Automation and Job Polarization: On the Decline of Middling Occupations in Europe*

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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 in industries which depend more on IT relative to industries which depend less. Similar results hold within gender and age groups, with notable differences in these groups. For instance, the share of employment in high wage occupations among males has increased less than among females with the fall in IT prices.

I. 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 computers, substitute for routine tasks. These tasks tend to be readily automatable and are usually performed by middle-wage occupations, such as stationary plant operators. They complement non-routine 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 non-routine 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 for 1993–2007 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 in industries with high dependence on IT relative to industries with low dependence on IT. 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 and age 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), Acemoglu and Autor (2011), Autor and Dorn (2013), and Goos, Manning and Salomons (2014), among others.

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

A possible common explanation for these results is that the efficiency (comparative advantage) of performing tasks in medium and high-wage occupations varies with gender and age. For example, males tend to be more endowed with hard motor skills (brawn) than females, and these skills are usually important in many of the medium-wage manufacturing occupations. In turn, a number of papers argue that females have better communication and social skills, which have a growing importance in the labour market and tend to be more important in leadership in high-wage occupations (e.g. Beaudry and Lewis, 2014; Borghans, Weel and Weinberg, 2014; Deming, 2017). The adoption and use of information technologies would then reduce employment in medium-wage occupations and increase employment in high-wage occupations among males less than among females. In turn, information technologies will have a lower effect on the share of employment in medium- and high-wage occupations among old if workers accumulate routine skills more than other types of skills as they age (see, for arguments supporting this conjecture, Autor and Dorn, 2009). 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 and age group in job polarization and suggest a need for a more nuanced view on the labour market effects of recent technological changes.
Job polarization is a pervasive phenomenon in developed economies. 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 computers (a type of IT) is associated with reduced employment in middle-wage (routine) occupations within industries. Autor and Dorn (2013) show that, in the US, the growth of workplace computer use has 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 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 demand for workers with medium-level of education. Using data from 11 OECD countries, Michaels, Natraj and van Reenen (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 independently explore the differences in the trends of polarization across genders using US data (e.g. Cerina, Moro and Rendall, 2017; Cortes, Jaimovich and Siu, 2018). Cerina et al. (2017) 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 main focus of this paper is on how the fall in IT prices has affected the demand for high-, medium- and low-wage occupations. Several recent studies suggest that structural transformation and changes in relative productivities of occupations and industries can also explain the observed changes in the demand for employment in these occupation groups (see, e.g. Aum, Lee and Shin, 2018; Bárány and Siegel, 2018; Gallipoli and Makridis, 2018).2 This evidence implies that more general processes than the fall in IT prices can have a role in job polarization. In line with this evidence, I show in the additional results section that changes in the prices of physical capital, a more ubiquitous processes, affect employment in these occupation groups and this is over and above the effects of information technologies.

The findings of this study complement the results of these papers. An innovation of this study is its identification strategy. I use the assignment of occupations into task/wage groups by Goos et al. (2014) to compute employment in occupation groups with different task content and utilize a difference-in-differences framework à la Rajan and Zingales (1998). In this framework, I employ the variation of IT prices over time and the industry-level variation of dependence on IT, which allows me to explicitly take into account the technological side of the effect of the fall in IT prices on employment. I provide international

1 These results also support a view held by, for example, the World Bank and the UN that IT can empower women (see, e.g. United Nations, 2005; Melhem, Morrell and Tandon, 2009).

2 Aum et al. (2018) and Gallipoli and Makridis (2018) emphasize the role of IT-producing and IT-intensive sectors and IT-intensive occupations in the processes of structural transformation and changes in the demand for occupations.
evidence corroborating the hypothesis for job polarization. By exploring differences among industries and in gender and age groups, I also uncover some more concealed features of the effects of recent technological changes on labour markets in Europe.

Section II describes a simple model to motivate the empirical test. Section III offers the empirical specification, and describes the data and its sources. Section IV summarizes the results. Section V concludes.

II. Theoretical background

Recent omnipresent advances in information technologies have caused the prices of these technologies to fall. Technological advances in IT and the resulting 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 is based on the models of Acemoglu and Autor (2011) and Autor and Dorn (2013). In particular, I model the demand for abstract and routine tasks and incorporate technological advances in IT in a similar way to Autor and Dorn (2013). I also incorporate comparative advantage differences in the performance of tasks among broad worker groups as in the model of Acemoglu and Autor (2011).

