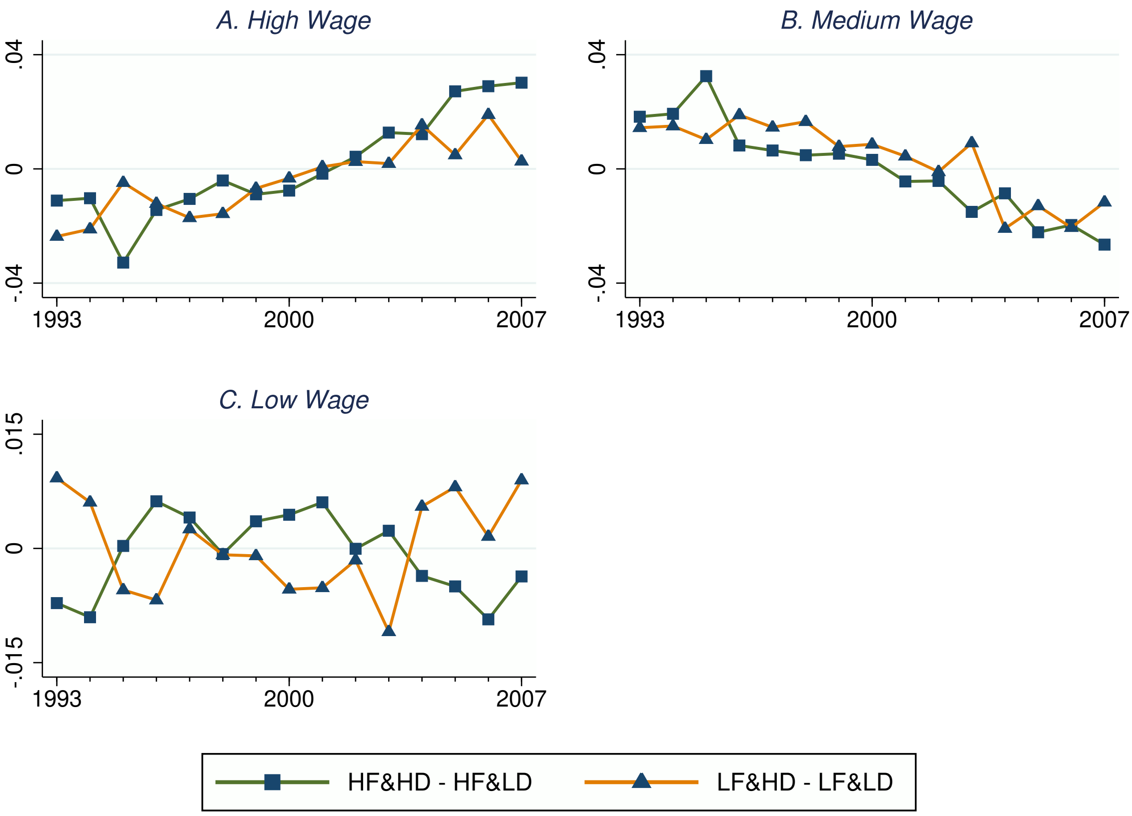
Note: This table offers the results from the estimation of the specification (7) for the shares of employment in high, medium and low wage occupations in sample industries. In Panel *A*, dependent variables are the shares of employment. In Panels *B* and *C*, dependent variables are the shares of employment in high, medium and low wage occupations within males and females, respectively. In Panels *D*, *E* and *F*, dependent variables are the shares of employment in high, medium and low wage occupations within young, medium-age and old workers (in employment hours), respectively. In Panels *G*, *H* and *I*, dependent variables are the shares of employment in high, medium and low wage occupations within highly, medium- and low-educated workers (in employment hours), respectively. See Table 6 in the Data Appendix for complete descriptions and sources of variables. All regressions include country-industry and country-year dummies and use the least squares estimation method. Standard errors are in parentheses. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. ** indicates significance at the 1% level, * at the 5% level, and at the 10% level.

Table 5: Further Results - Sample Restrictions, Instrumental Variables and Additional Variables

	(1) High Wage	(2) Medium Wage	(3) Low Wage	(1) High Wage	(2) Medium Wage	(3) Low Wage	(1) High Wage	(2) Medium Wage	(3) Low Wage
	A. W/o High IT Compensation Industries			*B. Instrumental Variables*			*C. Capital Dependence*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
IT Dependence	0.395***	-0.416***	0.021	0.220***	-0.202***	-0.018	0.215***	-0.210***	-0.005
× 1/IT Price	(0.057)	(0.060)	(0.044)	(0.029)	(0.028)	(0.016)	(0.026)	(0.024)	(0.018)
Capital Dependence							0.190*	-0.178*	-0.012
× 1/Capital Price							(0.108)	(0.100)	(0.070)
Obs	963	963	963	1,360	1,360	1,360	1,360	1,360	1,360
R2 (Partial)	0.083	0.151	0.000	0.083	0.122	-0.000	0.086	0.126	0.000
	D. Medium-Skill Dependence			*E. Industry Group × Year Dummies*			*F. Medium- and Low-Skill Wage Rates*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
IT Dependence	0.171***	-0.161***	-0.010	0.187***	-0.196***	0.010	0.305***	-0.275***	-0.030
× 1/IT Price	(0.030)	(0.026)	(0.018)	(0.033)	(0.027)	(0.024)	(0.043)	(0.035)	(0.032)
Medium-Skill Dependence	-0.012***	0.013***	-0.001						
× 1/IT Price	(0.003)	(0.003)	(0.002)						
Medium Skill							-0.028	0.138***	-0.109
Wage Rate							(0.088)	(0.046)	(0.069)
Low Skill							-0.085	0.196**	-0.111
Wage Rate							(0.143)	(0.088)	(0.106)
Obs	1,360	1,360	1,360	1,360	1,360	1,360	980	980	980
R2 (Partial)	0.102	0.158	0.000	0.037	0.065	0.000	0.107	0.176	0.006

Note: This table offers the results from the estimation of the specification (7) for the shares of employment in high, medium and low wage occupations. The dependent variable is employment share in the corresponding occupation group within industry-country-year cells. Panel *A* offers the results for a sample which, in each sample country and year, excludes industries that have IT compensation higher than the 75 percentile of the distribution of IT compensation across industries. Panel *B* offers the results from the estimation of the specification (7) where the interaction term is instrumented using the interaction between IT Dependence and the inverse of the price of communication technologies (CT Price). The first stage F statistic is highly significant $[F(1,9) = 84.40, p < 0.000]$. Panels *C*-*F* augment the specification (7) with additional variables. Panel *C* adds to the specification (7) the interaction between the inverse of non-IT capital price (Capital Price) and the dependence of industries on non-IT capital (Capital Dependence). Panel *D* adds to the specification (7) the interaction between 1/IT Price and Medium-Skill Dependence which is a proxy for α_{T_R}. Panel *E* adds industry group-year dummies to the specification (7). There are 5 groups of sample 1-digit NACE industries: (1) D and E; (2) F and G; (3) H and I; (4) J and K; and (5) N and O. Panel *F* adds to the specification (7) the shares of wage compensation of medium- and low-skill employees out of value added (Medium-Skill Wage Rate and Low-Skill Wage Rate). The estimation method is 2 stage GMM in Panel *B* and least squares in the remaining panels. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. ** indicates significance at the 1% level, * at the 5% level, and at the 10% level.

