# Age-Biased Offshoring and Automation*

Sotiris Blanas†

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**Abstract**

Using a sample of manufacturing and service industries in eleven developed countries over 1995–2005, this paper provides novel evidence on the effects of offshoring, industrial robots and other automation technologies (e.g. 3-D printers) on the relative demand for different age groups of workers. While offshoring to high-income countries increased the relative demand for the young and decreased the relative demand for the middle-aged, offshoring to lower-income countries decreased the demand for the young relative to the middle-aged and oldest workers. Similarly to offshoring to the latter group of countries, industrial robots and other automation technologies decreased the relative demand for the young. The effects are rationalised by the disproportionate employment of young workers in occupations with relatively high content of offshorable and routine tasks, which are more amenable to offshoring to lower-income countries and automation, and the disproportionate employment of older workers in occupations with relatively high content of abstract tasks, which are more amenable to offshoring to high-income countries, but less, if at all, amenable to offshoring to lower-income countries and automation. In addition, I provide evidence on the young having shifted disproportionately towards occupations with relatively high non-routine manual task content, which, despite being less exposed to offshoring and automation, are mostly lower-paying. Instead, older workers shifted disproportionately towards occupations with relatively high abstract task content, which are both better shielded from offshoring and automation and higher-paying.

**Keywords: offshoring; automation; relative demand; age**

**JEL Classification: F14, F16, F66, J21, J23, J24, J31**

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†AXES, IMT School for Advanced Studies Lucca; email: sotirios.blanas@imtlucca.it

# 1 Introduction

The rapid expansion of offshoring, representing the spanning of firms' production processes across multiple countries, has been one of the key features of the globalised economy since the 1980s (R. Feenstra, 2010). The vast literature that has emerged studying its effects on the labour markets of developed countries has focused primarily on workers with different skills (e.g. R. C. Feenstra & Hanson, 1996, 1999) and occupations (e.g. Goos et al., 2014).[1]

However, a worker trait that has been largely overlooked within this context is the age profile. To my knowledge, this has been considered directly or indirectly (e.g. based on years of experience, attachment to the labour market) only by a few recent studies examining the implications of import competition for the employment and earnings of individual workers (D. H. Autor et al., 2014; Devlin et al., 2021). Thus, my main objective in this paper is to draw the attention to this worker trait by studying the impact of offshoring to high- and lower-income countries on the relative demand for three different age groups of workers (young, middle-aged, oldest) in the manufacturing and service sectors of eleven advanced economies in 1995–2005. As automation is another key labour demand shifter, I study along with offshoring in a subsequent analysis the impact of industrial robots and other automation technologies (e.g. 3-D printers, automatic conveyors) on the relative demand for the three age groups. This is an additional contribution of this paper, as empirical evidence on the impact of modern technologies on the relative demand for workers with different age profiles is scant and inconclusive (Behaghel et al., 2014; Blanas et al., 2019).

Conducting this analysis is particularly relevant and timely for a number of reasons. First, I document in this paper that the three age groups of workers differ in their exposure to offshoring and automation, implying that these factors might have impacted differently their shares in the total wage bill. In addition, due to their longer experience and tenure, older workers may be less affected by optimal labour utilisation adjustments made by firms due to offshoring and automation (Oreopoulos et al., 2012). Relatedly, reforms in recent decades in advanced countries towards the flexibilisation of their labour markets (e.g. lower employment

[1] The first stream of literature finds that offshoring has increased the relative demand for the high-skilled or decreased the relative demand for the less skilled using industry-level data (e.g. R. C. Feenstra & Hanson, 1996, 1999), firm-level data (e.g. Biscourp & Kramarz, 2007; Mion & Zhu, 2013), or matched employer-employee data (e.g. Hummels et al., 2014). For a comprehensive survey of this stream of literature, see Hummels et al. (2018). The second stream of literature finds that offshoring has contributed to "job polarisation", that is, the decline in the employment of workers in middle-paying occupations, which comprise a relatively high fraction of offshorable and routine tasks, relative to high- and low-paying occupations, which comprise a relatively low fraction of offshorable tasks and a relative high fraction of non-routine tasks (e.g. Goos et al., 2014).

protection) have been borne disproportionately by young labour market entrants (Blossfeld et al., 2009). On the other hand, older workers' firm- or industry-specific knowledge and experience may render them less capable of adapting to new employers or transitioning to industries that are less exposed to offshoring and automation (Jacobson et al., 1993). This can also occur because some of the skills and knowledge of older workers become obsolete over the years, while young workers are more likely to learn directly the skills that are most in demand (Johansen, 1959; Rosen, 1975; Chari & Hopenhayn, 1991). Another reason is that older workers tend to have lower returns to training due to the relatively short time horizon that they have at their disposal to recoup investments in such activities (OECD, 2006; Friedberg, 2003; Battisti et al., 2020), while the catch-up process in terms of skills and knowledge becomes even harder within a context of rapid changes induced by globalisation and technological change (Deming & Noray, 2020). These factors are partly responsible for the rising popularity of early retirement schemes entitled to some older workers in advanced countries, which started losing ground only very recently. Also, demographic ageing itself, which most of the countries examined have been confronted with, could lead to important socio-economic challenges, let alone within a context of potentially unequal effects of the rapid expansion of offshoring and automation on the demand for different age groups of workers (OECD, 2006; Buchholz et al., 2009; European Policy Committee, 2001, 2003, 2006).

For the construction of the sample on which I conduct the empirical analysis, I combine data from two sources: the EU KLEMS and the World Input-Output Database (WIOD). EU KLEMS is well-suited to my analysis as it contains information on labour- and other production-related variables that is comparable across countries, industries and years. In particular, it contains information on the total wage bill and its breakdown by age group of workers – the young (aged 15–29), the middle-aged (30–49), and the oldest (50+), and on aggregate capital and value-added. Using industry-level information from WIOD on the value of imported inputs by trade partner, I construct the variable for total offshoring intensity,[2] as well as variables for the intensities of offshoring to high-income countries, which involves the relocation of abstract tasks (e.g. R&D, design), and to lower-income countries, which involves predominantly the relocation of routine tasks (e.g. assembly line, customer service, routine software development). For the classification of offshoring destination countries by income level, I rely primarily on the World Bank's Historical Country Classification by Income.[3]

[2]This is calculated as the ratio of the total value of imported inputs of a country-industry pair from the same industry of all the available trade partners normalised by the country-industry pair's gross value-added.

[3]In robustness checks, I consider additional classifications based on the income and development status of

Examining patterns and trends of offshoring intensities, I find that while offshoring to high-income countries accounted for the largest fraction of total offshoring in 1995–2005, it increased relatively little over that period as a fraction of industrial output. By contrast, offshoring to lower-income countries as a fraction of industrial output exhibited a remarkably increasing trend. Importantly, this trend was not solely driven by China's spectacular performance as exporter of intermediate and final manufacturing goods, but also by the rest of the countries in the lower-income group. Over the same period, the young experienced declines in their share in the total wage bill, while the oldest and middle-aged workers experienced large and moderate increases, respectively, in their wage bill shares.

In order to identify whether the expansion of offshoring contributed to the aforementioned wage bill share trends, I estimate wage bill share equations corresponding to the three age groups of workers with the intensities of offshoring to high- and lower-income countries as the two key regressors. Subsequently, I identify the effects of automation by adding to the wage bill share equations a relevant variable. For the construction of automation variables, I follow Blanas et al. (2019) in interacting the total value of imported industrial robots and other automation technologies (e.g. 3-D printers) of each country examined with the industry-level share of routine tasks in 1980 of D. H. Autor et al. (2003). Information on the value of imports of automation technologies is retrieved from UN COMTRADE and is available only as of 1996.[4] In addition to controlling for aggregate capital intensity (aggregate capital stock to value-added) and industrial output (log of value-added), I always control for country-industry and country-year fixed effects. In this way, the coefficients of offshoring and automation variables are identified based on year-by-year cross-industry variation within a country. The incorporation of country-year fixed effects is particularly important as, among other factors, these fixed effects account for aggregate labour supply shocks (e.g. demographic ageing), which are likely to have contributed to the wage bill share trends of the three age groups.

Initially, I estimate the wage bill share equations by OLS and interpret the coefficient estimates of offshoring and automation technology variables as conditional correlations. In order to allow for the causal interpretation of the results, I also estimate the equations by 2SLS after instrumenting for the key regressors. Importantly, the 2SLS estimates are qualitatively very similar to the OLS estimates. In quantitative terms, the former estimates are mostly of

offshoring destination countries, as well as the level of technological sophistication of their exports and their human capital abundance.

[4]Thus, the sample exploited in these estimations covers the years between 1996 and 2005.

larger magnitude. For the offshoring intensities, I implement two different IV strategies. In the benchmark IV, I instrument offshoring intensities with their first and second lags. This approach relies on the popular concept in the related literature that past values of these variables are expected to be strong predictors of their current values, while, for the exclusion restriction to hold, it is assumed that their past effects on wage bill shares do not persist over the years (e.g. Crinò, 2012).

In the alternative IV, I instrument offshoring intensities with interactions of their values in the start year of the sample (1995) and the number of mobile cellular subscriptions per 100 people in the corresponding countries over 1995–2005.[5] These are Bartik instruments based on the idea that offshoring intensity of an industry in the initial year and the time-varying intensity with which communication technologies are used in the country can jointly determine the future growth rates of offshoring intensity of the industry in that country. Indeed, communication technologies and infrastructure are among the key determinants of offshoring by facilitating the coordination of geographically dispersed production (Baldwin, 2016; Fort, 2016). I also adopt the Bartik logic for the instrumentation of imported industrial robots and other automation technologies.[6] Following Blanas et al. (2019), I use bilateral country-level data of UN COMTRADE on imports and exports of an automation technology (e.g. industrial robots) in order to create a variable capturing the greater exposure of each country examined to automation depending on its imports from countries with relatively high growth rates of exports of automation technologies to the rest of the world.

The econometric analysis reveals that offshoring to high-income countries increased the relative demand for young workers and decreased the relative demand for the middle-aged, while offshoring to lower-income countries exerted opposite effects: it decreased the relative demand for the young and increased the relative demand for the middle-aged and oldest workers. Accounting for the education level, offshoring to high-income countries increased the relative demand for highly-educated workers of all three age profiles, pointing to the complementarity of non-routine tasks transferred to high-income countries and these types of workers. By contrast, education was not sufficient to shield young workers from the transfer of predominantly routine tasks to lower-income countries, as the relative demand for the young high-skilled and low-skilled decreased with offshoring to such countries. In addition, industrial robots, 3-D printers, automatic conveyors and other automation technologies decreased

[5] I draw information on the country-level variable from the World Bank's World Development Indicators.

[6] When applying this IV, offshoring intensities are instrumented with their first and second lags.

the relative demand for the young, while some of these (e.g. industrial robots) also increased the relative demand for the oldest workers. The rationale for these effects is as follows. The disproportionate employment of young workers in both 1990 and 2005 in occupations with relatively high content of offshorable and routine tasks implies that they were disproportionately vulnerable to their tasks being transferred to lower-income countries and automated. By contrast, the disproportionate employment of older workers in both years in occupations with relatively high content of abstract tasks implies that they were relatively shielded from offshoring to lower-income countries and automation, but the (non-routine) tasks transferred to high-income countries were more complementary to the young than to them or directly substituted for them.

The remainder of the paper is structured as follows. In Section 3, I describe the data and construction of variables. I also present useful patterns and trends of offshoring intensities and wage bill shares of the three age groups along with their task offshorability and routine task intensity scores. In Section 4, I derive the econometric model and give a detailed account of the estimation strategy. In Section 5, I present and rationalise the main results. Finally, in Section 6, I conclude by summarising the key findings and highlighting their pertinence to other research questions and lessons for policy.

## 2 Related literature

Although how offshoring impacts workers of different age profiles has been barely investigated, some pertinent evidence is provided by two recent empirical contributions to the literature, which study the implications of import competition on individual workers' employment and earnings based on detailed data on their careers. Considering young (aged 22–35) and older workers (aged 36–49) in US manufacturing, D. H. Autor et al. (2014) show that the relatively large negative effects of import competition from China on the earnings of low-tenure workers were not driven by their young age, but rather, by their short engagement with their initial employer. With respect to this paper, I consider three age groups of workers, rather than two, and show that the demand for the young relative to the middle-aged and oldest workers decreased with offshoring to lower-income countries, and that this effect was not driven solely by China, but also by other lower-income countries. I also show that this effect is identified both on the sample comprising manufacturing and service industries of eleven advanced countries, including the US, and the sample comprising manufacturing industries only. On top of that, I find that while automation exerts similar effects to offshoring to lower-income countries, offshoring to high-income countries exerts opposite effects.

Similarly to my approach to distinguish between high- and lower-income offshoring destination countries, Devlin et al. (2021) show that while the intensified import competition from the US due to the 1988 Canada–U.S. Free Trade Agreement (CUSFTA) had small effects on the employment and earnings of workers in Canada, the effects of import competition from China were relatively large. The authors also find that relatively large effects of import competition from the US were exerted on workers with low initial attachment to the labour force, who are more likely to be of young age. With regards to the latter finding, my analysis shows that offshoring to high-income countries, such as the US, increased the relative demand for the young, implying that the non-routine tasks that are transferred to such countries are more complementary to them, who are more likely to perform routine tasks, or directly substitute for older workers, who are more likely to perform non-routine tasks.

Another significant contribution of D. H. Autor et al. (2014) and Devlin et al. (2021) is their robust evidence on labour mobility across firms, industries and sectors, as well as permanent labour market exists, being key channels of adjustment of individual workers to import competition from China.[7] The second study also finds that the adjustments of workers in Canada to import competition from the US were much smoother and made primarily by young labour market entrants, rather than incumbents.[8] The latter evidence is consistent with evidence on certain jobs becoming increasingly over-represented by relatively old workers in recent decades (D. Autor & Dorn, 2009). Although the industry-level data that I utilise in this paper do not allow me to conduct a similar analysis, I am still able to derive useful insights about the shifts that the three age groups have made across different types of jobs likely due to factors such as the expansion of offshoring and automation.

Given its novel evidence on the effects of industrial robots and other automation technologies on the relative demand for the three age groups of workers, this paper is also related to the stream of literature on the implications of technological change for workers with different age profiles. Early studies find that older workers use computers and other Information and

[7] D. H. Autor et al. (2014) also track worker mobility across US regions, but they find that this has played a negligible role for the adjustment of workers to import competition from China.

[8] Evidence on relatively smooth adjustments due to intensified import competition from China and Eastern Europe has also been provided for the German labour market (Dauth et al., 2014, 2017, 2021).

Communication Technologies (ICT) less intensively than younger workers (Friedberg, 2003; Schleife, 2006; de Koning & Gelderblom, 2006), while their evidence on how ICT impact the demand for young and older workers is inconclusive (Borghans & ter Weel, 2002; Aubert et al., 2006; Schleife, 2006; Beckmann & Schauenberg, 2007; Rønningen, 2007; Schøne, 2009; Behaghel et al., 2014). Instead, there is more consensus about the implications of ICT for retirement decisions of older workers. In particular, workers retire later when they are employed in US industries that adopt new technologies at faster rates, but unexpected variations in the adoption rates lead to increases in early retirement (Bartel & Sicherman, 1993). Similar evidence is available for Norway (Hægeland et al., 2007). Relatedly, older workers approaching retirement age are less likely to acquire computer skills, albeit acquisition of such skills allows older workers to prolong their stay in the labour market.