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

$$Y = \left( \frac{\alpha_{IT} IT^{\epsilon-1} + \alpha_{TR} T_R^{\epsilon-1}}{\alpha_{IT} IT^{\epsilon-1} + \alpha_{TR} T_R^{\epsilon-1} + \alpha_{TA} T_A^{\epsilon-1}} \right)^{\frac{\epsilon}{\epsilon - 1}} T_A^{1-\alpha},$$

where $\alpha_{IT}, \alpha_{TR}, \alpha_{TA} > 0$, $\alpha_{IT} + \alpha_{TR} + \alpha_{TA} = 1$, and $\epsilon > 1$. In the production of $Y$, $\alpha_{IT}$ measures the relative importance of IT and a higher $\alpha_{IT}$ implies higher share of compensation for IT. In this sense, it measures the technological dependence on IT. In turn, $\epsilon$ 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 $\epsilon > 1$, information technologies are more complementary to abstract tasks than to routine tasks.

The usual profit maximization implies the following conditions

$$IT = \frac{\alpha_{IT} IT^{\epsilon-1} - 1}{\alpha_{IT} IT^{\epsilon-1} + \alpha_{TR} T_R^{\epsilon-1}} p_{IT} Y,$$

$$T_R = \frac{\alpha_{TR} T_R^{\epsilon-1} - 1}{\alpha_{IT} IT^{\epsilon-1} + \alpha_{TR} T_R^{\epsilon-1}} p_{TR} Y,$$

$$T_A = (1 - \alpha) \frac{1}{p_{TA}} Y,$$

where $p_{IT}$, $p_{TR}$, and $p_{TA}$ are the prices of information technologies and task inputs, and the price of $Y$ is normalized to 1.

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I assume that information technologies input can be represented as $IT = \lambda \tilde{I}$, where $\lambda$ represents the quality/productivity of information technologies and it grows over time because of technological progress. I also assume that $p_{IT}, p_{TA},$ and $p_{TR}$ are determined at the country level and that the growth in $\lambda$ does not affect $p_{TA}$ and $p_{TR}$. This implies that the derivative of the demand for $TA$ relative to $TR$ with respect to $\lambda$ and the change of that derivative with $\lambda$ are given by

$$\frac{\partial T_A/T_R}{\partial \lambda} = \frac{\epsilon - 1}{\epsilon} \left( 1 - \frac{\alpha_p T_k}{p_{TA} \lambda \lambda^{\gamma-1}} \right) - \frac{1}{\lambda},$$

and

$$\frac{\partial}{\partial \lambda} \left( \frac{\partial T_A/T_R}{\partial \lambda} \right) = \frac{1}{\lambda} \frac{\partial T_A/T_R}{\partial \lambda}.$$

It is straightforward to show that the growth in $\lambda$ reduces $p_{IT}$. Moreover, it increases the demand for $TA$ more than the demand for $TR$ when $\epsilon > 1$, according to equation (5). According to equation (6), in a country, the demand for $TA$ relative to $TR$ would increase more in industries with higher $\alpha_{IT}$ than in industries with lower $\alpha_{IT}$ with the growth in $\lambda$ in such a case. This means that $T_A$ increases and $T_R$ declines with the growth of $\lambda$ and the corresponding decline in $p_{IT}$ if employment in $Y$ is fixed and these changes are larger in industries with a larger $\alpha_{IT}$.4

It can be shown that such differential changes can also hold within gender and age groups incorporating these demand functions into a simple Ricardian model of comparative advantage. To do so, I assume that workers are endowed with labour hours, which need to be converted into abstract and routine tasks in order to earn market income. I assume that the conversion function of task $k = T_A, T_R$ is given by the following: $\alpha_{L,k} (u_k L)^\gamma$, where $\alpha_{L,k} > 0$, $u_k$ is the share of labour hours $L$ converted to task $k$, and $\gamma \in (0, 1)$. I normalize the value of $\alpha_{L,T_A}$ to 1.