Figure 1: Employment Shares in High, Medium and Low Wage Occupations in High and Low IT Dependence Industries



Note: This figure illustrates the differences in the trends of employment shares of high, medium and low wage occupations in industry-country pairs with high and low fall in IT prices and high and low IT dependence. The curves with square tick symbols are the difference between the employment shares in industries with high IT Dependence and industries with low IT Dependence among countries and years where and when the fall in IT Price is relatively high (HF&HD - HF&LD). The curves with triangle tick symbols are the difference between the employment shares in industries with high IT Dependence and industries with low IT Dependence among countries and years where and when the fall in IT Price is relatively low (LF&HD - LF&LD). The employment shares in this figure are the residuals from an OLS regression of employment shares on country-industry and country-year dummies. In each of the four groups, these shares are averaged over countries and industries. An industry has high (low) dependence on IT if its IT Dependence is above (below) the median IT Dependence across industries. For a given year, the fall in IT Price in a country-year pair is relatively high (low) if the fall in IT Price (relative to its previous level) in that pair is lower (higher) than the median change in IT Price across countries in that year. It is sufficient to compare to the change because IT Price has declined everywhere. See Table 6 in the Data Appendix for complete descriptions and sources of variables and for the assignment of occupations into high, medium and low wage groups.

A Data Appendix

Table 6: Definitions and Sources of Variables

Variable Name	Definition and Source
Capital Dependence	The share of non-IT capital compensation out of value added in US industries, averaged over the period of 1993-2007. Source: EU KLEMS.
Capital Price	The price of investments in physical capital relative to the price of value added in sample industries. It is averaged across industries, within countries and years. All prices are normalized to 1 in 1995. I use the inverse of this measure in estimations. Source: EU KLEMS.
CT Price	The price of investments in communication technologies relative to the price of value added in sample industries. It is averaged across industries, within countries and years. All prices are normalized to 1 in 1995. I use the inverse of this measure in estimations. Source: EU KLEMS.
IT Dependence	The share of IT capital compensation out of value added in US industries, averaged over the period of 1993-2007. Source: Author's calculations using data from EU KLEMS.
IT Price	The price of investments in information technologies relative to the price of value added in sample industries (p_{IT}). It is averaged across industries, within countries and years. All prices are normalized to 1 in 1995. I use the inverse of this measure in estimations. Source: EU KLEMS.
Medium-Skill Dependence	The share of medium-skill/educated workers' wage compensation out of value added in US industries, averaged over the period of 1993-2007. Medium-skill/educated workers have education level 3-4 of ISCED-97, which corresponds to secondary to post-secondary and non-tertiary education. Source: EU KLEMS.
Medium-Skill Wage Rate	The share of medium-skill/educated workers' wage compensation out of value added in the industries of the sample Western European countries. Medium-skill/educated workers have education level 3-4 of ISCED-97, which corresponds to secondary to post-secondary and non-tertiary education. Source: EU KLEMS.

Table 6 − (Continued)

Variable Name	Definition and Source
Low-Skill Wage Rate	The share of low-skill/educated workers' wage compensation out of value added in the industries of the sample Western European countries. Low-skill/educated workers have education level 0-2 of ISCED-97, which corresponds to pre-primary to lower-secondary education. Source: EU KLEMS.
Group	**Description**
Age Group	There are three age groups: young (between 17 and 32), medium-age (between 32 and 47) and old (between 47 and 62).
High IT Compensation Industries	The industries that have IT compensation higher than the 75 percentile of the distribution of IT compensation across industries within each sample country and year. Source: EU KLEMS.
Occupation (Wage) Group	Occupations are grouped into three wage groups: high, medium and low wage. High wage occupations are ISCO-88 12, 13, 21, 22, 24, 31, 32 and 34. Medium wage occupations are ISCO-88 41, 42, 71, 72, 73, 74, 81, 82 and 83. Low wage occupations are ISCO-88 51, 52, 91 and 93. See Table 14 in the Appendix - Tables and Figures for occupation names. Source: Goos et al. (2014).

Data Sources: December 2015 release of the EU Labour Survey database; March 2011 update of November 2009 release of the EU KLEMS database (and March 2008 release of the EU KLEMS database for Portugal).

Industry Sample (NACE rev. 1): D, E, F, G, H, I, J, K, N, and O.

Acknowledgements

I would like to thank Matias Cortes, Štěpán Jurajda, Anna Kochanova and seminar participants at the the Armenian Economic Association Meeting in Yerevan (2016) for thoughtful comments. I gratefully acknowledge the financial support from the Spanish Ministry of Education and Science through grant ECO2015-66701-R and from the Generalitat of Catalonia through grant 2014SGR493. All errors remain my own.

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B Technical Appendix

I close the model assuming a representative consumer. The consumer derives utility from the consumption of a Cobb-Douglas aggregate of Y and manual tasks, T_M,

$$U = Y^{\mu} T_M^{1-\mu}, \tag{8}$$

were $\mu \in (0, 1)$. It supplies all the factor inputs and forms the demand for Y. Its expenditures are covered by the payments on factor inputs. The consumer solves the following problem

$$\max_{Y, T_A, T_R, T_M} U$$

$$s.t.$$

$$Y = p_A T_A + p_R T_R + p_{IT} IT, \tag{9}$$

$$T = A_A T_A + A_R T_R + T_M, \tag{10}$$

where A_A and A_R are productivity levels and the productivity of T_M is normalized to 1. The price of information technologies p_{IT} is exogenously given and information technologies IT have an undetermined/unlimited supply.

Let λ_1 and λ_2 be the shadow values attached to the constraints (9) and (10), respectively. The optimal rules that follow from the consumer's problem are

$$\lambda_1 Y = \mu Y^{\mu} T_M^{1-\mu}, \tag{11}$$

$$\lambda_2 T_M = (1 - \mu) Y^{\mu} T_M^{1-\mu}, \tag{12}$$

$$\lambda_1 p_{T_A} = \lambda_2 A_A, \tag{13}$$

$$\lambda_1 p_{T_R} = \lambda_2 A_R. \tag{14}$$

I normalize T_R to 1 in order to show that the inference in (6) also holds in general equilibrium. From (1), (3), (4), and (11)-(14) it follows that T_A, relative to T_R, can be solved from the following equation:

$$T_A = \frac{1-\alpha}{\alpha}\frac{A_R}{A_A}\left(\frac{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{T_R}} + 1\right).$$

This is basically the analogue of the ratio between (3) and (4), where prices are replaced by productivity levels. The derivative of T_A with respect to p_{IT} is given by

$$\frac{\partial T_A}{\partial p_{IT}} = \frac{\varepsilon-1}{\varepsilon}\frac{A_R}{A_A}\frac{1-\alpha}{\alpha}\frac{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{T_R} T_R^{\frac{\varepsilon-1}{\varepsilon}}}\frac{\partial \ln IT}{\partial p_{IT}}.$$

Clearly, this is negative when $\varepsilon > 1$. Therefore, T_A increases more than T_R with the decline of p_{IT}. The derivative of the absolute value of this expression with respect to α_{IT} is given by

$$\frac{\partial}{\partial \alpha_{IT}}\left|\frac{\partial T_A}{\partial p_{IT}}\right| = \frac{1}{\alpha_{IT}}\left|\frac{\partial T_A}{\partial p_{IT}}\right|,$$

which is positive. In turn, the derivative of the absolute value of this expression with respect to α_{T_R} is given by

$$\frac{\partial}{\partial \alpha_{T_R}}\frac{\partial T_A}{\partial IT} = -\frac{1}{\alpha_{T_R}}\left|\frac{\partial T_A}{\partial p_{IT}}\right|, \tag{15}$$

which is negative.