The most closely related analysis is conducted by Blanas et al. (2019), who study the effects of modern technologies (ICT, software and industrial robots) on the demand for workers with different characteristics, including the age profile. The evidence that I provide on the negative effects of industrial robots and other automation technologies (e.g. 3-D printers) on the wage bill share of the youngest workers (aged 15–29) is consistent with their evidence showing that industrial robots decreased the employment level and income share of these workers.[9] For the identification of the causal effects of automation, I adopt the IV strategy proposed by the authors, while for the identification of different automation technologies, I rely on Acemoglu & Restrepo (2021), who study how demographic ageing of countries impacts their adoption of industrial robots and other automation technologies. Finally, another related empirical contribution is made by Barth et al. (2020), who employ data from the US Census and find that middle-aged workers (aged 35–49) are more complementary to software than younger and older workers, and that software adoption increases the earnings gap between high- and low-wage workers and between high- and low-wage firms.

## 3 Data and descriptive statistics

In the first part of this section, I describe the data and construction of variables. In the second part, I present patterns and trends of offshoring intensities, wage bill shares of different age groups, and task offshorability and routine task intensity scores by age group.

[9] The income share is calculated as the ratio of the wage bill of an age group to industrial output, while the wage bill share is calculated as the share of the wage bill of an age group in the total wage bill.

### 3.1 Data and variables

The sample on which I conduct the empirical analysis comprises 21 manufacturing and service industries in 11 high-income countries in 1995–2005. Its composition is determined by data availability in the March 2008 Release of the EU KLEMS database and the 2013 Release of the World Input-Output Database (WIOD) for the construction of labour and offshoring variables, along with my focus on the labour market implications of offshoring in developed countries and the particular relevance of offshoring to manufacturing and service industries.[10] Most of the high-income countries of the sample are in Western Europe (Austria, Denmark, Finland, Germany, Italy, the Netherlands, Spain, United Kingdom) and the rest are outside this continent (Australia, Japan and the United States of America). The manufacturing and service industries are classified according to NACE Rev. 1.1 and are displayed in Table 1.

<< Table 1 about here >>

Utilising the EU KLEMS data has three major advantages. The first is the consistency of its information across countries, industries and years. The second is that it includes information on the wage bill and employment shares by age group of workers (aged 15–29, 30–49, 50+), as well as on the total wage bill and total employment. Employment is measured as hours worked by persons engaged.[11] The third advantage is the availability of information on other production-related variables such as real gross value-added and real fixed stock of aggregate capital. For the cross-country comparability of monetary variables, I convert their values from national currencies to US dollars using real exchange rate data from the OECD.

In accord with the "narrow" definition of offshoring (R. C. Feenstra & Hanson, 1996), I retrieve from WIOD information on the value of inputs in US dollars sourced by each manufacturing and service industry of each of the eleven high-income countries examined from the *same* industry of all countries available except for the corresponding sourcing country.[12] In

[10]Information in the March 2008 EU KLEMS release stops in 2005. Although the most recent release (September 2017) and its revision (July 2018) cover more recent years, they have a much more limited coverage of countries and industries, which makes their use inappropriate for this particular analysis. Most notably, either release covers the manufacturing sector as a whole, but none of its industries. Similarly, information in the 2013 Release of WIOD is available no earlier than 1995, while information in the most recent release (2016) is available only as of 2000. Covering the manufacturing and service sectors is also particularly relevant as they account jointly for relatively large fractions of total employment in the countries and period examined.

[11]This is preferred to the number of persons engaged, as workers may differ in the amount of hours that they work (Graetz & Michaels, 2018).

[12]In this way, the supplying industries are identical to the sourcing industries displayed in Table 1, while input sourcing of industries that takes place within a country (i.e., domestic outsourcing) is excluded.

total, there are 40 individual supplying countries, plus the Rest of World (RoW).[13] I calculate total offshoring intensity as the ratio of the total value of inputs sourced by each country-industry pair from the same industry of the 41 trade partners to real gross value-added of the corresponding country-industry pair. However, lumping together all available supplying countries masks the fact that routine tasks are transferred to lower-income countries, while non-routine tasks are predominantly transferred to high-income countries. Motivated by this rationale, I construct offshoring intensity measures while distinguishing supplying countries by their income status. Importantly, despite the exclusion of imports from RoW, which is unclassifiable, the sum of the intensities of offshoring to high- and lower-income countries accounts, on average, for 85% of total offshoring intensity.

For the classification of supplying countries by their income level, I rely on the World Bank's Historical Country Classification By Income. In particular, I consider a supplying country as high-income (HI) if it belongs to the group of high-income countries for at least half of the years of the 1995–2005 period, or as lower-income (LMI) if it belongs to the group of upper-middle-, lower-middle- or low-income countries.[14] Alternatively, classifying supplying countries year by year barely changes the composition of the HI and LMI groups.[15] In the robustness checks section, I create additional classifications based on income per capita, economic complexity, and human capital abundance of supplying countries, all of which yield offshoring intensity variables that are very highly correlated with the respective main variables.

[13]These are: Australia, Austria, Bulgaria, Belgium, Brazil, Canada, China, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Indonesia, India, Ireland, Italy, Japan, Korea, Lithuania, Luxembourg, Latvia, Mexico, Malta, the Netherlands, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Turkey, Taiwan, United Kingdom, United States of America.

[14]The high-income group includes: Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, Luxembourg, Malta, Netherlands, Portugal, Slovenia, Spain, Sweden, Taiwan, United Kingdom, and the United States of America. The lower-income group includes: Brazil, Bulgaria, China, Czech Republic, Estonia, Hungary, India, Indonesia, Latvia, Lithuania, Mexico, Poland, Romania, Russia, Slovakia, and Turkey.

[15]I deem as benchmark the time invariant version as sourcing strategies of firms represent relationship-specific investments, implying that a radical revision of these would be very costly, not least in a relatively short time frame such as the one that I consider in the analysis. This stickiness is likely to hold true even in the face of continuously rising labour costs and income per capita in supplying countries, as well as during temporary economic downturns in these countries which may lead to the downgrade of their income status while leaving their production base largely unscathed. Also, note that the HI Vs LMI distinction that I consider captures the case in which a country such as India has lower per capita income than another lower-income country but is a more attractive service offshoring destination than the other country due to its relative abundance in skills related to the provision of services (e.g. requirement for fluency in English in customer service).

## 3.2 Descriptive statistics

### 3.2.1 Offshoring intensity

Figure 1 plots the sample mean of the intensities of offshoring in 1995–2005 to all destination countries (Panel (a)), the group of high-income countries (Panels (b)), the group of lower-income countries with and without China included (Panels (c) and (d)), and to China. I calculate the sample means in two steps (Graetz & Michaels, 2018; Blanas et al., 2019; Blanas, 2021). First, I calculate the weighted average of offshoring intensities across industries within each country and year using as weights each industry's employment in total employment of the manufacturing and service industries examined in 1995. Then, I average across countries by year without using country weights.

<< Figure 1 about here >>

According to Panel (a), total offshoring intensity was on a continuous rise between 1995 and 2005, except for the 2000–2002 period when it slightly declined. As a result, the mean ratio of the value of imported inputs from all supplying countries to industrial output increased from 6.5% in 1995 to 8.1% in 2005 (bottom of Panel A of Table A1). However, as revealed by Panels (b) and (c) of the same figure, distinguishing between high- and lower-income offshoring destinations is not only crucial conceptually, but also because the intensities of offshoring to the two destination types exhibited largely different trends over the period examined. In particular, the mean intensity of offshoring to high-income countries increased only slightly following an erratic movement: while it was mostly on the rise until 2000, it experienced a steep decline in 2000–2003, after which it bounced back only partly. As a result, it increased by only 0.2 percentage points (from 5.4% in 1995 to 5.6% in 2005). By contrast, the intensity of offshoring to lower-income countries was on a continuous rise in 1995–2005 except for small declines in three non-consecutive years, resulting in an increase of 0.7 percentage points (from 0.6% in 1995 to 1.3% in 2005).

Interestingly, Panels (d) and (e) indicate that the remarkable rise in the intensity of offshoring to lower-income countries is driven by both China and other lower-income countries. In fact, the intensity of offshoring to the group of lower-income countries other than China increased by 0.4 percentage points (from 0.5% in 1995 to 0.9% in 2005) and the intensity of offshoring to China increased by 0.3 percentage points (from 0.1% in 1995 to 0.4% in 2005).

As China has been mostly a major supplier of manufacturing intermediate and final goods rather than services, I show that the patterns and trends in the last two panels also hold for the sample comprising manufacturing industries only (Panels (a) and (b) of Figure A1).[16] The evidence for China adds to similar evidence provided by Hanson (2012), who reports that an astonishing three quarters of growth in manufacturing value-added among lower-income countries in the second half of the 1990s and first half of 2000s was accounted for by China, and by D. H. Autor et al. (2014), who report that China's share of manufacturing exports worldwide increased from 2% to 5% between 1990 and 2000, to 12% in 2007 and to 16% in 2011.

In sum, although offshoring to high-income countries accounted for the bulk of total offshoring throughout the period examined, offshoring to China and other lower-income countries increased much faster. Similar patterns and trends of offshoring intensities are also observed by country (Panel A of Table A1) and by industry (Panel B of Table A1), albeit quantitative heterogeneity along these dimensions is salient.[17] In figures and tables that are available upon request, I show that the aforementioned patterns and trends also hold when I consider the alternative income classifications of offshoring destination countries.

### 3.2.2 Wage bill shares

Next, I turn to the developments in the labour market. Figure 2 plots the sample mean of the wage bill shares of the young (solid line), middle-aged (long-dashed line), and oldest workers (short-dashed line) in 1995–2005.[18] While older workers increased their share in the total wage bill on an annual basis over the period (from 18.8% in 1995 to 22.8% in 2005), the reverse was true for the young, whose wage bill share declined from 23.4% to 19.1%. As a result, although older workers held the smallest share in the total wage bill in 1995, they overtook young workers in this regard in 2002. Also, despite the middle-aged holding the largest share in the total wage bill throughout the period, this increased only slightly, from 57.8% to 58.1%, without exhibiting significant fluctuations in the meantime (see also bottom

[16] In particular, manufacturing offshoring to lower-income countries other than China expanded by 1.1 percentage points (from 1.2% in 1995 to 2.3% in 2005) and manufacturing offshoring to China expanded by roughly 0.8 percentage points (from 0.3% in 1995 to slightly more than 1% in 2005).

[17] For the calculation of the mean levels by country, I calculate the weighted average of offshoring intensities across industries within each country and year using as weights each industry's employment in total employment of the manufacturing and service industries examined in 1995. For the calculation of the mean levels by industry, I calculate the average of offshoring intensities across countries by year without using country weights (Graetz & Michaels, 2018; Blanas et al., 2019; Blanas, 2021).

[18] The statistics for wage bill shares are produced similarly to those for the offshoring intensity measures.

of Panel A of Table A2). These patterns and trends also hold by country and by industry (Panels A and B of Table A2).

<< Figure 2 about here >>

As a final remark, it is important to bear in mind that aggregate labour supply shocks over the period examined, most notably, the ageing of the workforce, permanent and temporary labour market exits, the increasing supply of skills, and the rising female participation in the labour market are very likely to have contributed to the aforementioned trends. As a consequence, the wage bill share trends in Figure 2 represent trends of both relative demand and relative supply. In the econometric analysis, however, I interpret wage bill shares as relative demand measures as I always control in the specification for aggregate supply shocks with the inclusion of country-year fixed effects (e.g. Michaels et al., 2014).

#### 3.2.3 Task offshorability and routine task intensity

Table 2 displays the values of the task offshorability and routine task intensity measures for the three age groups of workers in 1990 (columns (1)–(3)) and in 2005 (columns (4)–(6)), as well as their differences between the two years (columns (7)–(9)). These measures capture the exposure of each age group of workers to their tasks being offshored or undertaken by machines. For their construction, I use the offshorable, abstract, non-routine manual, and routine task content scores for 330 occupations in 1980, as calculated by D. H. Autor & Dorn (2013).[19] Following the same study, I calculate the routine task intensity of each occupation as: $RTI = \ln routine - \ln manual - \ln abstract$. To produce the task content measures for the three age groups, I calculate the weighted average of these across all occupations using as weights the employment shares of the young (aged 16–29), middle-aged (30–54) and oldest workers (55–64) in each occupation in 1990 and 2005. Information on the weights is retrieved from D. Autor & Dorn (2009).[20] Given that the occupation-level task content scores are fixed

[19] In line with the concept of offshorability, the authors rely on two variables from US O*NET, "Face-to-Face Contact" and "On-Site Job", capturing the degree to which an occupation requires either direct interpersonal interaction or proximity to a specific work location. Then, they calculate the offshorability measure as the simple average of these two variables. They also reverse the sign so that the measure is increasing, rather than decreasing, in offshorability. As regards the abstract, non-routine manual and routine task content scores by occupation, the authors calculate these by aggregating the original five task scores (routine cognitive, routine manual, non-routine cognitive analytical, non-routine cognitive interpersonal, non-routine manual) of D. H. Autor et al. (2003), who rely on the fourth (1977) edition of the US Department of Labor's Dictionary of Occupational Titles (DOT).

[20] The original source from which the authors obtain data on the employment level of the three age groups by occupation is the US Census IPUMS.

occupational characteristics, it is important to keep in mind that the changes in the values of the task content measures by age group between 1990 and 2005 are driven solely by changes in the employment share of each age group in each occupation.

According to Panels A and B, young workers (aged 15–29) were the most exposed to offshoring and routinisation in 1990, followed by the oldest workers (aged 50+). Young workers, however, were the only age group to decrease their exposure to offshoring by 2005 by shifting away from occupations with highly offshorable task content. Due to this shift, the oldest workers became the most exposed age group to offshoring in 2005. Despite the small increase in their exposure to offshoring between 1990 and 2005, the middle-aged remained the least exposed age group to this factor throughout. In contrast to offshoring, the young were the most exposed age group to routinisation also in 2005, despite having been the only age group that experienced a decline in the RTI score. The trends of the offshorability and RTI scores of the three age groups are reminiscent of the evidence of D. H. Autor & Dorn (2013) on the "ageing" of occupations that are more amenable to offshoring and automation.

<< Table 2 about here >>

What is more, according to the values of the three RTI components in Panel B, the young shifted towards occupations with a relatively high non-routine manual task content (e.g. food preparation, sales, cleaning services, security services) – which are nevertheless mostly low-paying, while the oldest workers shifted towards occupations with a relatively high abstract task content (e.g. management, engineering), which are mostly high-paying. Despite the increase in the routine task content of the middle-aged, this age group had the highest abstract task content and the second highest non-routine manual task content scores in both 1990 and 2005. These observations will be very useful for the rationalisation of the effects of offshoring and automation technologies on the relative demand for the three age groups of workers that I identify in the econometric analysis. They are also indicative of the types of jobs the three age groups have disproportionately found themselves in as a result of the expansion of offshoring and automation, among other factors, and are thus complementary to the evidence of D. H. Autor et al. (2014) and Devlin et al. (2021) on labour mobility across firms, industries and sectors induced by import competition shocks.

## 4 Econometric model and estimation strategy

In this section, I present the econometric model and describe the estimation strategy.

### 4.1 Econometric model

For the derivation of the econometric model, I follow the related empirical literature (e.g. Berman et al., 1994; R. C. Feenstra & Hanson, 1996). Considering that the representative firm employs capital, workers of different age profiles and imported material and service inputs, the cost-minimisation problem that it faces is as follows:

$$C_{SR}(W, Y, K, OFF) = \min(W \cdot E') \;\; s.t. Y = f(E, K, OFF)$$

$C_{SR}$ is the short-run cost of the firm which comprises only the total wage bill as capital is treated as a quasi-fixed factor. $W$ and $E$ are vectors of hourly wages and total hours of work, respectively, of different age groups of workers. $Y$ stands for output, $K$ for aggregate capital and $OFF$ for imported material and service inputs.