This setup implies that the supply of abstract tasks relative to the supply of routine tasks is given by the following:

$$\frac{p_{TA}}{p_{TR}} = \alpha_{L,T_A} \left( \frac{u_{T_R}}{u_{T_A}} \right)^{\gamma-1},$$

and the share of employment in abstract tasks is given by the following:

$$\%	ext{abstract tasks} = \frac{p_{TA}}{p_{TA} + p_{TR}}.$$

3 The latter assumption might not seem very strong since this paper focuses on the differential effects of growth in $\lambda$ and fall in $p_{IT}$ on the demand for tasks among industries with different $\alpha_{IT}$. I endogenize the supply of tasks and $p_{TA}$ and $p_{TR}$ at the end of this section and show that it is innocuous.

4 I extend this analysis and consider a two-sector model, where sectors have different levels of $\alpha_{IT}$ and the allocation of IT between sectors is endogenous, in the Online Technical Appendix. I show that the inference in equation (6) also holds in such an extended model. Another extension of the analysis considers a nested CES production function in equation (1). It can be shown that, in such an extension, a sufficient condition for a positive left-hand side in equations (5) and (6) is that the elasticity of substitution between IT and $T_R$, $\epsilon$, is larger than the elasticity of substitution between IT and $T_A$ and it is greater than 1.

5 Parameters $\alpha_{L,T_A}$ and $\alpha_{L,T_R}$ can admit a range of interpretations since they can represent both supply and demand side factors.
It is straightforward to show that in this model economy the growth in \( \lambda \) increases the share of employment in abstract tasks \( u_{T_d} \) and it has a stronger effect in industries which have a higher \( \lambda_{IT} \). However, these differential effects on employment shares are weaker in groups which have a comparative advantage in converting labour hours into routine tasks (i.e. a higher \( \lambda_{L,TR} \)): 

\[
\frac{\partial}{\partial \lambda_{L,TR}} \frac{\partial}{\partial \lambda_{IT}} \frac{\partial}{\partial \lambda} < 0. 
\]

The differential changes in \( T_A \) and \( T_R \) in industries which depend more on IT than in industries which depend less on IT should be observed in the data as differential changes in the employment in high and medium-wage occupations which perform these tasks. I look exactly for such disparities and differential changes in the empirical specification and utilize IT price variation as a proxy for technological advances/shocks in IT.

### III. Empirical methodology and data

I start with estimating the differential effect of the rapid fall in IT prices on employment shares in high-, middle- and low-wage occupations in industries which depend more on IT compared to industries which depend less. Let Employment Share \( c, i, t \) be the share of employment in one of the occupation groups, country \( c \), industry \( i \), 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:

\[
Employment Share_{c, i, t} = \beta \left[ Industry \ i's \ Dependence \ on \ IT, \times \ (1/IT \ Price)_{c, i} \right] + \sum_{c} \sum_{i} \zeta_{c, i} + \sum_{c} \sum_{t} \xi_{c, t} + \eta_{c, i, t}, \tag{10}
\]

where \( \zeta \) and \( \xi \) are country-industry and country-year fixed effects respectively, and \( \eta \) is an error term. In accordance with equation (6), this specification identifies the differential effect of the fall in IT prices on employment shares in occupation groups across industries with different levels of dependence on IT. The parameter of interest is \( \beta \). It is identified from the temporal variation of IT prices, the variation of technological dependence on IT across industries, and within country, time, and industry variation of the interaction term.

Rajan and Zingales (1998) have pioneered this type of difference-in-differences identification strategy and have used it to show how financial development affects industry performance. They focus on country and industry variation and regress industry growth measures on the interaction between a proxy of financial dependence of industries and country-level financial development indicators and country and industry fixed effects. In
contrast to Rajan and Zingales (1998), I also utilize temporal variation that allows a focus on significant and omnipresent advances in information technologies.6

An advantage of this test is that it alleviates endogeneity concerns because of omitted country- and industry-level variables. For example, country-industry and country-year fixed effects alleviate the potentially confounding effects of regulatory and discriminatory practices which affect the demand and supply of the tasks. These fixed effects also alleviate the potentially confounding effects of trends in relative wage rates. 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. Results, which show that such differences exist, themselves can be considered to be a contribution to the literature on job polarization.

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.

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 the 2-digit aggregation level 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.7 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 gender and age. The data for age are in five-year bands, and the minimum age is 15. I restrict the maximum age to 65 and create three age groups: young (younger than 30), middle-age (between 30 and 45), and old (older than 45). 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 commonly observed patterns. On average, men work more in high-wage occupations and less in low-wage occupations than women. The

6 I add industry-year fixed effects to the specification (10) and utilize only within country, time and industry variation in robustness tests in the Online Appendix – Further Robustness Checks and Results.