In what follows, I provide conditions which guarantee that T_A and T_M grow as p_{IT} declines and IT increases. I normalize A_A and A_R to one to keep notation to minimum. From (1), (3), (4), (10) and (11)-(14) it follows that the system of equilibrium equations can be rewritten and reduced to

$$0 = T - (1+\phi)\,T_A - \frac{\alpha}{1-\alpha}\frac{\alpha_{T_R}\left[T-(1+\phi)\,T_A\right]^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_{T_R}\left[T-(1+\phi)\,T_A\right]^{\frac{\varepsilon-1}{\varepsilon}}}T_A, \tag{16}$$

$$T_M = \phi T_A, \tag{17}$$

where $\phi = \frac{1-\mu}{\mu(1-\alpha)}$.

I use F to denote

$$F = T - (1+\phi)\,T_A - \frac{\alpha}{1-\alpha}\frac{\alpha_{T_R}\left[T-(1+\phi)\,T_A\right]^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_{T_R}\left[T-(1+\phi)\,T_A\right]^{\frac{\varepsilon-1}{\varepsilon}}}T_A.$$

The partial derivatives of F with respect to T_A and IT are given by

$$\begin{aligned}\frac{\partial F}{\partial T_A} = & -\frac{\alpha}{1-\alpha}\frac{\alpha_{T_R}\left[T-(1+\phi)\,T_A\right]^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{IT}IT^{\frac{\varepsilon-1}{\varepsilon}}+\alpha_{T_R}\left[T-(1+\phi)\,T_A\right]^{\frac{\varepsilon-1}{\varepsilon}}} \\ & -(1+\phi)\left\{1-\frac{\varepsilon-1}{\varepsilon}\frac{\alpha_{IT}IT^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{IT}IT^{\frac{\varepsilon-1}{\varepsilon}}+\alpha_{T_R}\left[T-(1+\phi)\,T_A\right]^{\frac{\varepsilon-1}{\varepsilon}}}\right\},\end{aligned} \tag{18}$$

and

$$\frac{\partial F}{\partial IT} = \left[T-(1+\phi)\,T_A\right]\frac{\varepsilon-1}{\varepsilon}\frac{\alpha_{IT}IT^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{IT}IT^{\frac{\varepsilon-1}{\varepsilon}}+\alpha_{T_R}\left[T-(1+\phi)\,T_A\right]^{\frac{\varepsilon-1}{\varepsilon}}}\frac{1}{IT}. \tag{19}$$

Clearly, $\partial F/\partial T_A$ is negative, and $\partial F/\partial IT$ is positive. The derivatives of T_A and T_M with respect to IT have the same sign and the derivative of T_A with respect to IT is given by

$$\frac{\partial T_A}{\partial IT} = -\frac{\partial F}{\partial IT}/\frac{\partial F}{\partial T_A}, \tag{20}$$

which is positive. Therefore, T_A and T_M grow as p_{IT} declines and IT increases, and T_R declines (when T is fixed).[13]

Using (18) and (19), it can be shown that

$$\begin{aligned}\frac{\partial}{\partial \alpha_{IT}}\frac{\partial F}{\partial T_A} &> 0, \\ \frac{\partial}{\partial \alpha_{IT}}\frac{\partial F}{\partial IT} &> 0,\end{aligned}$$

which implies that

$$\frac{\partial}{\partial \alpha_{IT}}\frac{\partial T_A}{\partial IT} > 0,$$

according to (20). Therefore, T_A grows as p_{IT} declines and IT increases and that growth is stronger in industries with a bigger α_{IT}.

[13]In this model, T_R tends to 0 as p_{IT} tends to 0 and IT tends to infinity.

C Appendix - Further Robustness Checks and Results

This section presents the results from further robustness check exercises. It also offers additional results. I conduct robustness checks with respect to the sample of years, industries and countries, identifying assumptions and measures.

Figure 1 suggests that there can be differences in the trends of employment before and after 2001. I estimate the specification (7) restricting sample period to 1993-2001 and present the results in Panel A of Table 7. Import competition can matter for employment shares in high, medium and low wage occupations (Autor, Dorn, and Hanson, 2015). Panel B of Table 7 reports the results when I exclude from the sample Manufacturing, the tradable industry. All of these results are qualitatively no different from the main results offered in Panel A of Table 4.

The measure of IT Dependence is defined as the share of IT capital compensation in US industries out of value added, averaged over the sample period. Around 90 percent of the variation in the share of IT capital compensation in US industries is at industry level according to Table 10. Therefore, this measure is likely to identify technological differences across industries. However, this measure of dependence would be valid for the current exercise if US industries are technologically similar to the industries of the sample Western European countries. This seems to be the case according to the correlations reported in Table 1.

In order to alleviate potential concerns, I use data from the sample Western European countries to construct an alternative measure of dependence on information technologies, IT Dependence EU. IT Dependence EU is defined as the share of IT capital compensation out of value added in industries of the sample Western European countries, averaged over the sample countries and period. The correlation between this measure and the main measure of dependence is 0.944.[14] I estimate the specification (7) with this measure and report the results in Panel A of Table 8. These are qualitatively no different from the

[14] According to Table 11, industry-level variation explains more than 50 percent of the variation of the share of IT compensation out of value added in industries of the sample Western European countries.

main results.

In the EU KLEMS database, the prices of information technologies relative to the prices of value added have a small variation across industries within each country and year according to Table 12. This can be the result of slight differences in terms of IT inputs across industries and differences of prices of industrial value added. In the main text, I take the average of these prices across industries within each country and year. In Panel B of Table 8, I use the prices of information technologies, relative to the prices of value added, without taking the averages (IT Price Ind). The results are similar to the main results.

I use the prices of information technologies to analyze the effects of recent technological changes on employment. This involves trade-offs. The prices of information technologies are usually better measured and constructed under less strict assumptions than the series of capital, for example. The variation of prices is more likely to reflect exogenous technical changes than the variation in investment and capital series because the latter entail an additional margin of decision making. However, the series of prices of information technologies might not fully reflect the actual adoption of information technologies. In Panel C of Table 8, I use real investments in IT relative to real value added in sample industries (IT Investments), instead of 1/IT Price, in order to alleviate such concerns.[15] The estimate on the interaction term is significant and positive for the share of employment in high wage occupations. It is negative for the share of employment in medium wage occupations. These results corroborate the hypothesis for job polarization suggesting that, as investments in IT have grown, industries which depend more on IT have increased (reduced) the demand for high (medium) wage occupations more than industries which depend less.