Considering further the cost function to be of translog form and differentiating with respect to wages yields wage bill share equations for the three age groups:[21]

$$\begin{aligned} Wsh^a_{cit} =& \alpha_{ci} + \alpha_{ct} + \beta^a_Y * Y_{cit} + \beta^a_K * K_{cit} + \beta^a_{OFF} * OFF_{cit} + \epsilon^a_{cit}, \\ & \forall a \in A = \{15-29, 30-49, 50+\} \end{aligned} \tag{1}$$

The dependent variable, $Wsh^a_{cit}$, is the wage bill share of age group $a$ in industry $i$ of country $c$ in year $t$. Country-industry fixed effects, $\alpha_{ci}$, absorb time-invariant factors, such as variation across country-industry pairs in their initial level of technological sophistication and factor endowments. Country-year fixed effects, $\alpha_{ct}$, capture country-specific trends that might have induced shifts in the wage bill shares. Most notably, they account for aggregate labour supply shocks such as the ageing of the workforce, permanent and temporary labour market exits, the increasing supply of skills, and the rising participation of women in the

[21] Unlike other functional forms such as the CES, Cobb-Douglas and Leontief, the translog is more flexible as it does not require restrictive assumptions about the substitutability between inputs. See among others: R. C. Feenstra & Hanson (1996, 1999) and Hijzen et al. (2005).

labour market. In addition, they capture the evolution over the years of trade policy and openness and of labour market institutions (e.g. employment protection legislation strictness, collective bargaining, minimum wage policy). With regards to the latter, assuming that wage bargaining takes place at the national level, country-year fixed effects also absorb variation in relative wages over time, which are thus eliminated from the main specification.[22]

The log of real gross value-added, $\ln Y_{cit}$, and the ratio of the fixed stock of aggregate capital to value-added, $K_{cit}$, control for industry scale and capital intensity, respectively. The variable of interest is offshoring intensity, $OFF_{cit}$, which is calculated as the ratio of imported inputs to value-added, and its coefficient estimate, $\beta^a_{OFF}$, captures the effect of offshoring intensity on the wage bill share of age group $a$. When I distinguish between offshoring destination countries by their income level, I incorporate in the specification the ratio of imported inputs from high-income countries to value-added ($OFF\_HI_{cit}$) and the ratio of imported inputs from lower-income countries to value-added ($OFF\_LMI_{cit}$). Note that, as capital and offshoring intensities represent shares, they enter the model without being in logs.[23] Unobserved factors affecting the wage bill shares are included in the error terms, $\epsilon^a_{cit}$.

Although estimations on long-differenced data have the advantage of accounting for possible lags in the adjustment of wage bill shares to offshoring, the insights derived from them are more comprehensive when combined with a supplementary analysis identifying workers' mobility across firms, industries and sectors, and permanent labour market exits (D. H. Autor et al., 2014; Devlin et al., 2021). As the latter type of analysis is not feasible with the industry-level data that I employ, the identification of instantaneous wage bill share (non-)adjustments to offshoring, based on estimations on annual data, is equally useful and possibly more appropriate in this setting. Nevertheless, for the completeness of the analysis, I also estimate Eq. 1 in long differences (i.e., between the end and start years), which replace country-industry dummies. On top of that, I perform a robustness check in which I account for cross-industry labour shifts in Eq. 1 by replacing country-industry dummies with industry-year dummies.

In addition to offshoring, my goal is to identify the effects of automation technologies on the wage bill shares of the three age groups. To this end, I augment the main specification

[22] This approach has been made by earlier studies exploiting the EU KLEMS data and addressing similar research questions: Michaels et al. (2014), Graetz & Michaels (2018), Blanas et al. (2019), and Blanas (2021). To ensure the insensitivity of the results to this approach, I perform a robustness check in which I assume that wage bargaining takes place at the industry level and estimate the main specification after replacing country-year dummies with industry-level relative wages and year dummies.

[23] See among others: Michaels et al. (2014), Graetz & Michaels (2018), Blanas et al. (2019), and Blanas (2021).

with an interaction term comprising the total value of imported industrial robots of country $c$ over 1996–2005 normalised by its initial value (1996) and D. H. Autor et al. (2003)'s share of routine tasks of industry $i$ in 1980:

$$
\begin{aligned}
Wsh^{a}_{cit} =& \alpha_{ci} + \alpha_{ct} + \beta^{a}_{Y} * Y_{cit} + \beta^{a}_{K} * K_{cit} + \beta^{a}_{OFF} * OFF_{cit} \\
& + \beta^{a}_{ROBOTS} * ROBOTS_{ct} * RSH_{i} + \epsilon^{a}_{cit}, \;\; \forall a \in A = \{15-29, 30-49, 50+\}
\end{aligned} \tag{2}
$$

I calculate the total value of imported industrial robots for each country-year pair as the sum of the value of imports of industrial robots from each trade partner by year using bilateral import data from the UN COMTRADE database, which are only available as of 1996 (Blanas et al., 2019). Thus, the sample period exploited in the estimations of Eq. 2 starts one year later compared to the estimations of Eq. 1. Industrial robots are identified by their HS 1996 code (847950). Following Acemoglu & Restrepo (2021), I rely on the same database in order to retrieve bilateral import data on other automation technologies, namely: dedicated machinery, including industrial robots (DEDIC. MACH.); 3-D printing machines (3-D PRINT); automatic data processing machines (DATA PROC.); automatic conveyors (CONVEYORS); automatic regulating instruments (REGUL. INSTR.); electronic calculating machines (CALC. MACH.); automatic machine tools (MACH. TOOLS); automatic welding machines (WELD. MACH.); automatic textile, knitting and weaving machines (TEXT. MACH.).[24] The fact that country-year fixed effects account for demographic ageing has an additional value in this specification, as Acemoglu & Restrepo (2021) have provided robust evidence that countries that age faster utilise more intensively industrial robots and other automation technologies.

### 4.2 Estimation strategy

As a first step in the estimation strategy, I estimate the wage bill share equations in (1) by OLS. These estimations, however, may suffer from the simultaneity bias as the representative firm is likely to make optimal choices over offshoring and domestic labour utilisation simultaneously. For this reason, the OLS estimates for offshoring intensities can be interpreted only as conditional correlations. In order to obtain estimates that could capture the causal effects

[24] The HS 1996 code(s) based on which I identify the additional automation technologies are: DEDIC. MACH. (847989); 3-D PRINT (847780); DATA PROC. (8471, 847330); CONVEYORS (8428); REGUL. INSTR. (9032); CALC. MACH. (8470, 847321); MACH. TOOLS (8456, 8457, 8468); WELD. MACH. (8515); TEXT. MACH. (8444, 8445, 8446, 8447, 8448).

of offshoring intensities on the wage bill shares of the three age groups, I implement two IV strategies aiming at dealing with the simultaneity bias.

In the benchmark IV, I instrument offshoring intensities with their first- and second-lagged values (e.g. Crinò, 2012; Blanas et al., 2019; Blanas, 2021).[25] The instruments are expected to be relevant as offshoring intensities in the past two years are likely to be strongly correlated with their current values. It is important, though, to bear in mind that the exclusion restriction holds only if past effects of offshoring intensities on wage bill shares do not persist for one or two years ahead.

In the alternative IV strategy, I follow the Bartik logic and instrument industry-level offshoring intensities by multiplying their values in the start year of the sample (1995) by the number of mobile cellular subscriptions per 100 people in the corresponding countries over 1995–2005. Information on the country-level variable is retrieved from the World Bank's World Development Indicators. The usage of communication technologies (CT), such as mobile telephony, is particularly useful for the coordination of production that is fragmented geographically (Baldwin, 2016; Fort, 2016). Hence, industries that have different initial offshoring intensities in countries that differ in the penetration rate of mobile telephony will experience different growth rates for their offshoring intensities in the subsequent years of the sample period. Therefore, I expect the selected instruments to be strongly correlated with the offshoring intensity measures. Equally importantly, the exclusion restriction is expected to be satisfied for the following reasons. First, industry-level offshoring intensities are held constant in the start year of the sample period (1995) and are thus deemed as exogenous.[26] Second, the other component of the interaction terms acting as instruments is also exogenous as the per capita mobile cellular subscriptions of a country could impact industry-level wage bill shares only through the differential capacity of industries to utilise this countrywide endowment based on their initial and pre-determined offshoring intensities.

Similarly to Eq. 1, I first estimate Eq. 2 by OLS. The coefficient estimate for the automation exposure variable will be capturing causal effects on the wage bill shares of the three age groups only if countries' imports of automation technologies are driven by exogenous factors (e.g. global technological progress) and not by idiosyncratic ones (e.g. factor endowments).

[25] The missing values generated by the lag operators are filled with zeros (Arellano & Bond, 1991).

[26] Similarly to other studies making the Bartik approach, it has to be acknowledged that this argument is predicated upon the assumption that the sources of the initial cross-industry differences in offshoring intensities in a country (e.g. demand conditions), which may impact industry-level wage bill shares, are not time persistent.

To account for the potential role of idiosyncratic factors, I proceed to the estimation of the specification by 2SLS after implementing the Bartik IV strategy proposed by Blanas et al. (2019). In these estimations, I also instrument offshoring intensities with their first and second lags.

The concept of the IV strategy is that the exposure of a country to an automation technology like industrial robots is higher if it imports these from countries with higher growth rates of exports of industrial robots. Based on this concept, I calculate for each year in 1996–2005 and each of the eleven countries of the sample the weighted sum of exports of an automation technology of each of its trade partners to all export countries save of the corresponding country examined. Then, I normalise this variable by its values in the initial year (1996). As weights, I use the corresponding country's share of imports of the automation technology from each trade partner in its total imports of the automation technology in 1996.[27] The weights are deemed to be exogenous as they are held fixed at the initial year of the sample. To address any remaining concerns over endogeneity, I eventually instrument for the imports of an automation technology using the first and second lags of the weighted sum of exports of the automation technology.

Figure 3 plots the year-by-year cross-country mean of the current values of the instrument for imports of industrial robots (Panel (a)), dedicated machinery (Panel (b)), 3-D printing machines (Panel (c)), data processing machines (Panel (d)), automatic conveyors (Panel (e)), and regulating instruments (Panel (f)). Despite some fluctuations in Panels (b) and (d), the lines in all panels point to the rising exposure of the eleven countries examined to these automation technologies. In particular, exposure to industrial robots between 1996 and 2005 increased by 141%, to regulating instruments by 97%, to 3-D printers by 68%, to dedicated machinery by 54%, to automatic conveyors by 49%, and to data processing machines by 23%. Except for the declining exposure of countries to automatic textile machines, the exposure of countries to calculating machines, machine tools and welding machines also increased (Figure A2).[28] Similar trends are also observed when I plot the values of the instrument over 1996–2005 by country (Figures A3 and A4).[29]

[27]Recall that the start year of the sample period covered in this particular analysis is 1996 due to the fact that data on imports and exports of automation technologies in the UN COMTRADE database are available only as of that year.

[28]Note that, in contrast to other automation technologies which are quite widespread across manufacturing and service industries, the use of textile machines is concentrated in a small number of manufacturing industries such as apparel and footwear.

[29]Note that for industrial robots, all lines are upward-sloping except for that corresponding to Japan. This

Finally, note that in the OLS and 2SLS estimations of Eqs. 1 and 2, I account for each industry's size relative to the total size of the manufacturing and service sectors by weighing equations by the industry's share of employment in total employment of the manufacturing and service industries in 1995 (Michaels et al., 2014, Graetz & Michaels, 2018, Blanas et al., 2019; Blanas, 2021).

## 5 Econometric results

### 5.1 Offshoring and labour demand by age

I begin the econometric analysis by studying the relationship between offshoring and relative demand for workers with different age profiles. To this end, I initially estimate the wage bill share equations in (1) by OLS. Columns (1)–(3) and (4)–(6) of Panel A in Table 3 display the results obtained when total offshoring intensity ($OFF$) is the key explanatory variable of the specification and when this variable is decomposed into the intensities of offshoring to high- and lower-income countries ($OFF\_HI$, $OFF\_LMI$). The positive and highly significant coefficient estimate of $OFF$ in column (1) suggests that total offshoring intensity is positively associated with the wage bill share of the young (aged 15–29), while its negative and highly significant coefficient estimate in column (2) suggests that total offshoring intensity is negatively associated with the wage bill share of the middle-aged (aged 30–49). The negative but statistically insignificant coefficient estimate of the same variable in column (3) suggests that there is no statistically significant association between total offshoring intensity and the wage bill share of the oldest workers (aged 50+).

<< Table 3 about here >>

From columns (1)–(3), one might draw the conclusion that offshoring intensity is positively and negatively biased, respectively, towards the young and middle-aged. Nonetheless, columns (4)–(6) of the same panel reveal that this is only one aspect of how offshoring intensity is associated with the relative demand for different age groups. According to the coefficient estimates of $OFF\_HI$ and $OFF\_LMI$, this aspect seems to be driven by the intensity of offshoring to high-income countries which, despite its relatively small increase between 1995

is due to the low reliance of this country on imports of industrial robots, given that it is the largest producer and exporter in the world of this automation technology.

and 2005, accounted for the largest fraction of total offshoring intensity (see Section 3.2.1). In particular, the intensity of offshoring to high-income countries is positively associated with the wage bill share of the young (column (4)) and negatively associated with the wage bill shares of the middle-aged and oldest (columns (5) and (6)). By contrast, the intensity of offshoring to lower-income countries is negatively associated with the wage bill share of the young (column (4)) and positively associated with the wage bill shares of the middle-aged and the oldest (columns (5) and (6)). Reassured that the distinction between high- and lower-income offshoring destination countries yields a more nuanced relationship between offshoring intensity and relative demand for the three age groups, I stick with that approach throughout the rest of the econometric analysis.

Regarding the control variables, the log of output is positively associated with the wage bill share of the young (columns (1) and (4)) and negatively associated with the wage bill share of the middle-aged (columns (2) and (5)). Instead, aggregate capital intensity is negatively associated with the wage bill share of the young (column (1)) and positively associated with the wage bill share of the middle-aged (column (2)), while the respective coefficient estimates in columns (4) and (5) have no and low statistical significance, respectively. The associations of the log of output and aggregate capital intensity with the wage bill share of the oldest workers are statistically insignificant at all conventional levels.

Despite some loss of significance, re-estimating by OLS the wage bill share equations of columns (4)–(6) on long-differenced data paints a very similar picture: Offshoring to high-income countries is positively associated with the wage bill share of the young, while its negative associations with the wage bill shares of older workers turn statistically insignificant. By contrast, offshoring to lower-income countries is negatively associated with the wage bill share of the young and positively associated with the wage bill share of the oldest, while its positive association with the wage bill share of the middle-aged becomes insignificant (Panel (a) of Figure B1).[30] Also, the main results remain largely unchanged when I account for labour mobility across industries by replacing country-industry dummies with industry-year dummies (Panel (b) of Figure B1).