7 Table 6 in the Data Appendix offers the assignment of occupations into high-, medium- and low-wage groups. Table A in the Online Appendix offers the shares of employment in sample occupations and industries. Figure A in the Online Appendix – Tables and Figures illustrates the trends of employment shares in high-, medium- and low-wage occupations.
TABLE 1

Sample countries, IT Price and correlations of IT Dependence

| Country  | Sample period | IT Dependence | A. Correlations | B. Basic statistics for IT Price |
|----------|---------------|---------------|-----------------|--------------------------------|
| Austria  | 1995–2007     | 0.616         | 0.350           | Mean SD Min Max Δ IT Price     |
| Denmark  | 1993–2007     | 0.595         | 0.453           | 0.102 1.000 −0.087             |
| Finland  | 1997–2007     | 0.920         | 0.218           | 0.077 0.562 −0.061             |
| Germany  | 1993–2007     | 0.787         | 0.538           | 0.094 1.376 −0.092             |
| Italy    | 1993–2007     | 0.935         | 0.451           | 0.083 1.404 −0.094             |
| Netherlands | 1993–2007 | 0.974         | 0.464           | 0.102 1.430 −0.095             |
| Portugal | 1993–2007     | 0.608         | 0.358           | 0.120 1.000 −0.088             |
| Spain    | 1993–2007     | 0.914         | 0.496           | 0.127 1.280 −0.082             |
| Sweden   | 1997–2007     | 0.909         | 0.545           | 0.228 0.849 −0.059             |
| UK       | 1993–2007     | 0.916         | 0.490           | 0.105 1.249 −0.082             |

Notes: Columns 1–2 of this table list sample countries and period. Panel A 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. Panel B offers basic statistics for the price of information technologies (IT Price). Column 5 of Panel B offers the average change in IT Price over the sample period in each country (Δ IT Price). See Table 6 in the Data Appendix for complete descriptions and sources of variables.

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.

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 industry value added to construct a proxy for industries’ dependence on information technologies. This proxy needs to identify the technological differences across industries, i.e. \( \pi_{IT} \). In the theoretical model, it is given by \( p_{IT} IT/Y \) and it increases with \( \pi_{IT} \) according to equation (2). \(^8\) However, it can also vary with factor inputs, which can be problematic if there are differences in the trends of use of factor inputs across countries and industry-country-specific taxes and subsidies to factor inputs. This can bias the estimate of \( \beta \) in ambiguous directions. As in the rest of the literature following Rajan and Zingales (1998), I use data from US industries to alleviate the effect of such a confounding variation (see, e.g. Barone and Cingano, 2011; Jerbashian and Kochanova, 2017).

The use of US data can be helpful since US is arguably the closest to a laissez faire economy. In US data, the industry-level variation of the share of IT capital compensation accounts for more than 90% of the total variation albeit there are significant positive trends in adoption of IT and negative trends in employment in routine tasks in all industries. The ranking of industries according to the share of IT capital compensation is very persistent. These observations suggest that the share of IT capital compensation in US industries is likely to identify the technological differences across industries but not the variation in factor input levels. The measure for industries’ dependence on information technologies (IT Dependence) is defined as the share of IT capital compensation in industry value added.

\(^8\) I present a two-sector version of this model in the Online Technical Appendix and show that the variation of \( \pi_{IT} \) across industries is a primary and key source of variation in \( p_{IT} IT/Y \) also in such an extended model.
### TABLE 2

Average employment shares in sample industries and IT Dependence

| Industry name                                      | Industry code | A. Average employment shares | B. IT Dependence |
|----------------------------------------------------|---------------|------------------------------|------------------|
|                                                    |               | Observations | 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       | 0.002    | 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                   |