Left-hand side variables in all regressions are shares and are between 0 and 1. I estimate the specification (7) using Tobit with $(0, 1)$ censoring. Panel A of Table 9 summarizes the results. These are almost identical to the main results.

I also estimate the specification (7) for all NACE 1-digit industries for which there

[15]The correlation between IT Investments and IT Price Ind is -0.381 and is significant at the 1% level.

are data in the ELFS and EU KLEMS databases. Panel *B* of Table 9 reports the results, which are very close to the main results.

C.A Not Reported Robustness Checks and Results

I continue performing robustness checks, but do not report the results for brevity. Offshoring can matter for employment shares according to Goos et al. (2014), although its effect in industries with different levels of dependence on IT is not *a priori* clear. To check whether offshoring can affect the results, I exclude from the analysis occupations which have offshorability score higher than the 75th percentile of offshorability index offered by Goos et al. (2014). Excluding these occupations does not have any significant effect on the results.

Panel *B* of Table 7 reports the results when I exclude from the sample Manufacturing, the tradable industry. All of these results are qualitatively no different from the main results offered in Panel *A* of Table 4.

In the main text, I compute employment shares in industry-occupation pairs using (usual) weekly hours worked. I have checked that the results are robust to using the number of persons employed instead of the number of hours.

The possible changes of employment in manual tasks are disregarded in equation (6). As a robustness check, I compute industry-level employment as a sum of employment in high and medium wage occupations and compute employment shares in industry-occupation pairs using this measure of employment. The results which I obtain are very similar to the main results for high and medium wage occupations.

An alternative way of measuring the dependence on IT uses the share of IT compensation of the industries of the sample Western European countries and allows it to vary across years and countries. Another alternative measure predicts IT Dependence EU using the measure identified with US data, IT Dependence. I use these alternative measures and obtain results very similar to the main results.

A flexible way of controlling for possible trends and differences in initial values is to include the lagged dependent variable in the regression. I do so and obtain results which are qualitatively similar to the main results.[16]

In the main text, the coefficient of interest β is identified from temporal and country-level variation of 1/IT Price and industry-level variation of IT Dependence. As a robustness check, I disregard country-level variation taking the averages of the shares of employment and 1/IT Price across countries and estimating a version of specification (7) with industry and year dummies. I obtain results which are similar to the main results, though the inference regarding the differences across genders is somewhat weaker.

There can be problems with the kinkiness of the data which can be observed for some occupation groups. I fit third order polynomials on the shares of employment in each occupation group-industry-country triple using time variation. I use these polynomials in the estimation of the specification (7). The results that I obtain are similar to the main results. I also drop the first and the last percentiles of the distribution of employment shares in each country. Again, the results are close to the main results.

The number of observations has a small variation in samples which I use for estimations for gender, education-level and age groups. I check that all the results hold in case the samples are restricted to be equal.

I use the March 2011 update of the November 2009 release of the EU KLEMS database for all countries except Portugal. For Portugal, I use the March 2008 release of the EU KLEMS database. I exclude Portugal from the sample of counties and obtain results which are similar to the main results. In the ELFS and EU KLEMS databases there is information for the Czech Republic and Slovenia. I include these countries in the analysis. This does not effect the results.

I use all the available temporal variation in order to identify β. This allows to fully utilize the significant and omnipresent advances in information technologies over the sample period. I also attempt to estimate β using long differences. I take the differences between sample initial and end values in industry-country pairs in the specification (7) and estimate it for those differences including industry-fixed effects in it. This exercise provides estimates of β which have the same sign as the main estimates, but are not

[16] This exercise might be taken with caution because of the fixed effects estimation and the resulting mechanical endogeneity of the lagged dependent variable.

statistically significant. A reason for this is that taking long differences reduces the number of observations by about 10 times.

I also perform all these robustness checks for the shares of employment in high, medium and low wage occupations within education-level, gender and age groups and obtain results which are similar to the main findings. The results from all not reported robustness checks are available upon request.

D Appendix - Tables and Figures

Table 7: Robustness Checks - Sample Restrictions

	High Wage	Medium Wage	Low Wage	High Wage	Medium Wage	Low Wage
	A. Sample Period Till 2001			*B. W/o Tradeable Industries*		
	(1)	(2)	(3)	(1)	(2)	(3)
IT Dependence	0.211***	-0.170***	-0.041	0.217***	-0.213***	-0.004
$\times$ 1/IT Price	(0.062)	(0.060)	(0.032)	(0.026)	(0.025)	(0.018)
Obs	780	780	780	1,224	1,224	1,224
R2 (Partial)	0.035	0.031	0.002	0.087	0.133	0.000

Note: This table offers the results from the estimation of the specification (7) for the shares of employment in high, medium and low wage occupations. The dependent variable is employment share in the corresponding occupation group within industry-country-year cells. Panel *A* offers the results from the estimation of the specification (7) where years after 2001 are excluded from the sample. In Panel *A*, IT Dependence is defined as the share if IT capital compensation out of value added in US industries, averaged over 1993-2001. In Panel *B*, tradeable industries (Manufacturing, NACE D) are excluded from the sample. See Table 6 in the Data Appendix for complete descriptions and sources of variables. All regressions include country-industry and country-year dummies and and use the least squares estimation method. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. ** indicates significance at the 1% level, * at the 5% level, and at the 10% level.

Table 8: Robustness Checks - Measures for Industry Dependence and IT Price, and IT Investments

	High Wage	Medium Wage	Low Wage	High Wage	Medium Wage	Low Wage	High Wage	Medium Wage	Low Wage
	A. IT Dependence EU			*B. IT Price Ind*			*C. IT Investments*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
IT Dependence EU	0.278***	-0.246***	-0.031						
× 1/IT Price	(0.034)	(0.033)	(0.024)						
IT Dependence				0.213***	-0.206***	-0.007			
× 1/IT Price Ind				(0.028)	(0.025)	(0.020)			
1/IT Price Ind				-0.009***	0.009***	0.000			
				(0.002)	(0.001)	(0.002)			
IT Dependence							11.656***	-11.758***	0.102
× IT Investments							(1.499)	(1.454)	(1.041)
IT Investments							-0.035	0.147***	-0.113***
							(0.053)	(0.038)	(0.038)
Obs	1,360	1,360	1,360	1,360	1,360	1,360	1,360	1,360	1,360
R2 (Partial)	0.068	0.082	0.001	0.103	0.151	0.000	0.051	0.066	0.009

Note: This table offers the results from the estimation of the specification (7) for the shares of employment in high, medium and low wage occupations. The dependent variable is employment share in the corresponding occupation group within industry-country-year cells. Panel *A* offers the results from the estimation of the specification (7) where I use an alternative measure for dependence on information technologies, IT Dependence EU. This measure is defined as the share of IT capital compensation in industries of the sample Western European countries, averaged over the sample countries and period. In Panel *B*, I use IT prices which vary between industries, within each country and year (IT Price Ind). In Panel *C*, I use the ratio of real IT investments and value added in industries of sample countries (IT Investments) in the interaction term, instead of IT Price. See Table 6 in the Data Appendix and Table 15 for complete descriptions and sources of variables. All regressions include country-industry and country-year dummies and use the least squares estimation method. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. ** indicates significance at the 1% level, * at the 5% level, and at the 10% level.