As the OLS estimates of the offshoring intensity variables can be interpreted only as conditional correlations, I now proceed to 2SLS estimations of Eq. 1 while implementing

[30] As long differences account for unobserved heterogeneity across country-industry pairs, I incorporate in these equations only the country-year dummies.

the benchmark and alternative IV strategies described in Section 4.2. The 2SLS estimations, especially those based on the alternative (Bartik) IV, should allow for the causal interpretation of the relationships of offshoring intensities with the wage bill shares of the three age groups. Panel B of Table 3 reveals that the 2SLS estimates are, by and large, qualitatively similar to the corresponding OLS estimates but mostly of larger size. Columns (1)–(3) and (4)–(6) portray the results obtained from the benchmark and alternative IV, respectively. In the benchmark IV, the offshoring intensity variables are instrumented with their first- and second-lagged values, while in the alternative IV, these variables are instrumented with interactions of their values in the start year of the sample (1995) with the per capita number of mobile cellular subscriptions in 1995–2005. In both approaches, the log of output and aggregate capital intensity are not instrumented.

According to Panel B, the intensity of offshoring to high-income countries increases the wage bill share of the young (columns (1) and (4)) and decreases the wage bill share of the middle-aged, albeit the latter effect is significant only under the benchmark IV (columns (2) and (5)). The same key regressor exerts no statistically significant effect on the wage bill share of the oldest workers under either IV strategy (columns (3) and (6)). The intensity of offshoring to lower-income countries exerts opposite effects: it increases the wage bill share of the oldest (columns (3) and (6)) and decreases the wage bill shares of the young (columns (1) and (4)) and the middle-aged (columns (2) and (5)). It is also noteworthy that their coefficient estimates are statistically different from each other, as the the p-value of the relevant F-test is below 10% in all columns of Panel B and the last three columns of Panel A. Regarding the control variables, the coefficient estimates of the log of output maintain their signs and levels of significance with respect to the OLS ones. The coefficient estimates of aggregate capital intensity maintain their signs, but lose significance in all columns except for (2), where it drops to 10%.

Regarding the first-stage results of the estimations in Panel B, the coefficient estimates of the selected instruments are mostly significant at 1%, pointing to their strong correlation with the instrumented variables (Figure 4). The statistics of the under-identification and weak identification tests, shown at the bottom of Panel B, also point to the relevance of the selected instruments. The p-value of the Hansen J statistic, which is relevant only to the benchmark IV, is below 10% in two out of the three columns, calling for some caution about the test for over-identifying restrictions.[31] In sum, the first-stage results lend support to my discussion in Section 4.2 about the relevance and validity of the benchmark and alternative IV strategies.

Motivated by the rapidly-growing literature on the implications of the spectacular rise of China for the labour markets of advanced countries (e.g. D. H. Autor et al., 2013; D. H. Autor et al., 2014), I showed in Section 3.2.1 that the sizeable and rapid growth of the intensity of offshoring to lower-income countries was not solely driven by China, but also by the other countries in this group. Adopting this approach in the econometric analysis, I re-estimate the main specification after replacing the intensity of offshoring to lower-income countries with the intensity of offshoring to all lower-income countries but China or the intensity of offshoring to China.[32] As China is mostly a leading producer and exporter of intermediate and final manufacturing goods, rather than services, I primarily make these estimations on the sample of manufacturing industries (Table B1).[33] Due to the change of estimating sample, I first ensure that estimating the main specification on the manufacturing sample yields similar results to the main ones (columns (1)–(3)). Indeed, I find that offshoring to high-income countries increased the relative demand for the young and decreased the relative demand for the middle-aged, while offshoring to lower-income countries decreased the relative demand for the young. These effects are also identified when the second key regressor is the intensity of offshoring to lower-income countries other than China or to China only (columns (4)–(6) and (7)–(9)). In line with the main results, I also find that the intensity of offshoring to China increases the relative demand for the oldest workers (column (9)).

In sum, my analysis shows that the intensities of offshoring to high- and lower-income countries exert opposite effects on the relative demand for the three age groups of workers: The intensity of offshoring to the first group of countries increases the relative demand for the young and decreases the relative demand for the middle-aged, while the intensity of offshoring to the second group of countries decreases the demand for the young relative to the middle-aged and oldest workers. Importantly, these effects also hold in the manufacturing sector alone. Equally importantly, the effects of offshoring to lower-income countries are not driven only by China, but also by the remaining countries in this group. The main effects can

[31] In the alternative IV, the Hansen J is not applicable as the number of instruments is equal to the number of instrumented variables.

[32] To avoid multi-collinearity, I do not include these two variables jointly in the specification.

[33] In a table that is available upon request, I show that using the sample of manufacturing and service industries yields very similar results.

be rationalised based on Table 2. Offshoring to lower-income countries, involving primarily the relocation of routine tasks (e.g. assembly line, client service, routine software programming), decreased the demand for the young relative to older workers because workers of the first age group were disproportionately employed in both 1990 and 2005 in occupations with relatively high content of offshorable and routine tasks. That is, the (routine) tasks offshored to lower-income countries substituted for young workers or were more complementary to the older ones employed domestically, who were more likely to perform non-routine tasks. Conversely, offshoring to high-income countries, involving the relocation of non-routine tasks (e.g. engineering, R&D, design, marketing), increased the demand for middle-aged workers relative to the young because the middle-aged were disproportionately employed in occupations that have relatively low content of offshorable tasks and relatively high content of abstract tasks. That is, the (non-routine) tasks offshored to high-income countries substituted for the middle-aged or were more complementary to the young, who were more likely to perform routine tasks.

#### 5.1.1 Robustness

Throughout the econometric analysis, I assume that wages are set at the national level and are thus captured by the country-year fixed effects. Accounting for the possibility that wages are set at the industry level, I add to the specification relative wages and replace country-year fixed effects with year fixed effects. For the calculation of relative wages, I first compute the ratio of the wage bill of each age group to its total hours of work, and then, I compute the ratio of the hourly wage of an age group to the hourly wage of the reference group, which is chosen to be that of the oldest workers (i.e., aged 50+). Similarly to the other explanatory variables under the benchmark IV, I instrument relative wages using their first- and second-lagged values. The 2SLS estimates in Panel (c) of Figure B1 suggest that estimating this version of the specification produces very similar results to the main ones.

In addition, I show that the main results are insensitive to classifying offshoring destination countries as high- and lower-income based on their income status in the initial year of the sample period (1995), as well as to distinguishing between OECD and non-OECD offshoring destination countries based on their OECD membership status by 1995.[34] These results are

[34] The composition of countries in the two groups under these classifications is very similar to the main classification.

available upon request. Deviating from the income status of offshoring destination countries, I consider the level of technological sophistication of their exports using data on the economic complexity index (ECI) of the ATLAS of Economic Complexity. I include an offshoring destination country in the group of countries of relatively high (low) economic complexity if its ECI is above or equal to (below) the $75^{th}$ percentile value of ECI, which is calculated on the sample of all offshoring destination countries available by year.[35] I also distinguish offshoring destination countries by their human capital abundance using data on the human capital index of the Penn World Tables version 10.0. Similarly to economic complexity, I consider that a country is relatively abundant (scarce) in human capital if its human capital index is above or equal to (below) the $75^{th}$ percentile value of the human capital index, which is calculated on the sample of all offshoring destination countries available by year.[36] The offshoring intensity variables based on these two alternative classifications are almost identical to the corresponding ones based on the benchmark classification, as indicated by their extremely high correlations ranging between 79% and 99%.[37] As a consequence, the 2SLS estimations based on the main IV yield very similar results to the main ones (Panels (d) and (e) of Figure B1). This is also the case for the OLS estimations and the 2SLS estimations based on the alternative IV (results available upon request).

#### 5.1.2 Accounting for the education level of age groups

To understand better the effects of offshoring on the relative demand for different age groups, I consider in this section the age profile of workers jointly with their skill profile. In doing so, I exploit information from the EU KLEMS on the breakdown of the wage bills of the three age groups by skill. Skill is measured by the level of education. By and large, workers with at least a bachelor's degree are labeled as high-skilled (HS), while the rest (e.g. with upper-secondary education, vocational training, lower-secondary education or no formal qualification) are labeled as lower-skilled (LS). Hence, I consider in total six age-skill groups

[35] The group of countries of relatively high economic complexity includes all countries of the high-income group under the benchmark classification except for Australia, Canada, Cyprus, Greece, Luxembourg, Malta, Netherlands, Portugal, Spain and Taiwan, which pertain to the group of countries of relatively low economic complexity in all or most years of the sample. Also, Czech Republic, which pertains to the lower-income group under the benchmark classification, is included in most years in the group of countries of relatively high economic complexity.

[36] The group of countries with relative human capital abundance comprises all high-income countries of the benchmark classification except for Cyprus, Greece, Italy, Malta, Portugal, Spain and Taiwan. Also, Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Poland, Romania, Russia, and Slovakia pertain mostly or exclusively to this group, while they are considered as lower-income under the benchmark classification.

[37] The pair-wise correlations are available upon request.

comprising the young, middle-aged and oldest high-skilled and lower-skilled workers.

Table 4 displays the results obtained from 2SLS estimations of the wage bill share equations for the six age-skill groups while implementing the alternative IV. With respect to the effects in Table 3, offshoring to high-income countries did not increase the wage bill share of all young workers, but only of the high-skilled (column (1)), while that of the lower-skilled was unaffected (column (2)). Also, offshoring to the same group of countries did not decrease the wage bill share of all middle-aged and oldest workers, but only of the lower-skilled (columns (4) and (6)), while it increased the wage bill share of those of high skill (columns (3) and (5)). Recall that no statistically significant effect on the wage bill share of the oldest was identified when skill was unaccounted for. As regards offshoring to lower-income countries, it decreased the wage bill share of the young and increased the wage bill share of the oldest workers, regardless of their skill profile. Instead, offshoring to the same group of countries did not increase the wage bill share of all middle-aged workers, but only of those of high skill. The relevance and validity of the IV strategy is confirmed by the first-stage statistics (bottom of the table) and first-stage results (Figure B2). Also, implementing the main IV yields very similar results (Table B2).

<< Table 4 about here >>

Taking stock, the results suggest that although high education level made all age groups (more) complementary to offshoring to high-income countries, this was not the case for offshoring to lower-income countries. In fact, the latter substituted for young workers, regardless of their education level, or was less complementary to them compared to high- and lower-skilled older workers. The latter is a very important result demonstrating the difficulty facing even the highly-educated young workers compared to older workers of high- and low-education in shifting away from tasks that have a high propensity to be offshored to lower-income countries and towards tasks that are not only more shielded from offshoring, but also offer relatively high wages. In this way, it enriches the existing evidence showing that the high-skilled succeeded in shifting away from declining industries and sectors and towards rising ones, while the low-skilled moved to other firms within a declining industry or another industry within a declining sector (D. H. Autor et al., 2014). It also demonstrates that various factors (e.g. greater experience, longer tenure) might have resulted in a greater capacity of older workers to retain their jobs, at least in the short term.

## 5.2 Offshoring, automation and labour demand by age

Having identified and rationalised the effects of offshoring on the relative demand for the three age groups of workers, I now add to the analysis another key labour demand shifter, namely, automation technology. To this purpose, I estimate the specification in (2), which includes the interaction between country-level imports of industrial robots and D. H. Autor et al. (2003)'s industry-level share of routine tasks ($ROBOTS * RSH$). The OLS and 2SLS results are shown in columns (1)–(3) and (4)–(6), respectively, of Table 5. In the 2SLS estimations, offshoring intensity variables are instrumented with their first and second lags, while the robot import variable is instrumented with the first and second lags of the robot exposure variable described in Section 4.2.

<< Table 5 about here >>

The coefficient estimates of offshoring intensities are largely unchanged compared to those obtained when the variable for the adoption of industrial robots is not included in the specification (see columns (4)–(6) of Panel A and columns (1)–(3) of Panel B in Table 3). The coefficient estimates of $ROBOTS * RSH$ in the first three columns of the table suggest that the adoption of industrial robots is positively associated with the wage bill share of the oldest workers, while its associations with the wage bill shares of the young and the middle-aged are statistically insignificant. Turning to the last three columns, the coefficient estimates of the same regressor suggest that the adoption of industrial robots increases the wage bill share of the oldest workers, decreases the wage bill share of the young, while it exerts no statistically significant effect on the wage bill share of the middle-aged. According to the first-stage results (Figure B3) and statistics (bottom of Table 5), the variables that I use as instruments for the offshoring intensities and robot imports are relevant and valid. Note also that the coefficient estimates of the three key regressors are statistically different from each other in all cases but one, as indicated by the p-values of the relevant F-test. I identify very similar effects, especially on the wage bill share of the young, after considering other automation technologies, such as dedicated machinery, 3-D printers, data processing machines, automatic conveyors, regulating instruments (Figure 5), as well as calculating machines, machine tools, welding machines, and textile machines (Figure B4).

<< Figure 5 about here >>

Repeating the 2SLS estimations of columns (4)–(6) of Table 5 on the sample of manufacturing industries, where reliance on offshoring and industrial robots is more intensive, yields very similar results except for the fact that leads to the weakening or loss of significance of the effects of offshoring to lower-income countries (columns (1)–(3) of Table B3). This is largely the case for additional estimations in which I replace the intensity of offshoring to lower-income countries with the intensity of offshoring to this group of countries save of China (columns (4)–(6) of Table B3). Note also that the coefficient estimates of the robot exposure variable are not statistically different from the coefficient estimates of the intensity of offshoring to lower-income countries (see p-values of the relevant F-tests in columns (1)–(3)) and columns (4)–(6) of Table B3). By contrast, the intensity of offshoring to China exerts effects that are similar to the main ones and statistically different from those exerted by the adoption of industrial robots (columns (7)–(9) of Table B3).

In conclusion, the adoption of industrial robots and other automation technologies exerts qualitatively similar effects to those of offshoring to lower-income countries, while the main effects of offshoring to high-income countries still hold. The former effects are intuitive: automation technologies decreased the relative demand for the young because these workers were disproportionately employed in 1990 and 2005 in occupations with relative high content of routine tasks, which are amenable to automation. By contrast, such technologies increased the relative demand for older workers because these workers were disproportionately employed in 1990 and 2005 in occupations that have relative high content of abstract tasks, which are better or fully shielded from automation.

# 6 Conclusion

Using a sample of manufacturing and service industries in eleven developed countries over 1995–2005, this paper provides novel evidence on the effects of offshoring and automation technologies (e.g. industrial robots) on the relative demand for three different age groups of workers.

While offshoring to high-income countries increased the relative demand for the young and decreased the relative demand for the middle-aged, offshoring to lower-income countries exerted opposite effects: it decreased the demand for the young relative to the middle-aged and oldest workers. Interestingly, although high education level allowed workers of all three age profiles to become more complementary to the non-routine tasks offshored to high-income countries, it did not help young workers to be better shielded from offshoring to lower-income countries, as the latter decreased the relative demand for both the high-skilled and lower-skilled young. Similarly to offshoring to the latter group of countries, the adoption of industrial robots and other automation technologies decreased the relative demand for the young. There is also evidence that some automation technologies (e.g. industrial robots) increased the relative demand for the oldest workers. The effects are explained by the fact that young workers were disproportionately employed in both 1990 and 2005 in occupations that have relatively high content of offshorable and routine tasks, which are amenable to offshoring to lower-income countries and automation. By contrast, older workers were disproportionately employed in both years in occupations that have relatively high content of abstract tasks. Such tasks have little or no exposure to offshoring to lower-income countries and automation, but are less complementary to or directly replaced by tasks offshored to high-income countries.

In addition to the detrimental effects on the relative demand for the young, it is worrisome that although workers of this age group shifted away from occupations that have relatively high offshorable and routine task content between 1990 and 2005, they shifted towards occupations that have relatively high non-routine manual task content. Albeit better shielded from offshoring to lower-income countries and automation, the latter group of occupations offer mostly relatively low wages. By contrast, the middle-aged remained in 2005 the least exposed age group to offshoring to lower-income countries and automation as they were disproportionately employed in occupations that have relatively high abstract task content, while the oldest workers increased their share of employment in such occupations.