**Notes:** 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 the source of variables.
**TABLE 3**

*Shares of employment in high-, medium- and low-wage occupations within gender and age groups*

| Occupation group | A. Share within genders | B. Share within age groups |
|------------------|-------------------------|---------------------------|
|                  | Gender | Observations | Mean | SD  | Min  | Max  | Age group | Observations | Mean | SD  | Min  | Max  |
| High wage        | Male   | 1,392        | 0.440 | 0.212 | 0.038 | 0.954 | Young     | 1,359        | 0.295 | 0.182 | 0.013 | 0.899 |
| Medium wage      | 1,392  | 0.381        | 0.255 | 0.002 | 0.838 |         |           | 1,359        | 0.421 | 0.265 | 0.017 | 0.936 |
| Low wage         | 1,392  | 0.179        | 0.171 | 0.000 | 0.907 |         |           | 1,359        | 0.284 | 0.248 | 0.001 | 0.929 |
|                  | Female | 1,386        | 0.355 | 0.145 | 0.0329 | 0.846 | Medium    | 1,383        | 0.422 | 0.188 | 0.040 | 0.941 |
| Medium wage      | 1,386  | 0.371        | 0.225 | 0.015 | 0.863 |         |           | 1,383        | 0.373 | 0.246 | 0.009 | 0.844 |
| Low wage         | 1,386  | 0.274        | 0.231 | 0.002 | 0.937 |         |           | 1,383        | 0.205 | 0.192 | 0.002 | 0.919 |
|                  | Old    | 1,396        | 0.423 | 0.172 | 0.045 | 0.906 |           | 1,396        | 0.372 | 0.241 | 0.008 | 0.830 |
|                  | Low wage | 1,396        | 0.205 | 0.181 | 0.002 | 0.920 |           |              |        |       |       |       |

*Notes:* This table offers basic statistics for the shares of employment in high-, medium- and low-wage occupations within gender and age groups in sample industries, countries and time. There are three age groups: young (between 15 and 30), medium-age (between 30 and 45), and old (between 45 and 65). See Table 6 in the Data Appendix for complete descriptions and sources of variables.
in US industries, averaged over the period 1993–2007. This measure firmly correlates with similar measures used in the literature (see, e.g., Chen, Niebel and Saam, 2016; Jerbashian and Kochanova, 2016, 2017). According to Panel A of Table 1, it also firmly correlates with the share of IT capital compensation in the industries of sample Western European countries, which I average over sample countries and period. I perform a range of robustness checks for it in the Online Appendix – Further Robustness Checks and Results.

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. These technologies include computers and machines which use and depend on computers. Following the model, I normalize the price of investments in information technologies with the price of value added in each industry. The price of investments in information technologies, as well as its normalized counterpart, displays 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 occurred over the sample years and mostly in the US. The country-level variation is likely to be stemming from regulations that affect the access to and adoption of 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 the price of information technologies, $p_{IT}$.

In the estimations of the baseline specification (10), I use the inverse of this measure. According to the theoretical model, $\beta$ is then expected to be positive for high-wage occupations and negative for medium-wage occupations as $p_{IT}$ declines and its inverse increases. This parsimonious theoretical model has no predictions for low-wage occupations.
Figure 2. Employment shares in high-, medium- and low-wage occupations in high and low IT dependence industries

Notes: 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 countries according to the change in IT Price 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.

Nevertheless, $\beta$ can be expected to be nil for these occupations since information technologies are not likely to directly affect employment in these occupations (Autor et al., 2003; Autor and Dorn, 2013).9

Table 1 offers basic statistics for the price of information technologies in Panel B. The price of information technologies has fallen everywhere according to the last column of this panel. I average the price of information technologies across sample countries and illustrate its trend over time in Figure 1. Panel B of Table 2 reports the values of the dependence

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9 I show that the results are robust to excluding low-wage occupations and computing industry-level employment as the sum of employment in high- and medium-wage occupations in the Online Appendix – Further Robustness Checks and Results.
measure in sample industries. Table 6 in the Data Appendix offers the detailed descriptions of all measures used in this paper.

It is worth clarifying the interpretation of the coefficient of interest, $\beta$. Roughly speaking, the difference-in-differences estimator in the specification (10) splits the sample into four groups according to the magnitude of the fall in prices of information technologies and technological dependence. 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 $\beta$, 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.

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. Figure 2 summarizes the results for the shares of employment in occupation groups, which are relative to their means given that the residuals are demeaned. IT prices have declined over time everywhere, and Panels A and B show that employment has increased (declined) in high (medium) wage occupations with the fall in IT prices in industries with high IT dependence compared to industries with low IT dependence. Moreover, according to Panels A and B, these trends in employment shares are stronger in countries where IT prices have declined at a higher rate than in countries where IT prices have declined at a lower rate. In turn, Panel C of Figure 2 shows that there are almost no apparent 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 may not be affected by the fall in IT prices, at least directly.10

IV. Results

Panel A of Table 4 presents the results from the estimation of the specification (10) for the shares of employment in high-, medium- and low-wage occupations. The estimates of the coefficient $\beta$ 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 a higher demand for high-wage occupations and lower demand for medium-wage occupations in industries which depend more on these technologies as compared to industries which depend less. Conversely, the estimate of the coefficient $\beta$ 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.