Table 9: Robustness Checks - Tobit and All Industries

	High Wage	Medium Wage	Low Wage	High Wage	Medium Wage	Low Wage
	A. Tobit			*B. All Industries*		
	(1)	(2)	(3)	(1)	(2)	(3)
IT Dependence	0.217***	-0.212***	-0.005	0.204***	-0.207***	0.003
$\times$ 1/IT Price	(0.025)	(0.025)	(0.018)	(0.029)	(0.024)	(0.015)
Obs	1,360	1,360	1,360	1,895	1,895	1,895
R2 (Partial)				0.040	0.057	0.000

Note: This table offers the results from the estimation of the specification (7) for the shares of employment in high, medium and low wage occupations. The dependent variable is employment share in the corresponding occupation group within industry-country-year cells. Panel *A* offers the results from the estimation of the specification (7) using Tobit with $(0, 1)$ censoring. In Panel *B*, I add Agriculture, Hunting, and Fishing (NACE A-B), Mining and Quarrying (NACE C), Public Administration; Social Security (NACE L), Education (NACE M), and Extra-territorial Organizations and Bodies (NACE Q) to the sample of industries. See Table 6 in the Data Appendix and Table 15 for complete descriptions and sources of variables. All regressions include country-industry and country-year dummies. Standard errors are clustered at industry-level in Panel *A*. The estimation method is least squares in Panel *B*, and standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. ** indicates significance at the 1% level, * at the 5% level, and at the 10% level.

Table 10: *ANOVA for the Share of IT Compensation in US Industries*

Source	Partial SS	df	MS
Total	0.037	149	0.000
Industry	0.033	9	0.004
Year	0.001	14	0.000
Industry $\times$ Year	0.002	126	0.000

Note: This table reports the results from an ANOVA exercise for the share of IT compensation of US industries out of value added. The variation in the data are at industry-year level, and I perform ANOVA along each of these dimensions. The number of observations is 150, RMSE = 0.

Table 11: *ANOVA for the Share of IT Compensation in Industries of Sample Countries*

Source	Partial SS	df	MS
Total	0.290	1359	0.000
Industry	0.150	9	0.017
Country	0.042	9	0.005
Industry × Country	0.062	81	0.001
Year	0.005	14	0.000
Year × Industry	0.008	126	0.000
Year × Country	0.005	112	0.000
Year × Industry × Country	0.018	1008	0.000

Note: This table reports the results from an ANOVA exercise for the share of IT compensation in industries of the sample Western European countries out of value added. The variation in the data are at industry-country-year level, and I perform ANOVA along each of these dimensions. The number of observations is 1360, RMSE = 0.

Table 12: *ANOVA for IT Price Ind*

Source	Partial SS	df	MS
Total	186.631	1359	0.137
Industry	0.498	9	0.055
Country	9.717	9	1.080
Industry × Country	0.656	81	0.008
Year	170.876	14	12.205
Year × Industry	0.278	126	0.002
Year × Country	2.865	112	0.026
Year × Industry × Country	0.555	1008	0.001

Note: This table reports the results from an ANOVA exercise for the price of information technologies relative to the price of value added (IT Price Ind). All prices are normalized to 1 in 1995. The variation in the data are at industry-country-year level, and I perform ANOVA along each of these dimensions. The number of observations is 1360, RMSE = 0. See Table 6 in the Data Appendix and Table 15 for complete descriptions and sources of variables.

Table 13: *Correlations between Wage Rates and Employment Shares*

	1	2	3	4	5
1. High-Skill Wage Rate					
2. Medium-Skill Wage Rate	-0.690				
3. Low-Skill Wage Rate	-0.061	-0.680			
4. Employment Share in High Wage Occupations	0.548	-0.149	-0.350		
5. Employment Share in Medium Wage Occupations	-0.325	0.144	0.130	-0.576	
6. Employment Share in Low Wage Occupations	-0.078	-0.047	0.144	-0.170	-0.708

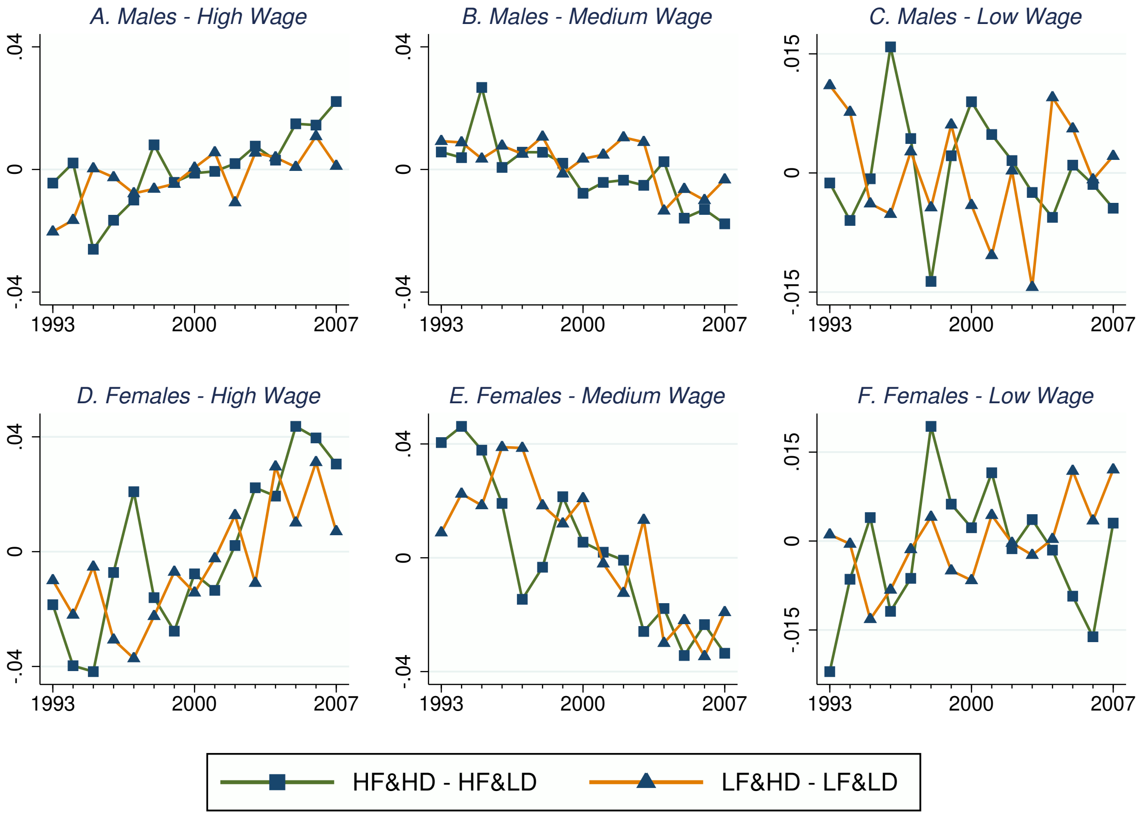
Note: This table reports pairwise correlations for wage compensations of high-, medium- and low-skill (education-level) employees relative to value added and employment shares in high, medium and low wage occupations. The variation in the data are at industry-country-year level. All correlations are significant at least at the 10% significance level.