Looking to the immediate and more distant future, recent advancements in the fields of Artificial Intelligence (e.g. Machine Learning) and Robotics have the potential to impact directly the relative demand for different age groups through displacement or creation of new tasks. These cutting-edge technologies, whose adoption may have accelerated since the onset of the Covid-19 pandemic, could also exert indirect effects, by shaping anew offshoring and global value chains. Further research in this direction would be particularly useful. Be that as it may, the gist of my analysis is that advanced economies should rise to the challenge of securing a more shared prosperity between young and older workers. This likely entails the design and implementation of a mix of policies, ranging from education and lifelong training to labour market reforms to pension scheme reforms, leading to a new “inter-generational contract” that would be consistent with the demands of an ever-evolving globalised and technology-dependent economy.

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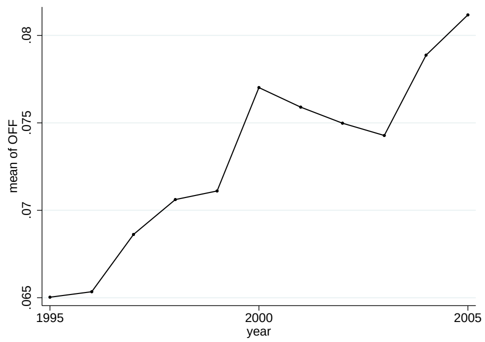
# Main descriptive statistics

Table 1: Industries

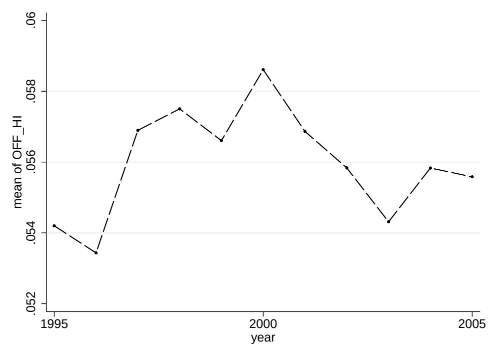
| NACE Rev 1.1 | Industry Name | NACE Rev 1.1 | Industry Name |
|---|---|---|---|
| 15–16 | Food products, Beverages and Tobacco | 34–35 | Transport Equipment |
| 17–19 | Textiles, Textile Products, Leather and Footwear | 36–37 | Manufacturing n.e.c.; Recycling |
| 20 | Wood and Products of Wood and Cork | 50 | Wholesale and Retail; motor vehicles |
| 21–22 | Pulp, Paper, Paper Products, Printing and Publishing | 51 | Wholesale, expect motor vehicles |
| 23 | Coke, Refined Petroleum Products and Nuclear Fuel | 52 | Retail, except motor vehicles |
| 24 | Chemicals and Chemical Products | 60–63 | Transportation and storage |
| 25 | Rubber and Plastics Products | 64 | Post and Telecommunications |
| 26 | Other Non-Metallic Mineral Products | 70 | Real Estate |
| 27–28 | Basic Metals and Fabricated Metal Products | 71–74 | Other business activities |
| 29 | Machinery and Equipment, n.e.c. | J | Financial Intermediation |
| 30–33 | Electrical and Optical Equipment | | |

*Source*: EU KLEMS.

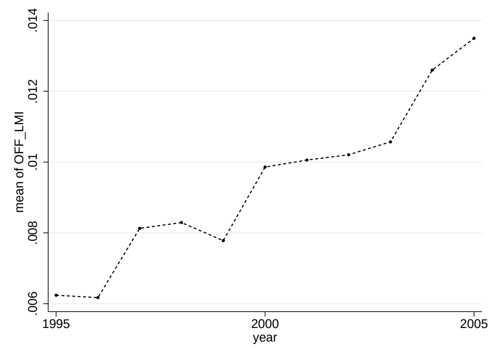
Figure 1: Offshoring intensities



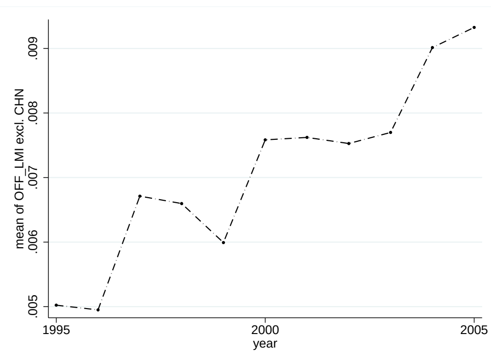

(a) All destination countries



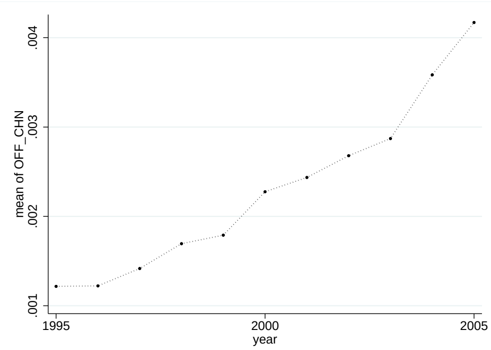

(b) High-income destination countries




(c) Lower-income destination countries




(d) Lower-income excl. China

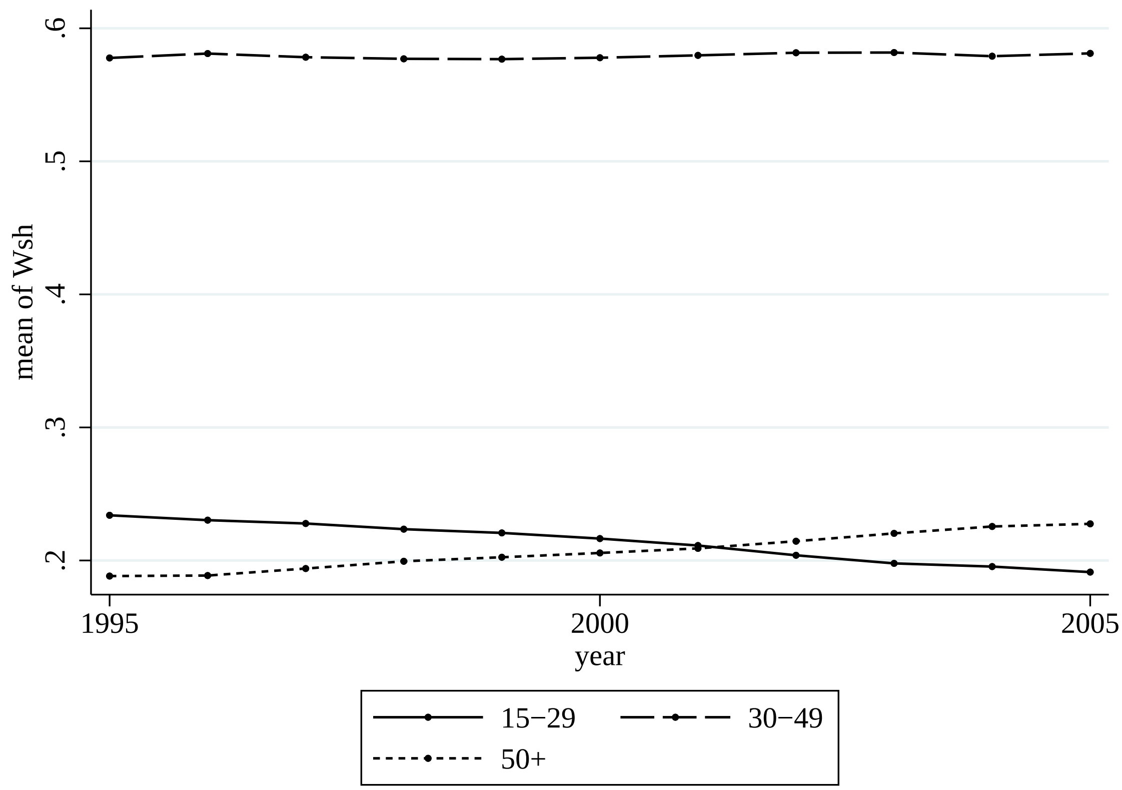



(e) China

*Notes*: The figure displays the intensities of offshoring to all available destination countries (Panel a), to high-income countries (Panel b), to lower-income countries (Panel c), to lower-income countries excluding China (Panel d), and to China (Panel e) for the whole sample by year. Offshoring intensities are calculated as ratios of real imports of a country-industry pair from the same industry of the respective set of countries to real gross value-added. Countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): the offshoring destination country belongs to the group of high-income (upper-middle-income, lower-middle-income or low-income) countries for at least half of the years of the period examined. For the calculation of the sample means, I first average offshoring intensities across industries within each country and year using as weights each industry's employment in total employment of the manufacturing and service industries examined in 1995. Then, I average across countries by year without using country weights.

*Source*: Author's calculations based on WIOD and EU KLEMS.

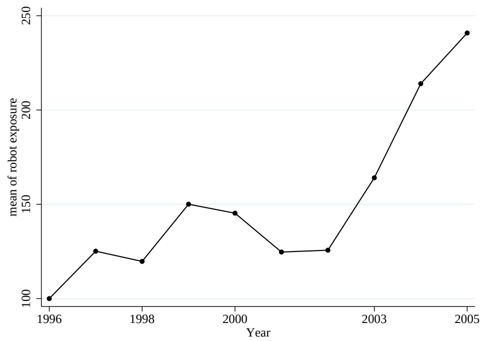
Figure 2: Wage bill shares by age



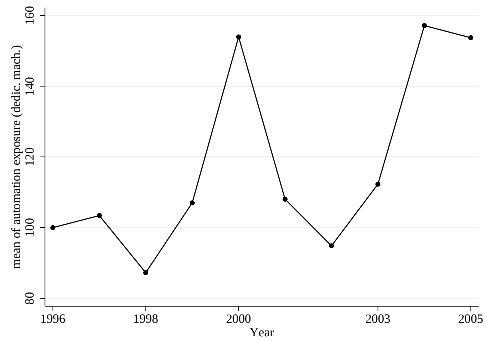

*Notes:* The figure displays the mean wage bill shares (Wsh) of young (aged 15–29), middle-aged (30–49) and older (aged 50+) workers for the whole sample by year. For the calculation of the mean shares, I first average the wage bill shares across industries within each country and year using as weights each industry's employment in total employment of the manufacturing and service industries examined in 1995. Then, I average across countries by year without using country weights.

*Source*: Author's calculations based on EU KLEMS.

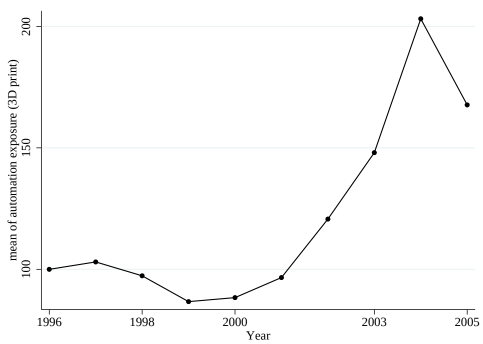
Figure 3: Exposure to automation, main technologies



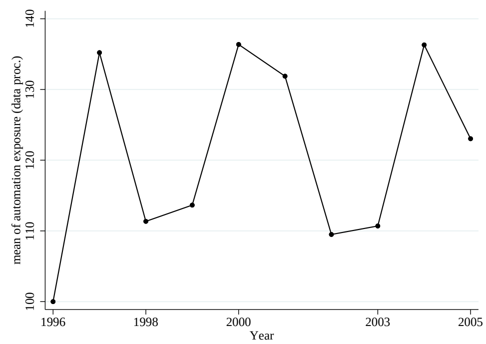

(a) Industrial robots



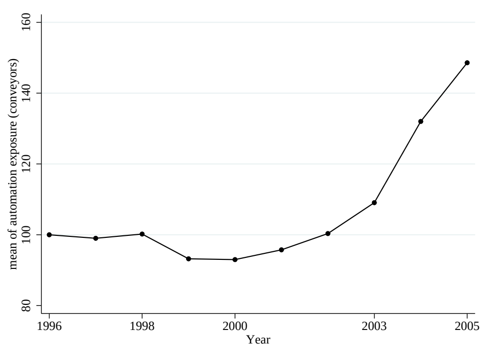

(b) Dedicated machinery, incl. industrial robots



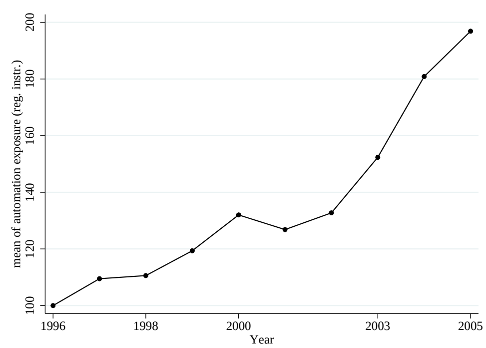

(c) 3-D printing machines




(d) Data processing machines




(e) Automatic conveyors




(f) Regulating instruments

*Notes*: The figure displays the year-by-year cross-country unweighted average of the measure of exposure of each country examined to: industrial robots (Panel (a)), dedicated machinery, incl. industrial robots (Panel (b)), 3-D printing machines (Panel (c)), data processing machines (Panel (d)), automatic conveyors (Panel (e)), and regulating instruments (Panel (f)). The country-level measures are created based on the IV strategy proposed by Blanas et al. (2019).

*Source*: Author's calculations based on UN COMTRADE.

Table 2: Offshorability and RTI scores by age group

| Panel A: Offshorability | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1990 | | | 2005 | | | Ch. 1990-2005 | | |
| | 15–29 | 30–49 | 50+ | 15–29 | 30–49 | 50+ | 15–29 | 30–49 | 50+ |
| Offshorability | 0.077 | -0.022 | 0.050 | 0.065 | -0.013 | 0.076 | -0.012 | 0.008 | 0.026 |
| **Panel B: Routine task intensity (RTI)** | | | | | | | | | |
| | 1990 | | | 2005 | | | Ch. 1990-2005 | | |
| | 15–29 | 30–49 | 50+ | 15–29 | 30–49 | 50+ | 15–29 | 30–49 | 50+ |
| Abstract | 2.601 | 3.051 | 2.826 | 2.549 | 3.001 | 2.964 | -0.053 | -0.050 | 0.138 |
| Routine | 4.695 | 4.606 | 4.524 | 4.670 | 4.639 | 4.474 | -0.024 | 0.033 | -0.049 |
| Non-routine manual | 1.335 | 1.300 | 1.269 | 1.392 | 1.296 | 1.203 | 0.058 | -0.004 | -0.066 |
| RTI | 1.194 | 1.003 | 1.109 | 1.173 | 1.027 | 1.122 | -0.020 | 0.023 | 0.013 |

*Notes*: For the calculation of the scores by age group in 1990 and 2005, I rely on the measures of the offshorable, abstract, routine and non-routine manual task content of 330 occupations (occ1990d) in 1980 created by D. H. Autor & Dorn (2013). The authors calculate occupation-specific offshorability as the simple average of two variables from US O*NET, "Face-to-Face Contact" and "On-Site Job", and then reverse its sign so that the measure is increasing in the offshorable task content of an occupation. Also, the authors calculate the scores of the abstract, routine and manual task content of occupations by aggregating the original five task scores (routine cognitive, routine manual, non-routine cognitive analytical, non-routine cognitive interpersonal, non-routine manual) of D. H. Autor et al. (2003) who rely on the 1997 DOT. Following D. H. Autor & Dorn (2013), I calculate the routine task intensity of each occupation as: $RTI = \ln routine - \ln manual - \ln abstract$. Then, I calculate for each age group (16–29, 30–54, 55–64) the weighted average of all these scores across occupations using as weights the employment shares of the corresponding age group in each occupation in 1990 and 2005. Information on the weights is readily available in D. Autor & Dorn (2009) who create these variables using the US Census IPUMS data. The last three columns display the difference in the scores by age group between 1990 and 2005.
*Source*: Author's calculations based on D. H. Autor & Dorn (2013) and D. Autor & Dorn (2009).