10 Figures B and C in the Online Appendix – Tables and Figures offer similar evidence for employment shares in high-, Medium- and low-wage occupations in gender and age groups.
**TABLE 4**

*Main results for employment shares in high-, medium- and low-wage occupations*

| IT Dependence × 1/IT Price | High wage (1) | Medium wage (2) | Low wage (3) | High wage (1) | Medium wage (2) | Low wage (3) | High wage (1) | Medium wage (2) | Low wage (3) |
|-----------------------------|---------------|-----------------|--------------|---------------|-----------------|--------------|---------------|-----------------|--------------|
| A. All                      | 0.217***      | −0.211***       | −0.005       | 0.156***      | −0.152***       | −0.004       | 0.235***      | −0.237***       | 0.001        |
| (0.027)                     | (0.024)       | (0.019)         |              | (0.028)       | (0.028)         | (0.020)      | (0.034)       | (0.033)         | (0.019)      |
| Observations                | 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        |

| IT Dependence × 1/IT Price | High wage (1) | Medium wage (2) | Low wage (3) | High wage (1) | Medium wage (2) | Low wage (3) | High wage (1) | Medium wage (2) | Low wage (3) |
|-----------------------------|---------------|-----------------|--------------|---------------|-----------------|--------------|---------------|-----------------|--------------|
| B. Within males             | 0.219***      | −0.220***       | −0.000       | 0.235***      | −0.232***       | −0.004       | 0.160***      | −0.132***       | −0.028       |
| (0.039)                     | (0.042)       | (0.020)         |              | (0.034)       | (0.031)         | (0.019)      | (0.034)       | (0.027)         | (0.025)      |
| Observations                | 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        |

**Notes:** This table offers the results from the estimation of the specification (10) 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. 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.
One way to compute the magnitude of these results is as follows. I take the industries that rank in the 90th and 10th percentiles of the distribution of IT Dependence and compute the difference between dependence levels in these industries. Further, I take the countries and years where IT Price is in the 10th and 90th percentiles of the distribution of IT Price and compute the difference between the levels of the inverse of IT Price for them. Finally, I compute

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

where \( \Delta \) stands for the difference operator. Focusing on statistically significant estimates of \( \hat{\beta} \), the computed effect for the share of high-wage occupations is 0.034 and \(-0.033\) for medium-wage occupations. These numbers correspond to the effect of moving from the pair of country-year with IT Price in the 90th percentile to the pair with IT Price in the 10th percentile in the industry with IT Dependence in the 90th percentile relative to the industry with IT Dependence in the 10th percentile. They suggest that the fall in IT prices 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.

I also estimate the specification (10) for the shares of employment in high-, medium- and low-wage occupations within each gender and age group. The results are reported in Panels B–F 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 among gender and age groups. The fall in IT prices has increased the share of employment in high-wage occupations and reduced the share of employment in medium-wage occupations among women by about 50% more than among men in industries which depend more on IT relative to industries which depend less. It has also increased the share of employment in high-wage occupations and reduced the share of employment in medium-wage occupations among old workers by about 50% less than among young and among medium-age workers. These differences are economically large. They are also statistically significant for genders and for age groups in medium-wage occupations at least at the 10% level according to the standard \( t \) test. The differences are at the borderline of statistical significance for age groups in high-wage occupations.