Table 14: Employment Shares of Occupations in Industries

Occupation Name and Wage Group	Code	Industry Code D	E	F	G	H	I	J	K	N	O
High Wage Occupations											
Corporate Managers	12	0.067	0.069	0.044	0.071	0.068	0.047	0.105	0.070	0.022	0.046
Physical, Mathematical, and Engineering Science Professionals	21	0.041	0.080	0.029	0.010	0.001	0.022	0.034	0.141	0.004	0.011
Life Science and Health Professionals	22	0.002	0.005	0.000	0.007	0.001	0.001	0.002	0.009	0.183	0.004
Other Professionals	24	0.023	0.032	0.005	0.012	0.005	0.017	0.066	0.134	0.039	0.171
General Managers	13	0.022	0.011	0.036	0.132	0.187	0.030	0.015	0.037	0.006	0.036
Physical and Engineering Science Associate Professionals	31	0.062	0.129	0.045	0.017	0.003	0.059	0.022	0.105	0.013	0.037
Other Associate Professionals	34	0.052	0.073	0.019	0.112	0.020	0.060	0.324	0.139	0.054	0.112
Life Science and Health Associate Professionals	32	0.004	0.006	0.001	0.011	0.003	0.001	0.001	0.006	0.217	0.013
Medium Wage Occupations											
Stationary-plant and Related Operators	81	0.040	0.073	0.003	0.002	0.001	0.002	0.002	0.003	0.001	0.005
Metal, Machinery, and Related Trades Workers	72	0.160	0.180	0.055	0.090	0.003	0.050	0.003	0.017	0.004	0.014
Drivers and Mobile-plant Operators	83	0.028	0.022	0.058	0.028	0.005	0.365	0.003	0.009	0.007	0.028
Office Clerks	41	0.080	0.135	0.039	0.095	0.017	0.181	0.232	0.130	0.058	0.097
Precision, Handicraft, Printing, and Related Trades Workers	73	0.033	0.008	0.002	0.005	0.000	0.001	0.001	0.005	0.003	0.003
Extraction and Building Trades Workers	71	0.033	0.103	0.566	0.015	0.005	0.006	0.002	0.019	0.005	0.015
Customer Services Clerks	42	0.003	0.026	0.002	0.024	0.028	0.053	0.175	0.013	0.015	0.029
Machine Operators and Assemblers	82	0.160	0.013	0.007	0.009	0.003	0.002	0.001	0.006	0.003	0.017
Other Craft and Related Trades Workers	74	0.102	0.003	0.007	0.023	0.014	0.002	0.001	0.002	0.003	0.005
Low Wage Occupations											
Labourers in Mining, Construction, Manufacturing, and Transport	93	0.056	0.023	0.081	0.035	0.005	0.038	0.001	0.009	0.006	0.015
Personal and Protective Services Workers	51	0.005	0.010	0.001	0.010	0.500	0.033	0.005	0.029	0.300	0.221
Models, Salespersons, and Demonstrators	52	0.013	0.006	0.002	0.272	0.023	0.006	0.002	0.008	0.001	0.009
Sales and Services Elementary Occupations	91	0.013	0.030	0.005	0.026	0.124	0.030	0.014	0.114	0.059	0.118

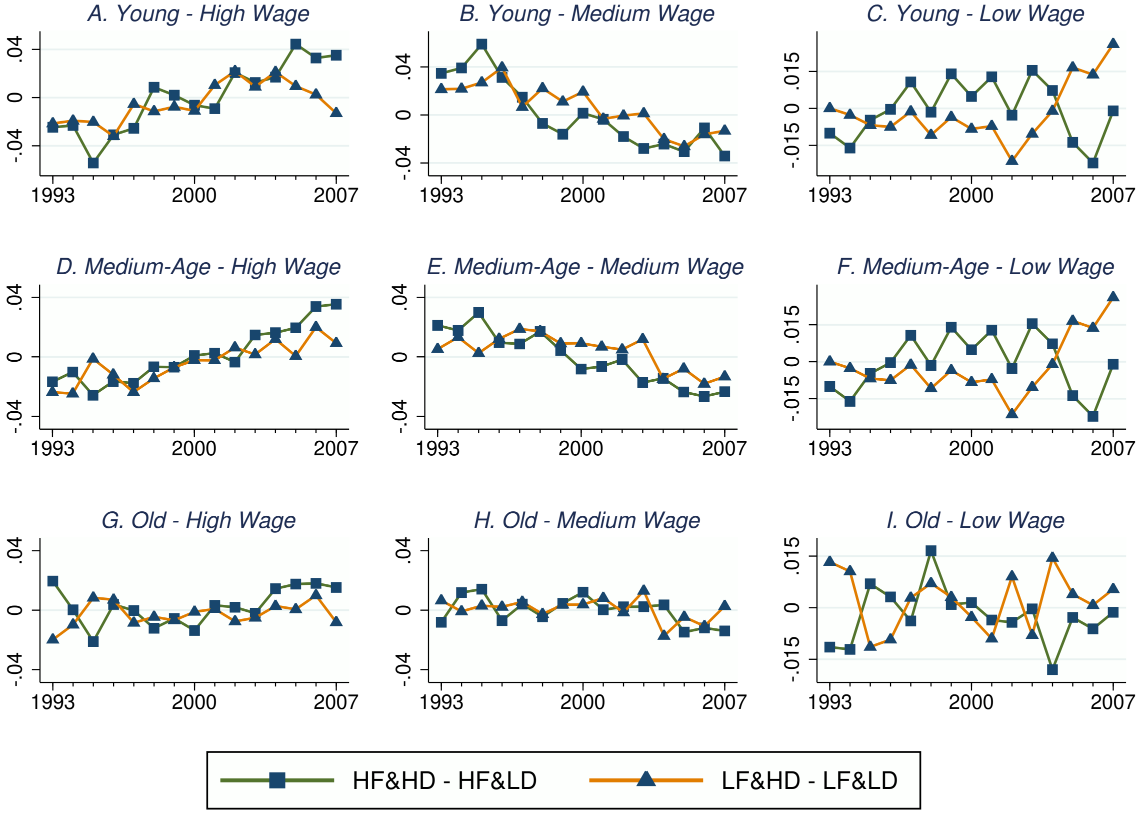
Note: This table offers the shares of employment in each 2-digit ISCO-88 occupation and groups of high, medium and low wage occupations in sample industries. These shares are averaged over sample countries and years. Occupations are ordered by their mean wage in accordance with Table 1 of Goos et al. (2014). Similarly to Goos et al. (2014), the analysis excludes NACE industries A-B, C, L, M, and Q and occupations Legislators and Senior Officials (ISCO-88 11); Teaching Professionals and Teaching Associate Professionals (ISCO-88 23 and 33); Skilled Agricultural and Fishery Workers (ISCO-88 61); and Agricultural, Fishery and Related Laborers (ISCO-88 92). I also exclude from the analysis industry Households with Employed Persons (NACE P) because there is no data for it in the EU KLEMS database.