# Main econometric results

Table 3: Offshoring and labour demand by age, OLS and 2SLS

| Panel A: OLS | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dep var: Wsh | 15-29 | 30-49 | 50+ | 15-29 | 30-49 | 50+ |
| ln Y | 0.017*** | -0.011** | -0.0047 | 0.017*** | -0.012** | -0.0048 |
| | [0.004] | [0.005] | [0.003] | [0.003] | [0.005] | [0.003] |
| K | -0.0023** | 0.0024** | 0.00043 | -0.0016 | 0.0017* | 0.00036 |
| | [0.001] | [0.0010] | [0.0005] | [0.001] | [0.0010] | [0.0005] |
| OFF | 0.058*** | -0.054*** | -0.0013 | | | |
| | [0.01] | [0.01] | [0.007] | | | |
| OFF_HI | | | | 0.087*** | -0.069*** | -0.017* |
| | | | | [0.01] | [0.01] | [0.009] |
| OFF_LMI | | | | -0.14*** | 0.070** | 0.075*** |
| | | | | [0.04] | [0.03] | [0.03] |
| Observations | 2539 | 2541 | 2527 | 2539 | 2541 | 2527 |
| $R^2$ | 0.981 | 0.965 | 0.986 | 0.981 | 0.965 | 0.986 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMI}$ | | | | 0.000000301 | 0.000305 | 0.00102 |
| **Panel B: 2SLS, main and alternative IV** | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dep var: Wsh | 15-29 | 30-49 | 50+ | 15-29 | 30-49 | 50+ |
| ln Y | 0.017*** | -0.012** | -0.0043 | 0.017*** | -0.012** | -0.0049 |
| | [0.003] | [0.005] | [0.003] | [0.003] | [0.005] | [0.003] |
| K | -0.0012 | 0.0018* | 0.000097 | -0.00074 | 0.0014 | 0.000053 |
| | [0.001] | [0.0010] | [0.0005] | [0.001] | [0.001] | [0.0005] |
| OFF_HI | 0.069** | -0.092*** | 0.025 | 0.10** | -0.071 | -0.029 |
| | [0.03] | [0.03] | [0.02] | [0.04] | [0.05] | [0.03] |
| OFF_LMI | -0.26*** | 0.082* | 0.17*** | -0.53*** | 0.21** | 0.32*** |
| | [0.05] | [0.05] | [0.04] | [0.08] | [0.08] | [0.07] |
| Observations | 2539 | 2541 | 2527 | 2539 | 2541 | 2527 |
| $R^2$ | 0.0678 | 0.0269 | -0.00924 | 0.000368 | 0.0223 | -0.0297 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMI}$ | 2.92e-09 | 0.00164 | 0.000348 | 1.92e-14 | 0.00174 | 0.000000384 |
| Kleibergen-Paap rk LM | 39.16 | 39.03 | 38.58 | 27.28 | 27.30 | 26.99 |
| Kleibergen-Paap rk LM (p-value) | 1.60e-08 | 1.71e-08 | 2.13e-08 | 0.000000176 | 0.000000174 | 0.000000205 |
| Kleibergen-Paap Wald rk F | 23.97 | 23.88 | 23.49 | 16.04 | 16.06 | 15.81 |
| Hansen J | 9.657 | 2.783 | 8.884 | N/A | N/A | N/A |
| Hansen J (p-value) | 0.00800 | 0.249 | 0.0118 | N/A | N/A | N/A |
| IV strategy | ln Y and K treated as exogenous<br>First and second lags of<br>OFF_HI, OFF_LMI | | | ln Y and K treated as exogenous<br>OFF_HI, OFF_LMI in 1995 interacted<br>with mobile cellular subscriptions<br>per 100 people in 1995–2005 | | |

*Notes:* OLS and 2SLS estimations with robust standard errors in all columns. Country-industry and country-year fixed effects are included in the equations. The equations are weighted by the share of each industry's employment in total employment of the manufacturing and service industries examined in 1995. Asterisks denote significance at 1% (***), 5% (**), and 10% (*). For the description of the variables, see Table B4.

Table 4: Offshoring and labour demand by age-skill, 2SLS, alternative IV

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep var: Wsh | 15-29,HS | 15-29,LS | 30-49,HS | 30-49,LS | 50+,HS | 50+,LS |
| ln Y | 0.0027 | 0.015*** | 0.0072 | -0.019*** | 0.0032* | -0.0085*** |
| | [0.003] | [0.003] | [0.007] | [0.007] | [0.002] | [0.003] |
| K | -0.0055** | 0.0048*** | -0.010*** | 0.011*** | 0.00039 | -0.00062 |
| | [0.002] | [0.001] | [0.003] | [0.004] | [0.0004] | [0.0004] |
| OFF_HI | 0.057*** | 0.044 | 0.12** | -0.19*** | 0.057*** | -0.087*** |
| | [0.02] | [0.04] | [0.05] | [0.06] | [0.02] | [0.03] |
| OFF_LMI | -0.11** | -0.41*** | 0.29** | -0.090 | 0.064* | 0.26*** |
| | [0.05] | [0.08] | [0.1] | [0.1] | [0.04] | [0.07] |
| Observations | 2540 | 2540 | 2541 | 2541 | 2527 | 2541 |
| $R^2$ | 0.112 | 0.0300 | 0.0640 | 0.109 | -0.0555 | -0.0477 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMI}$ | 0.00812 | 1.27e-08 | 0.152 | 0.456 | 0.849 | 7.98e-08 |
| Kleibergen-Paap rk LM | 27.28 | 27.30 | 27.30 | 27.30 | 26.99 | 27.30 |
| Kleibergen-Paap rk LM (p-value) | 0.000000176 | 0.000000174 | 0.000000174 | 0.000000174 | 0.000000205 | 0.000000174 |
| Kleibergen-Paap Wald rk F | 16.04 | 16.05 | 16.06 | 16.06 | 15.81 | 16.06 |
| Hansen J | N/A | N/A | N/A | N/A | N/A | N/A |
| Hansen J (p-value) | N/A | N/A | N/A | N/A | N/A | N/A |
| | ln Y and K treated as exogenous | | | | | |
| IV strategy | Offshoring intensities instrumented with interactions between their values in 1995 and mobile cellular subscriptions per 100 people in 1995–2005 | | | | | |

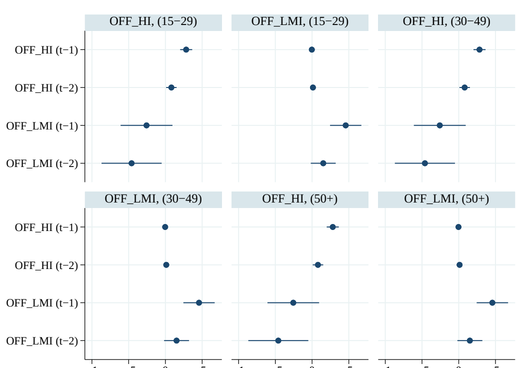
*Notes:* 2SLS estimations with robust standard errors in all columns. Country-industry and country-year fixed effects are included in the equations. The equations are weighted by the share of each industry's employment in total employment of the manufacturing and service industries examined in 1995. Asterisks denote significance at 1% (***), 5% (**), and 10% (*). For the description of the variables, see Table B4.

Table 5: Offshoring, industrial robots and labour demand by age, 1996–2005, 2SLS

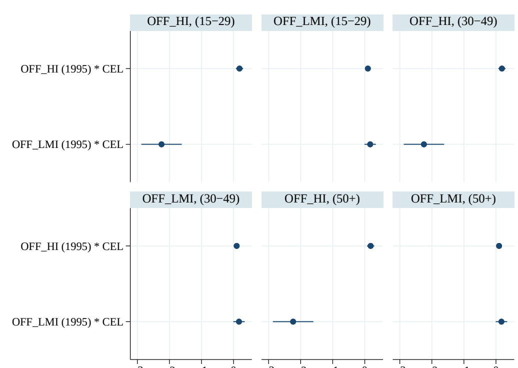
| Dep var: Wsh | (1)<br>15-29 | (2)<br>30-49 | (3)<br>50+ | (4)<br>15-29 | (5)<br>30-49 | (6)<br>50+ |
|---|---|---|---|---|---|---|
| ln Y | 0.015*** | -0.012** | -0.0025 | 0.012*** | -0.011* | -0.00052 |
| | [0.004] | [0.005] | [0.003] | [0.004] | [0.006] | [0.004] |
| K | -0.0015 | 0.0015 | 0.00055 | -0.0018 | 0.0016 | 0.00084 |
| | [0.001] | [0.001] | [0.0005] | [0.001] | [0.001] | [0.0006] |
| OFF_HI | 0.091*** | -0.067*** | -0.023** | 0.089*** | -0.058* | -0.031* |
| | [0.01] | [0.02] | [0.009] | [0.03] | [0.03] | [0.02] |
| OFF_LMI | -0.19*** | 0.11*** | 0.083*** | -0.16*** | 0.062 | 0.095** |
| | [0.04] | [0.04] | [0.03] | [0.05] | [0.06] | [0.04] |
| ROBOTS * RSH | -0.0013 | -0.00062 | 0.0020** | -0.011** | 0.0026 | 0.0090** |
| | [0.0009] | [0.0010] | [0.0008] | [0.005] | [0.005] | [0.004] |
| Observations | 2287 | 2289 | 2280 | 2287 | 2289 | 2280 |
| $R^2$ | 0.983 | 0.967 | 0.987 | 0.0131 | 0.0219 | -0.0262 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMI}$ | 2.13e-12 | 0.0000379 | 0.000431 | 0.00000865 | 0.0503 | 0.00492 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{ROBOTS}$ | 5.80e-11 | 0.0000302 | 0.00703 | 0.000255 | 0.0714 | 0.0389 |
| F-test $H_0$: $\beta_{OFF\_LMI} = \beta_{ROBOTS}$ | 0.000000111 | 0.00264 | 0.00335 | 0.00780 | 0.310 | 0.0642 |
| Kleibergen-Paap rk LM | N/A | N/A | N/A | 117.3 | 117.2 | 117.1 |
| Kleibergen-Paap rk LM (p-value) | N/A | N/A | N/A | 2.03e-24 | 2.11e-24 | 2.25e-24 |
| Kleibergen-Paap Wald rk F | N/A | N/A | N/A | 19.89 | 19.88 | 19.87 |
| Hansen J | N/A | N/A | N/A | 3.333 | 6.685 | 3.807 |
| Hansen J (p-value) | N/A | N/A | N/A | 0.343 | 0.0827 | 0.283 |
| IV strategy | N/A | N/A | N/A | ln Y and K treated as exogenous<br>Offshoring intensities instrumented with their first and second lags<br>Imports of industrial robots instrumented with the first and second lags of the robot exposure variable | | |

*Notes:* 2SLS estimations with robust standard errors in all columns. Country-industry and country-year fixed effects are included in the equations. The equations are weighted by the share of each industry's employment in total employment of the manufacturing and service industries examined in 1995. Asterisks denote significance at 1% (***), 5% (**), and 10% (*). For the description of the variables, see Table B4.

Figure 4: First stages of 2SLS in Panel B of Table 3



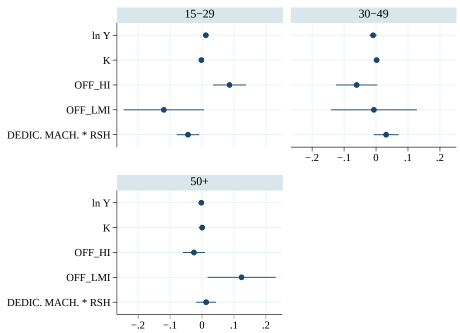

(a) Columns (1)–(3) of Panel B



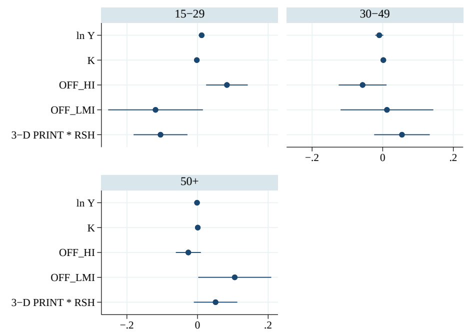

(b) Columns (4)–(6) of Panel B

*Notes*: For the description of the variables, see Table B4.

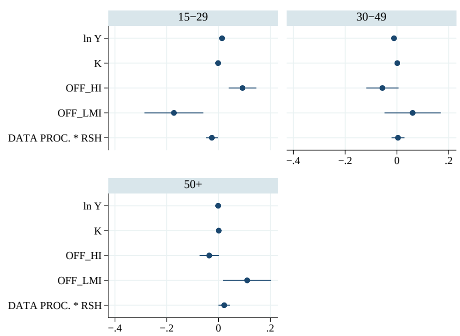
Figure 5: Offshoring, automation and labour demand by age, 1996–2005, 2SLS



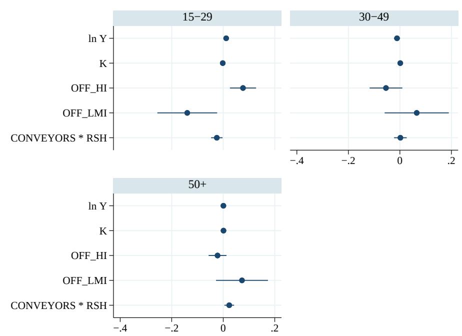

(a) Dedicated machinery, incl. industrial robots



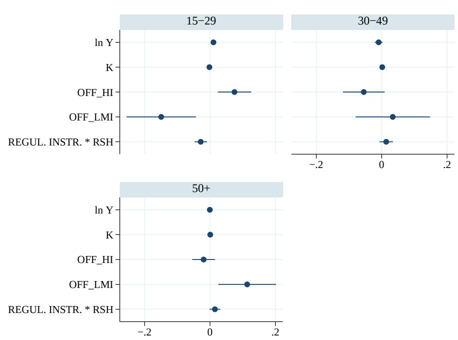

(b) 3-D printing machines




(c) Data processing machines




(d) Automatic conveyors



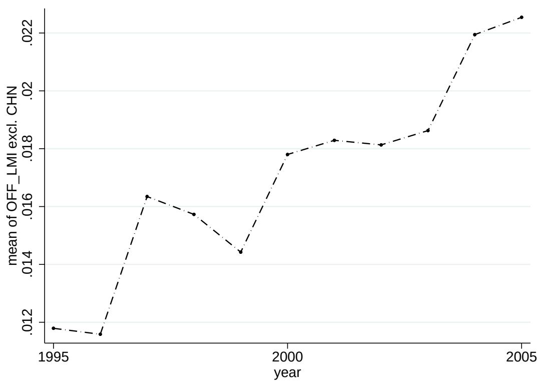

(e) Regulating instruments

*Notes*: 2SLS estimations with robust standard errors in all panels. Country-industry and country-year fixed effects are included in the equations. The equations are weighted by the share of each industry's employment in total employment of the manufacturing and service industries examined in 1996. For the description of the variables, see Table B4.