A possible and common interpretation of these results is that the comparative advantage of performing tasks in medium-wage and high-wage occupation groups varies with gender and age. For example, males tend to be better endowed with hard motor skills (brawn) than females and these skills are commonly more important in many of the medium-wage occupations. Meanwhile, women are argued to have an advantage in communication and social skills, which seem to be more important in high-wage occupations. All else equal, the adoption and use of information technologies would then reduce employment in medium-wage occupations and increase employment in high-wage occupations among males less than among females. In turn, information technologies will have a lower effect on the share of employment in high- and medium-wage occupations among old if workers accumulate routine skills more than other types of skills as they age (i.e. if \( \alpha_{L,T} \) increases with age).\(^\text{11}\)

\(^{11}\)These hypotheses are a useful place to start. Testing them is out of the scope of this paper.
Further results and robustness checks

The demand for IT is a potential source of reverse causality if industries’ demand for employment of different tasks affect it. Country-industry and country-year fixed effects in the specification (10) are likely to alleviate such reverse causality concerns given that the main source of variation in IT prices will be technological. Nevertheless, I attempt to further circumvent the reverse causality concerns in two ways. Industries with the heaviest use of information technologies are plausible candidates that affect the prices of information technologies. In Panel A of Table 5, I exclude industries which have expenditure on IT higher than the 75 percentile of the distribution of IT expenditure across industries in each country and year. The results in this panel are close to those in Panel A of Table 4.

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 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 an evident complement or substitute for these tasks. The data for the prices of communication technologies are from the EU KLEMS database. Panel B of Table 5 presents the results when I instrument IT Price using the prices of communication technologies. These results are very 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 et al., 2000). The movements in the prices of new physical capital goods could be the result of 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 the same way as the measures of dependence on IT (see Table 6 in the Data Appendix for details). I add to the specification (10) an interaction term between the measure of dependence of industries on physical capital and the inverse of the price of physical capital. Panel C 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.12

12 The changes in the prices of physical capital can lead to structural changes in the economy. In this respect, these results provide supporting evidence to several recent studies, which link job polarization and structural changes in the economy (e.g., Bárány and Siegel, 2018).
## TABLE 5
Further results – Sample restrictions, instrumental variables and additional variables

|               | High wage (1) | Medium wage (2) | Low wage (3) | High wage (1) | Medium wage (2) | Low wage (3) | High wage (1) | Medium wage (2) | Low wage (3) |
|---------------|---------------|----------------|-------------|---------------|----------------|-------------|---------------|----------------|-------------|
| **A. W/o high IT compensation industries** |               |                |             |               |                |             |               |                |             |
| IT Dependence × 1/IT Price | 0.395*** (0.057) | −0.416*** (0.060) | 0.021 (0.044) | 0.221*** (0.029) | −0.203*** (0.027) | −0.018 (0.016) | 0.214*** (0.026) | −0.209*** (0.024) | −0.005 (0.018) |
| Capital Dependence × 1/Capital Price |               |                |             |               |                |             |               |                |             |
| Observations  | 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** |               |                |             |               |                |             |               |                |             |
| IT Dependence × 1/IT Price | 0.171*** (0.030) | −0.160*** (0.027) | −0.010 (0.019) | 0.186*** (0.034) | −0.196*** (0.030) | 0.010 (0.024) | 0.305*** (0.039) | −0.275*** (0.033) | −0.030 (0.033) |
| Medium-Skill Dependence × 1/IT Price | −0.012*** (0.003) | 0.013*** (0.003) | −0.001 (0.002) |               |                |             |               |                |             |
| Medium-Skill Wage Rate |               |                |             | −0.028 (0.090) | 0.138*** (0.049) | −0.109 (0.071) |               |                |             |
| Low-Skill Wage Rate |               |                |             | −0.085 (0.140) | 0.195** (0.085) | −0.111 (0.106) |               |                |             |
| Observations  | 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        |

Notes: This table offers the results from the estimation of the specification (10) 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 (10) 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 (10) with additional variables. Panel C adds to the specification (10) 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 (10) the interaction between 1/IT Price and Medium-Skill Dependence, which is a proxy for \( \alpha_T \). Panel E adds industry group-year dummies to the specification (10). 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 (10) the shares of wage compensation of medium- and low-skill employees out of total wage compensation (Medium-Skill Wage Rate and Low-Skill Wage Rate). The estimation method is 2-step GMM in Panel B and least squares in the remaining panels. 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.
According to the theoretical model, the parameter which measures the relative importance of routine tasks in value added, \( \alpha_{T_R} \), should be important for the analysis similarly to \( \alpha_{IT} \). It can be easily shown from equation (5) that the fall in IT prices increases (reduces) the demand for abstract (routine) tasks more in industries with a low \( \alpha_{T_R} \) than in industries with a high \( \alpha_{T_R} \). 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 \( \alpha_{T_R} \) can be constructed similarly to the proxy for \( \alpha_{IT} \). 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. According to Michaels et al. (2014), this can be a valid proxy because routine-intensive occupations are the middle wage occupations and medium skill/education-level employment tends to be over-represented in these occupations at least in the US.\(^{13}\) I measure \( \alpha_{T_R} \) using the share of compensation of medium education-level employees out of value added in US industries, averaged over the period 1993-2007. I add the interaction of this share with the inverse of IT Price to the specification (10). 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.