Figure 2: Employment Shares in High, Medium and Low Wage Occupations in High and Low IT Dependence Industries within Genders



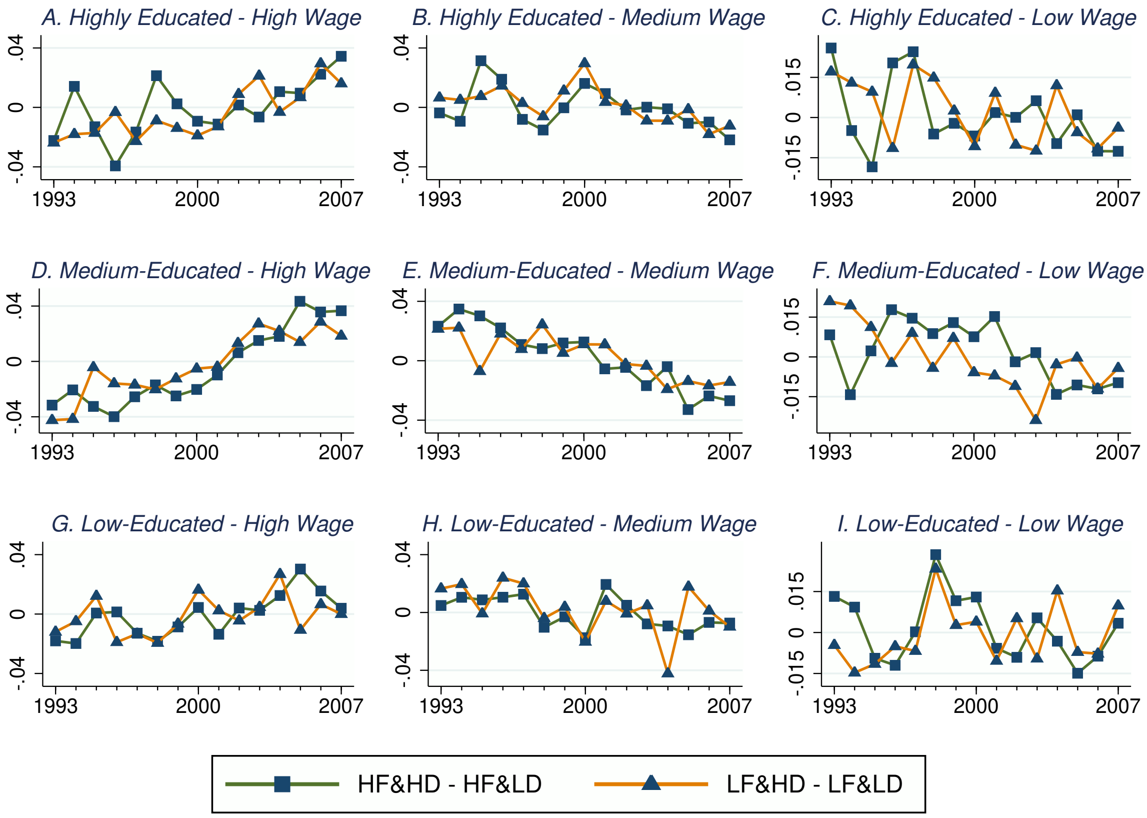
Note: This figure illustrates the differences in the trends of employment shares of high, medium and low wage occupations within genders in industry-country pairs with high and low fall in IT prices and high and low IT dependence. The curves with square tick symbols are the difference between the employment shares within genders in industries with high IT Dependence and industries with low IT Dependence among countries and years where and when the fall in IT Price is relatively high (HF&HD - HF&LD). The curves with triangle tick symbols are the difference between the employment shares within genders in industries with high IT Dependence and industries with low IT Dependence among countries and years where and when the fall in IT Price is relatively low (LF&HD - LF&LD). The employment shares in this figure are the residuals from an OLS regression of employment shares on country-industry and country-year dummies. In each of the four groups, these shares are averaged over countries and industries. An industry has high (low) dependence on IT if its IT Dependence is above (below) the median IT Dependence across industries. For a given year, the fall in IT Price in a country-year pair is relatively high (low) if the fall in IT Price (relative to its previous level) in that pair is lower (higher) than the median change in IT Price across countries in that year. It is sufficient to compare to the change because IT Price has declined everywhere. See Table 6 in the Data Appendix for complete descriptions and sources of variables. See Table 6 in the Data Appendix for the assignment of occupations into high, medium and low wage groups.

Figure 3: Employment Shares in High, Medium and Low Wage Occupations in High and Low IT Dependence Industries within Age Groups



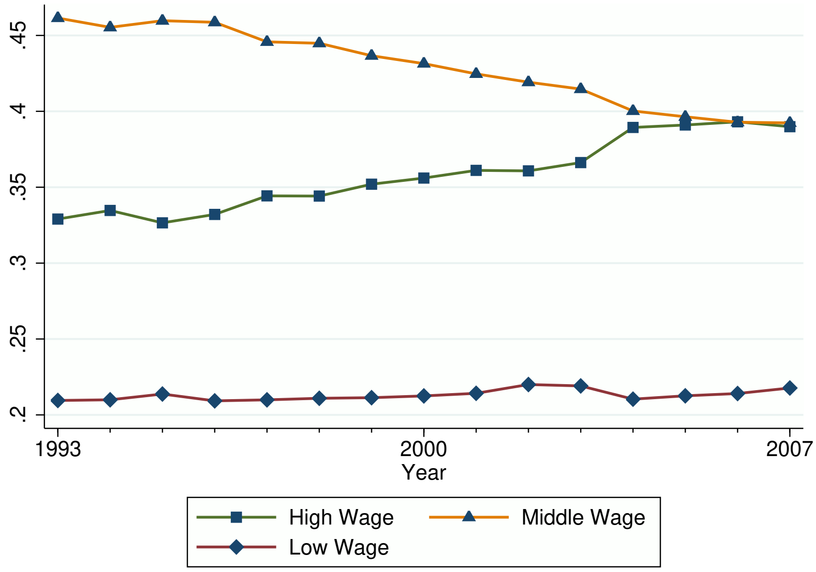
Note: This figure illustrates the differences in the trends of employment shares of high, medium and low wage occupations within age groups in industry-country pairs with high and low fall in IT prices and high and low IT dependence. The curves with square tick symbols are the difference between the employment shares within age groups in industries with high IT Dependence and industries with low IT Dependence among countries and years where and when the fall in IT Price is relatively high (HF&HD - HF&LD). The curves with triangle tick symbols are the difference between the employment shares within age groups in industries with high IT Dependence and industries with low IT Dependence among countries and years where and when the fall in IT Price is relatively low (LF&HD - LF&LD). The employment shares in this figure are the residuals from an OLS regression of employment shares on country-industry and country-year dummies. In each of the four groups, these shares are averaged over countries and industries. An industry has high (low) dependence on IT if its IT Dependence is above (below) the median IT Dependence across industries. For a given year, the fall in IT Price in a country-year pair is relatively high (low) if the fall in IT Price (relative to its previous level) in that pair is lower (higher) than the median change in IT Price across countries in that year. It is sufficient to compare to the change because IT Price has declined everywhere. See Table 6 in the Data Appendix for complete descriptions and sources of variables. See Table 6 in the Data Appendix for the assignment of occupations into high, medium and low wage groups.