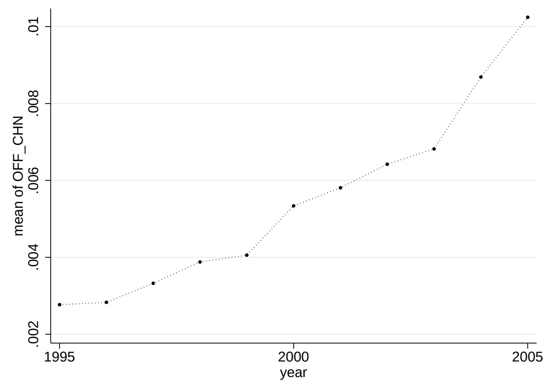
# Appendix

## A Additional descriptive statistics

Figure A1: Offshoring intensities, manufacturing



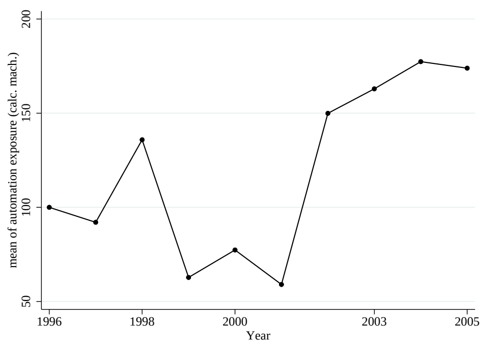

(a) Lower-income excl. China



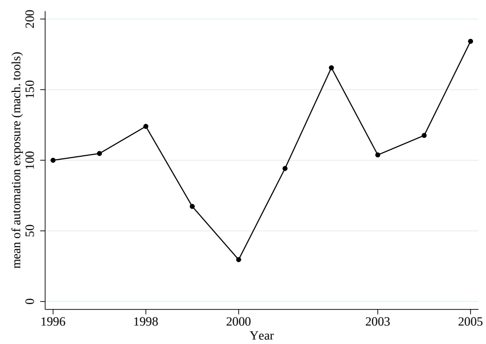

(b) China

*Notes*: The figure displays the intensities of offshoring to lower-income countries excluding China (Panel a), and to China (Panel b) for the sample comprising manufacturing industries only by year. Offshoring intensities are calculated as ratios of real imports of a country-industry pair from the same (manufacturing) industry of the respective set of countries to real gross value-added. Countries are classified as lower-income according to the World Bank's Historical Country Classification By Income. Lower-income: the offshoring destination country belongs to the group of upper-middle-income, lower-middle-income or low-income countries for at least half of the years of the period examined. For the calculation of the (manufacturing) sample means, I first average offshoring intensities across industries within each country and year using as weights each industry's employment in total employment of the manufacturing industries examined in 1995. Then, I average across countries by year without using country weights.
*Source*: Author's calculations based on WIOD and EU KLEMS.

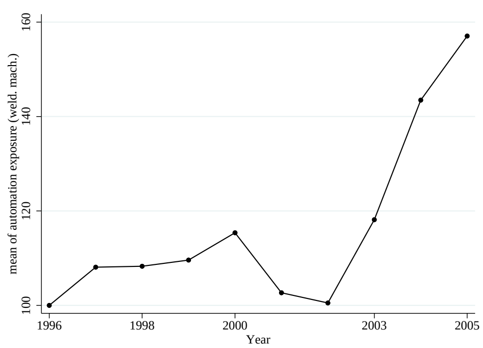
Figure A2: Exposure to automation, additional technologies



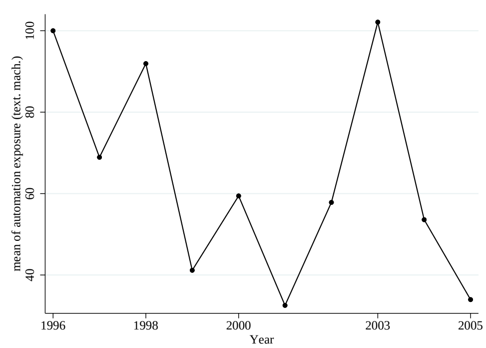

(a) Calculating machines




(b) Machine tools




(c) Welding machines

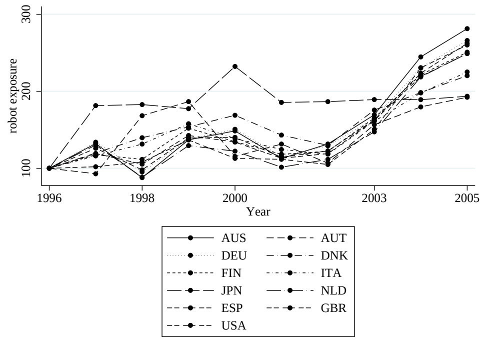



(d) Textile machines

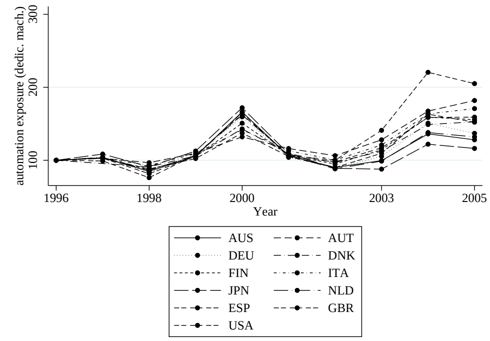
*Notes*: The figure displays the year-by-year cross-country unweighted average of the measure of exposure of each country examined to: calculating machines (Panel (a)), machine tools (Panel (b)), welding machines (Panel (c)), and textile machines (Panel (d)). The country-level measures are created based on the IV strategy proposed by Blanas et al. (2019).

*Source*: Author's calculations based on UN COMTRADE.

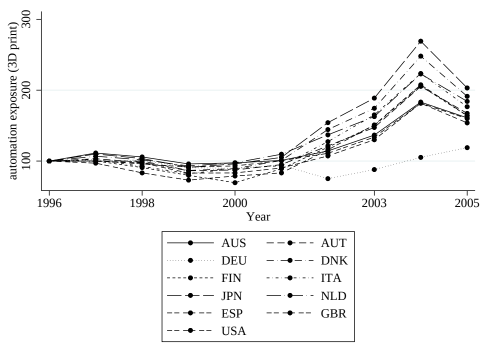
Figure A3: Exposure to automation by country, main technologies



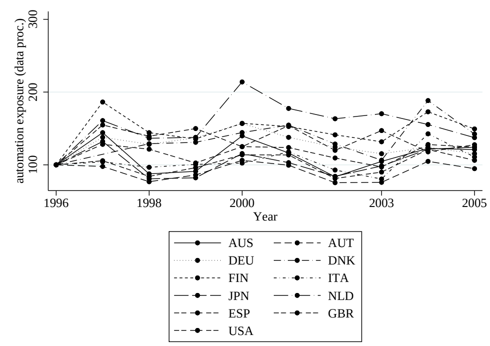

(a) Industrial robots



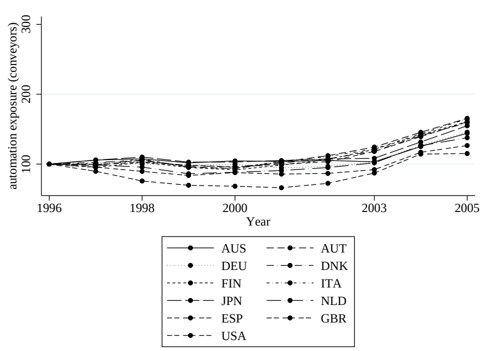

(b) Dedicated machinery, incl. industrial robots



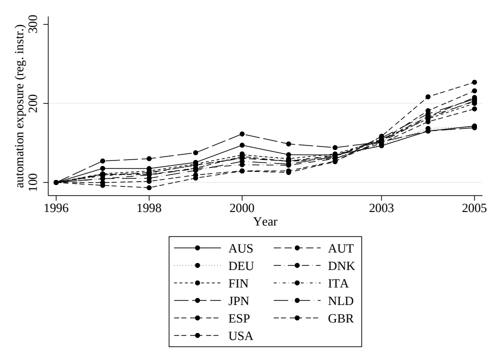

(c) 3-D printing machines




(d) Data processing machines



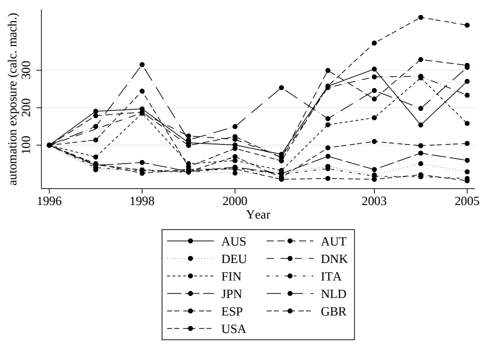

(e) Automatic conveyors



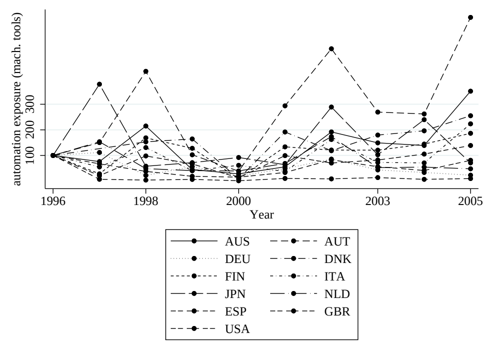

(f) Regulating instruments

*Notes*: The figure displays the annual variation of the measure of exposure of each country examined to: industrial robots (Panel (a)), dedicated machinery, incl. industrial robots (Panel (b)), 3-D printing machines (Panel (c)), data processing machines (Panel (d)), automatic conveyors (Panel (e)), and regulating instruments (Panel (f)). The country-level measures are created based on the IV strategy proposed by Blanas et al. (2019). *Source*: Author's calculations based on UN COMTRADE.

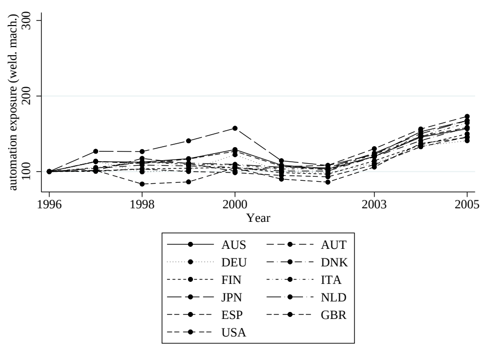
Figure A4: Exposure to automation by country, additional technologies



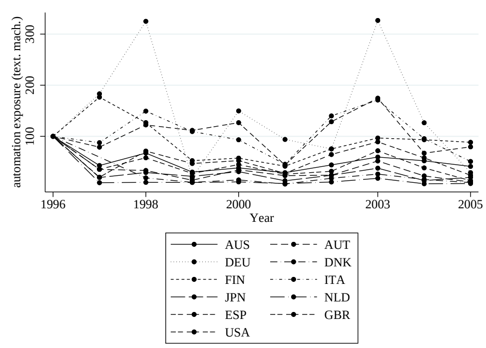

(a) Calculating machines




(b) Machine tools




(c) Welding machines




(d) Textile machines

*Notes*: The figure displays the annual variation of the measure of exposure of each country examined to: calculating machines (Panel (a)), machine tools (Panel (b)), welding machines (Panel (c)), and textile machines (Panel (d)). The country-level measures are created based on the IV strategy proposed by Blanas et al. (2019).
*Source*: Author's calculations based on UN COMTRADE.

Table A1: Offshoring intensities by country and by industry

| Panel A: By country | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Country | Mean level 1995 | | | | | Mean level 2005 | | | | |
| | OFF | OFF_HI | OFF_LMI | OFF_LMInC | OFF_CHN | OFF | OFF_HI | OFF_LMI | OFF_LMInC | OFF_CHN |
| Australia | 0.035 | 0.025 | 0.005 | 0.003 | 0.002 | 0.033 | 0.016 | 0.006 | 0.002 | 0.004 |
| Austria | 0.084 | 0.074 | 0.007 | 0.006 | 0.000 | 0.132 | 0.098 | 0.019 | 0.016 | 0.002 |
| Denmark | 0.081 | 0.071 | 0.007 | 0.006 | 0.001 | 0.109 | 0.080 | 0.014 | 0.010 | 0.004 |
| Finland | 0.088 | 0.072 | 0.007 | 0.006 | 0.001 | 0.089 | 0.058 | 0.017 | 0.013 | 0.004 |
| Germany | 0.068 | 0.056 | 0.008 | 0.007 | 0.001 | 0.109 | 0.069 | 0.027 | 0.021 | 0.006 |
| Italy | 0.066 | 0.056 | 0.009 | 0.008 | 0.001 | 0.081 | 0.054 | 0.017 | 0.012 | 0.005 |
| Japan | 0.017 | 0.009 | 0.004 | 0.002 | 0.002 | 0.025 | 0.009 | 0.008 | 0.002 | 0.006 |
| Netherlands | 0.117 | 0.093 | 0.007 | 0.006 | 0.001 | 0.122 | 0.084 | 0.012 | 0.008 | 0.004 |
| Spain | 0.062 | 0.058 | 0.005 | 0.004 | 0.001 | 0.096 | 0.076 | 0.012 | 0.008 | 0.004 |
| United Kingdom | 0.072 | 0.062 | 0.006 | 0.005 | 0.001 | 0.070 | 0.052 | 0.009 | 0.006 | 0.004 |
| United States | 0.026 | 0.019 | 0.004 | 0.003 | 0.001 | 0.027 | 0.015 | 0.007 | 0.004 | 0.003 |
| Unweighted mean | 0.065 | 0.054 | 0.006 | 0.005 | 0.001 | 0.081 | 0.056 | 0.013 | 0.009 | 0.004 |

| Panel B: By industry | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Industry | Mean level 1995 | | | | | Mean level 2005 | | | | |
| | OFF | OFF_HI | OFF_LMI | OFF_LMInC | OFF_CHN | OFF | OFF_HI | OFF_LMI | OFF_LMInC | OFF_CHN |
| 15T16 | 0.0539 | 0.0343 | 0.0083 | 0.0082 | 0.0002 | 0.0656 | 0.0333 | 0.0075 | 0.0070 | 0.0005 |
| 17T19 | 0.2598 | 0.2047 | 0.0500 | 0.0335 | 0.0165 | 0.2328 | 0.1287 | 0.0953 | 0.0483 | 0.0470 |
| 20 | 0.1551 | 0.1104 | 0.0227 | 0.0213 | 0.0014 | 0.1822 | 0.1117 | 0.0432 | 0.0367 | 0.0065 |
| 21T22 | 0.1496 | 0.1293 | 0.0066 | 0.0062 | 0.0004 | 0.1376 | 0.1136 | 0.0098 | 0.0087 | 0.0011 |
| 23 | 0.0835 | 0.0514 | 0.0101 | 0.0100 | 0.0000 | 0.6421 | 0.2947 | 0.0771 | 0.0756 | 0.0015 |
| 24 | 0.2864 | 0.2285 | 0.0140 | 0.0132 | 0.0007 | 0.3061 | 0.2258 | 0.0225 | 0.0155 | 0.0071 |
| 25 | 0.0586 | 0.0508 | 0.0054 | 0.0035 | 0.0019 | 0.0765 | 0.0598 | 0.0120 | 0.0076 | 0.0044 |
| 26 | 0.0399 | 0.0347 | 0.0047 | 0.0042 | 0.0005 | 0.0432 | 0.0315 | 0.0069 | 0.0051 | 0.0018 |
| 27T28 | 0.2807 | 0.2132 | 0.0292 | 0.0271 | 0.0020 | 0.3441 | 0.2270 | 0.0490 | 0.0404 | 0.0086 |
| 29 | 0.1001 | 0.0911 | 0.0040 | 0.0035 | 0.0005 | 0.1395 | 0.1107 | 0.0151 | 0.0113 | 0.0039 |
| 30T33 | 0.2782 | 0.2291 | 0.0150 | 0.0071 | 0.0078 | 0.2702 | 0.1819 | 0.0625 | 0.0310 | 0.0315 |
| 34T35 | 0.2733 | 0.2622 | 0.0109 | 0.0102 | 0.0007 | 0.4597 | 0.3982 | 0.0559 | 0.0496 | 0.0063 |
| 36T37 | 0.0241 | 0.0191 | 0.0022 | 0.0019 | 0.0003 | 0.0380 | 0.0235 | 0.0103 | 0.0092 | 0.0011 |
| 50 | 0.0002 | 0.0002 | 0.0000 | 0.0000 | 0.0000 | 0.0004 | 0.0002 | 0.0002 | 0.0002 | 0.0000 |
| 51 | 0.0032 | 0.0022 | 0.0009 | 0.0009 | 0.0000 | 0.0029 | 0.0018 | 0.0010 | 0.0008 | 0.0001 |
| 52 | 0.0003 | 0.0001 | 0.0001 | 0.0001 | 0.0000 | 0.0004 | 0.0002 | 0.0002 | 0.0002 | 0.0000 |
| 60T63 | 0.0191 | 0.0385 | 0.0096 | 0.0066 | 0.0030 | 0.0308 | 0.0132 | 0.0090 | 0.0048 | 0.0041 |
| 64 | 0.0054 | 0.0045 | 0.0008 | 0.0006 | 0.0002 | 0.0197 | 0.0141 | 0.0034 | 0.0022 | 0.0012 |
| 70 | 0.0008 | 0.0003 | 0.0001 | 0.0001 | 0.0000 | 0.0010 | 0.0005 | 0.0000 | 0.0000 | 0.0000 |
| 71T74 | 0.0291 | 0.0191 | 0.0009 | 0.0008 | 0.0001 | 0.0425 | 0.0268 | 0.0045 | 0.0033 | 0.0012 |
| J | 0.0178 | 0.0141 | 0.0014 | 0.0013 | 0.0000 | 0.0323 | 0.0287 | 0.0014 | 0.0013 | 0.0000 |