In the specification (10), country-year fixed effects will not fully capture the trends in relative wage rates if these vary among industries. Such a variation can be expected to be weak according to Kambourov and Manovskii (2009). However, it can confound the identification of \( \beta \) if the interaction term is correlated with it. In order to alleviate these concerns, I include in the specification (10) industry group-year dummies and present the results in Panel E of Table 5. I also add to the specification (10) the shares of wage compensation of medium- and low-skill employees out of total wage compensation. 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 Online Appendix – Further Robustness Checks and Results provides a range of additional robustness check exercises and results. I also perform all of these robustness checks for the shares of employment in high-, medium- and low-wage occupations among gender and age groups.

V. Conclusions

The price of information technologies has fallen in the past few decades because of rapid technological advances. In this study, I use evidence from 10 Western European countries to identify the effect of the fall in IT prices on employment shares in high-, medium- and low-wage occupations in industries with high dependence on IT relative to industries with low dependence on IT. Taken together, my results offer robust evidence that the share

\(^{13}\) The Online Appendix – Education Levels in Occupation Groups offers an analysis of the relation between employment in middle-wage occupations and medium education-level employment for European countries.
of employment in high-wage occupations has increased and the share of employment in medium-wage occupations has declined with the fall in IT prices in industries which depend more on IT compared to industries which depend less. 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 gender and age groups. These results corroborate the polarization hypothesis.

I find certain important differences across gender and age groups, however. The fall in IT prices has increased the share of employment in high-wage occupations and reduced the share of employment in medium-wage occupations among males by about 50% less than among females in the industries which depend more on IT. In these industries, it has also increased the share of employment in high-wage occupations and reduced the share of employment in medium-wage occupations among old workers by about 50% less than among young and medium-age workers. A possible common explanation for such results is that the comparative advantage of performing tasks specific to medium and high-wage occupations varies with gender and age. All in all, these results suggest a need for a more nuanced view on the labour market effects of recent technological changes.

Data Appendix

| 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. 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, in each country and year. I use the inverse of this measure in estimations. Communication technologies include telephones, telephony related equipment and equipment to connect to the internet. 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, in each country and year. I use the inverse of this measure in estimations. Information technologies include computers and machines which use and depend on computers. Source: EU KLEMS |

(continued)
TABLE 6
Continued

| Variable name                  | Definition and source                                                                 |
|--------------------------------|--------------------------------------------------------------------------------------|
| Medium-Skill Dependence        | The share of wage compensation of workers with medium-level of education out of value added in US industries, averaged over the period of 1993–2007. Medium-level of education corresponds to secondary to post-secondary and non-tertiary education (3–4 of ISCED-97). Source: EU KLEMS |
| Medium-Skill Wage Rate         | The share of wage compensation of workers with medium-level of education out of total wage compensation in the industries of the sample Western European countries. Medium-level of education corresponds to secondary to post-secondary and non-tertiary education (3-4 of ISCED-97). Source: EU KLEMS |
| Low-Skill Wage Rate            | The share of wage compensation of workers with low-level of education out of total wage compensation in the industries of the sample Western European countries. Low-level education corresponds to preprimary to lower-secondary education (0–2 of ISCED-97). Source: EU KLEMS |

| Group                          | Description                                                                 |
|--------------------------------|-----------------------------------------------------------------------------|
| Age Group                      | There are three age groups: young (between 15 and 30), medium-age (between 30 and 45) and old (between 45 and 65) |
| 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 A in the Online Appendix – Tables and Figures for occupation names. Source: Goos et al. (2014) |

Data Sources: December 2015 release of the EU Labour Force 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.
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**Supporting Information**

Additional supporting information may be found in the online version of this article:

**Appendix A.** Further robustness checks and results.
**Appendix B.** Education levels in occupation groups.
**Appendix C.** Tables and figures.
**Appendix D.** Online Technical Appendix.