Figure 4: Employment Shares in High, Medium and Low Wage Occupations in High and Low IT Dependence Industries within Education-Level Groups



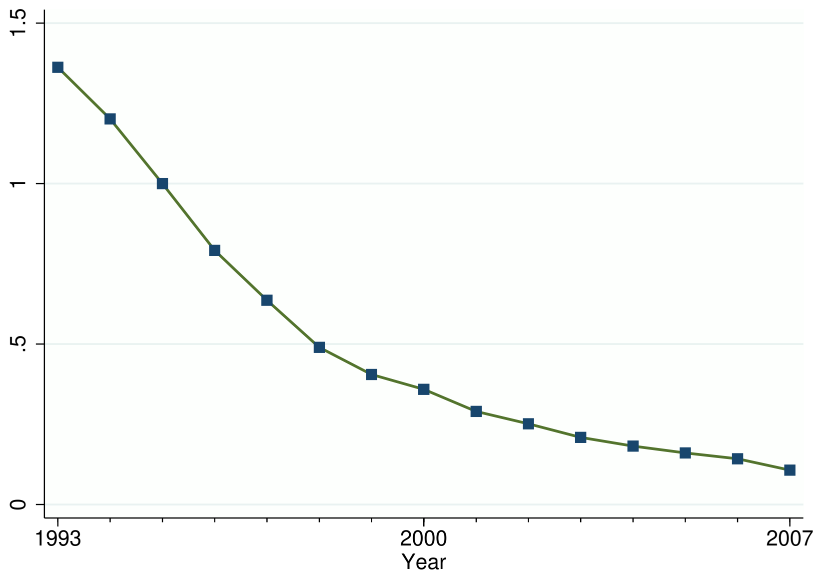
Note: This figure illustrates the differences in the trends of employment shares of high, medium and low wage occupations within education-level groups in industry-country pairs with high and low fall in IT prices and high and low IT dependence. The curves with square tick symbols are the difference between the employment shares within education-level groups in industries with high IT Dependence and industries with low IT Dependence among countries and years where and when the fall in IT Price is relatively high (HF&HD - HF&LD). The curves with triangle tick symbols are the difference between the employment shares within education-level groups in industries with high IT Dependence and industries with low IT Dependence among countries and years where and when the fall in IT Price is relatively low (LF&HD - LF&LD). The employment shares in this figure are the residuals from an OLS regression of employment shares on country-industry and country-year dummies. In each of the four groups, these shares are averaged over countries and industries. An industry has high (low) dependence on IT if its IT Dependence is above (below) the median IT Dependence across industries. For a given year, the fall in IT Price in a country-year pair is relatively high (low) if the fall in IT Price (relative to its previous level) in that pair is lower (higher) than the median change in IT Price across countries in that year. It is sufficient to compare to the change because IT Price has declined everywhere. See Table 6 in the Data Appendix for complete descriptions and sources of variables. See Table 6 in the Data Appendix for the assignment of occupations into high, medium and low wage groups.

Figure 5: Employment Shares in High, Medium and Low Wage Occupations in Sample Countries



Note: This figure illustrates the trends in the shares of employment in high, medium and low wage occupation groups. These employment shares are averaged over the sample countries. See Table 6 in the Data Appendix for the assignment of occupations into high, medium and low wage groups.

Figure 6: The Price of Information Technologies (IT Price)



Note: This figure illustrates the evolution of the price of information technologies relative to the price of value added p_{IT} (IT Price). This relative price is averaged across countries. See Table 6 in the Data Appendix for complete descriptions and sources of variables.

Table 15: Additional Definitions and Sources of Variables

Variable Name	Definition and Source
IT Dependence EU	The share of IT capital compensation out of value added in the industries of sample Western European countries, averaged over sample countries and period. Source: Author's calculations using data from EU KLEMS.
IT Price Ind	The price of investments in information technologies relative to the price of value added in sample industries. In contrast to IT Price, this measure is not averaged across industries, within countries and years. All prices are normalized to 1 in 1995. I use the inverse of this measure in estimations. Source: EU KLEMS.
IT Investments	The ratio of real investments in information technologies and real value added in sample industries. Source: EU KLEMS.

Abstrakt

Tato studie dokumentuje, na datech z deseti zemí západní Evropy, vztah mezi nižšími cenami informačních technologií ve spojitosti s nižším podílem zaměstnanosti ve středně placených zaměstnáních a zároveň vyšším podílem zaměstnanosti ve vysoce placených zaměstnáních. Nižší ceny informačních technologií nemají robustní efekt na podíl zaměstnanosti v nízko placených zaměstnáních. Podobné výsledky platí, až na několik důležitých výjimek, pro skupiny stejného pohlaví, věku nebo vzdělání. Mezi tyto výjimky se řadí například růst podílu zaměstnanosti žen oproti mužům ve vysoce placených zaměstnáních. Tento fakt je v souladu s argumentem, který tvrdí, že ženy mají komparativní výhodu oproti mužům v komunikačních a sociálních dovednostech, které jsou komplementární k informačním technologiím a vysoce poptávané ve vysoce placených zaměstnáních.

Working Paper Series
ISSN 1211-3298
Registration No. (Ministry of Culture): E 19443

Individual researchers, as well as the on-line and printed versions of the CERGE-EI Working Papers (including their dissemination) were supported from institutional support RVO 67985998 from Economics Institute of the CAS, v. v. i.

Specific research support and/or other grants the researchers/publications benefited from are acknowledged at the beginning of the Paper.

Published by
Charles University, Center for Economic Research and Graduate Education (CERGE)
and
Economics Institute of the CAS, v. v. i. (EI)
CERGE-EI, Politických vězňů 7, 111 21 Prague 1, tel.: +420 224 005 153, Czech Republic.
Printed by CERGE-EI, Prague
Subscription: CERGE-EI homepage: http://www.cerge-ei.cz

Phone: + 420 224 005 153
Email: office@cerge-ei.cz
Web: http://www.cerge-ei.cz

Editor: Jan Zápal

The paper is available online at http://www.cerge-ei.cz/publications/working_papers/.

ISBN 978-80-7343-383-3 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-399-3 (Národohospodářský ústav AV ČR, v. v. i.)

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