*Notes:* Offshoring intensities are calculated as ratios of real imports of a country-industry pair from the same industry of the respective set of countries to real gross value-added. OFF: imports from all countries available; OFF_HI: imports from high-income countries; OFF_LMI: imports from lower-income countries; OFF_LMInC: imports from lower-income countries excluding China; OFF_CHN: imports from China. Countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): the offshoring destination country belongs to the group of high-income (upper-middle-income, lower-middle-income or low-income) countries for at least half of the years of the period examined. For the calculation of the mean levels by country (Panel A), I calculate the average of offshoring intensities across industries within each country and year using as weights the share of each industry's employment in total employment of the manufacturing and service industries examined in 1995. For the calculation of the mean levels by industry (Panel B), I calculate the average of offshoring intensities across countries by industry and year without using country weights.
*Source*: Author's calculations based on WIOD and EU KLEMS.

Table A2: Wage bill shares of age groups by country and by industry

| Panel A: By country | | | | | | |
|---|---|---|---|---|---|---|
| Country | Mean level 1995 | | | Mean level 2005 | | |
| | 15–29 | 30–49 | 50+ | 15–29 | 30–49 | 50+ |
| Australia | 0.274 | 0.561 | 0.165 | 0.229 | 0.519 | 0.252 |
| Austria | 0.258 | 0.552 | 0.190 | 0.204 | 0.598 | 0.198 |
| Denmark | 0.238 | 0.550 | 0.213 | 0.159 | 0.589 | 0.252 |
| Finland | 0.152 | 0.651 | 0.197 | 0.147 | 0.562 | 0.291 |
| Germany | 0.162 | 0.622 | 0.216 | 0.134 | 0.625 | 0.240 |
| Italy | 0.298 | 0.656 | 0.046 | 0.268 | 0.694 | 0.038 |
| Japan | 0.204 | 0.512 | 0.285 | 0.150 | 0.523 | 0.327 |
| Netherlands | 0.231 | 0.589 | 0.180 | 0.186 | 0.581 | 0.234 |
| Spain | 0.201 | 0.551 | 0.248 | 0.189 | 0.570 | 0.241 |
| United Kingdom | 0.252 | 0.549 | 0.199 | 0.194 | 0.567 | 0.239 |
| United States | 0.305 | 0.564 | 0.132 | 0.243 | 0.565 | 0.192 |
| Unweighted mean | 0.234 | 0.578 | 0.188 | 0.191 | 0.581 | 0.228 |

| Panel B: By industry | | | | | | |
|---|---|---|---|---|---|---|
| Industry | Mean level 1995 | | | Mean level 2005 | | |
| | 15–29 | 30–49 | 50+ | 15–29 | 30–49 | 50+ |
| 15T16 | 0.235 | 0.567 | 0.198 | 0.181 | 0.582 | 0.237 |
| 17T19 | 0.243 | 0.555 | 0.202 | 0.173 | 0.577 | 0.250 |
| 20 | 0.224 | 0.565 | 0.214 | 0.171 | 0.571 | 0.258 |
| 21T22 | 0.211 | 0.583 | 0.206 | 0.166 | 0.583 | 0.251 |
| 23 | 0.174 | 0.615 | 0.202 | 0.135 | 0.619 | 0.246 |
| 24 | 0.193 | 0.605 | 0.202 | 0.150 | 0.604 | 0.246 |
| 25 | 0.217 | 0.584 | 0.199 | 0.174 | 0.581 | 0.245 |
| 26 | 0.201 | 0.588 | 0.211 | 0.155 | 0.587 | 0.257 |
| 27T28 | 0.215 | 0.581 | 0.204 | 0.167 | 0.582 | 0.251 |
| 29 | 0.216 | 0.594 | 0.190 | 0.161 | 0.598 | 0.241 |
| 30T33 | 0.229 | 0.601 | 0.170 | 0.170 | 0.609 | 0.221 |
| 34T35 | 0.205 | 0.605 | 0.187 | 0.155 | 0.606 | 0.239 |
| 36T37 | 0.239 | 0.567 | 0.194 | 0.184 | 0.580 | 0.235 |
| 50 | 0.270 | 0.550 | 0.180 | 0.223 | 0.565 | 0.212 |
| 51 | 0.247 | 0.562 | 0.191 | 0.209 | 0.571 | 0.220 |
| 52 | 0.296 | 0.525 | 0.179 | 0.261 | 0.534 | 0.206 |
| 60T63 | 0.198 | 0.599 | 0.203 | 0.155 | 0.597 | 0.248 |
| 64 | 0.192 | 0.631 | 0.177 | 0.169 | 0.618 | 0.213 |
| 70 | 0.215 | 0.580 | 0.205 | 0.189 | 0.555 | 0.256 |
| 71T74 | 0.230 | 0.598 | 0.172 | 0.198 | 0.589 | 0.213 |
| J | 0.191 | 0.639 | 0.170 | 0.147 | 0.636 | 0.217 |

*Notes*: For the calculation of the mean levels by country (Panel A), I calculate the average of wage bill shares across industries within each country and year using as weights the share of each industry's employment in total employment of the manufacturing and service industries examined in 1995. For the calculation of the mean levels by industry (Panel B), I calculate the average of wage bill shares across countries by industry and year without using country weights.
*Source*: Author's calculations based on EU KLEMS.

# B Additional econometric results

Table B1: Offshoring and labour demand by age, 2SLS, main IV, manufacturing

| Dep var: Wsh | (1)<br>15-29 | (2)<br>30-49 | (3)<br>50+ | (4)<br>15-29 | (5)<br>30-49 | (6)<br>50+ | (7)<br>15-29 | (8)<br>30-49 | (9)<br>50+ |
|---|---|---|---|---|---|---|---|---|---|
| ln Y | 0.0075*** | 0.00082 | -0.0076*** | 0.0080*** | -0.00031 | -0.0069*** | 0.0053** | 0.0018 | -0.0066*** |
| | [0.003] | [0.003] | [0.002] | [0.003] | [0.003] | [0.003] | [0.003] | [0.003] | [0.002] |
| K | 0.00019 | 0.00081** | -0.00037 | 0.00021 | 0.00068* | -0.00020 | -0.000049 | 0.00093*** | -0.00034 |
| | [0.0003] | [0.0004] | [0.0004] | [0.0003] | [0.0004] | [0.0004] | [0.0003] | [0.0004] | [0.0003] |
| OFF_HI | 0.085*** | -0.10*** | 0.019 | 0.088*** | -0.11*** | 0.026 | 0.065*** | -0.089*** | 0.025 |
| | [0.02] | [0.02] | [0.02] | [0.02] | [0.03] | [0.02] | [0.02] | [0.03] | [0.02] |
| OFF_LMI | -0.12*** | 0.061 | 0.056 | | | | | | |
| | [0.04] | [0.05] | [0.04] | | | | | | |
| OFF_LMInC | | | | -0.14** | 0.12* | 0.0097 | | | |
| | | | | [0.06] | [0.07] | [0.06] | | | |
| OFF_CHN | | | | | | | -0.28** | 0.025 | 0.26** |
| | | | | | | | [0.1] | [0.1] | [0.1] |
| Observations | 1571 | 1573 | 1559 | 1571 | 1573 | 1559 | 1571 | 1573 | 1559 |
| $R^2$ | 0.0203 | -0.000773 | 0.0155 | 0.00462 | -0.0152 | 0.0103 | 0.0514 | 0.0105 | 0.0298 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMI}$ | 0.0000160 | 0.00404 | 0.378 | | | | | | |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMInC}$ | | | | 0.00144 | 0.00698 | 0.810 | | | |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_CHN}$ | | | | | | | 0.00103 | 0.346 | 0.0121 |
| Kleibergen-Paap rk LM | 42.78 | 42.48 | 42.76 | 69.69 | 69.80 | 69.21 | 64.54 | 64.37 | 64.24 |
| Kleibergen-Paap rk LM (p-value) | 2.74e-09 | 3.18e-09 | 2.76e-09 | 4.97e-15 | 4.70e-15 | 6.31e-15 | 6.31e-14 | 6.85e-14 | 7.30e-14 |
| Kleibergen-Paap Wald rk F | 34.54 | 34.17 | 34.67 | 21.16 | 21.19 | 21.21 | 32.59 | 32.50 | 32.37 |
| Hansen J | 1.347 | 3.458 | 4.904 | 1.737 | 3.053 | 4.447 | 0.473 | 4.209 | 5.679 |
| Hansen J (p-value) | 0.510 | 0.177 | 0.0861 | 0.420 | 0.217 | 0.108 | 0.789 | 0.122 | 0.0585 |
| IV strategy | ln Y and K treated as exogenous<br>Offshoring intensities instrumented with their first and second lags | | | | | | | | |

*Notes:* 2SLS estimations with robust standard errors on the sample of manufacturing industries in all columns. Country-industry and country-year fixed effects are included in the equations. The equations are weighted by the share of each manufacturing industry's employment in total employment of the manufacturing industries examined in 1995. Asterisks denote significance at 1% (***), 5% (**), and 10% (*). For the description of the variables, see Table B4.

Table B2: Offshoring and labour demand by age-skill, 2SLS, main IV

| Dep var: Wsh | (1)<br>15-29,HS | (2)<br>15-29,LS | (3)<br>30-49,HS | (4)<br>30-49,LS | (5)<br>50+,HS | (6)<br>50+,LS |
|---|---|---|---|---|---|---|
| ln Y | 0.0023 | 0.015*** | 0.0063 | -0.018*** | 0.0026 | -0.0076*** |
| | [0.003] | [0.003] | [0.007] | [0.006] | [0.002] | [0.002] |
| K | -0.0054** | 0.0042*** | -0.0090** | 0.011** | 0.00056 | -0.00096** |
| | [0.002] | [0.001] | [0.004] | [0.004] | [0.0003] | [0.0004] |
| OFF_HI | 0.0095 | 0.060** | 0.0086 | -0.10*** | 0.0085 | 0.015 |
| | [0.010] | [0.02] | [0.02] | [0.03] | [0.008] | [0.02] |
| OFF_LMI | -0.050** | -0.20*** | 0.16*** | -0.080 | 0.053*** | 0.12*** |
| | [0.02] | [0.05] | [0.05] | [0.06] | [0.02] | [0.04] |
| Observations | 2540 | 2540 | 2541 | 2541 | 2527 | 2541 |
| $R^2$ | 0.126 | 0.0668 | 0.0861 | 0.127 | 0.00419 | -0.00403 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMI}$ | 0.0204 | 0.000000303 | 0.00387 | 0.769 | 0.0188 | 0.00677 |
| Kleibergen-Paap rk LM | 39.16 | 39.05 | 39.03 | 39.03 | 38.58 | 39.03 |
| Kleibergen-Paap rk LM (p-value) | 1.61e-08 | 1.70e-08 | 1.71e-08 | 1.71e-08 | 2.13e-08 | 1.71e-08 |
| Kleibergen-Paap Wald rk F | 23.98 | 23.87 | 23.88 | 23.88 | 23.49 | 23.88 |
| Hansen J | 5.734 | 2.351 | 1.035 | 2.290 | 3.575 | 13.35 |
| Hansen J (p-value) | 0.0569 | 0.309 | 0.596 | 0.318 | 0.167 | 0.00126 |
| IV strategy | ln Y and K treated as exogenous<br>Offshoring intensities instrumented with their first and second lags | | | | | |

*Notes:* 2SLS estimations with robust standard errors in all columns. Country-industry and country-year fixed effects are included in the equations. The equations are weighted by the share of each industry's employment in total employment of the manufacturing and service industries examined in 1995. Asterisks denote significance at 1% (***), 5% (**), and 10% (*). For the description of the variables, see Table B4.

Table B3: Offshoring, industrial robots and labour demand by age, manufacturing, 2SLS

| Dep var: Wsh | (1) 15-29 | (2) 30-49 | (3) 50+ | (4) 15-29 | (5) 30-49 | (6) 50+ | (7) 15-29 | (8) 30-49 | (9) 50+ |
|---|---|---|---|---|---|---|---|---|---|
| ln Y | 0.0050* | 0.0036 | -0.0079*** | 0.0047 | 0.0031 | -0.0070*** | 0.0032 | 0.0045 | -0.0072*** |
| | [0.003] | [0.003] | [0.003] | [0.003] | [0.003] | [0.003] | [0.002] | [0.003] | [0.002] |
| K | 0.000081 | 0.00061* | -0.00017 | 0.000014 | 0.00057 | -0.0000088 | -0.000034 | 0.00066** | -0.00019 |
| | [0.0003] | [0.0004] | [0.0003] | [0.0003] | [0.0004] | [0.0004] | [0.0002] | [0.0003] | [0.0003] |
| OFF_HI | 0.071*** | -0.071*** | 0.00064 | 0.070*** | -0.075*** | 0.0066 | 0.055*** | -0.061** | 0.0059 |
| | [0.02] | [0.02] | [0.02] | [0.02] | [0.02] | [0.02] | [0.02] | [0.02] | [0.02] |
| OFF_LMI | -0.081* | 0.040 | 0.037 | | | | | | |
| | [0.05] | [0.05] | [0.04] | | | | | | |
| OFF_LMInC | | | | -0.068 | 0.062 | -0.0023 | | | |
| | | | | [0.06] | [0.07] | [0.06] | | | |
| OFF_CHN | | | | | | | -0.27** | 0.067 | 0.20** |
| | | | | | | | [0.1] | [0.1] | [0.09] |
| ROBOTS * RSH | -0.016** | 0.0057 | 0.011* | -0.017** | 0.0057 | 0.012* | -0.016** | 0.0056 | 0.010* |
| | [0.008] | [0.008] | [0.006] | [0.008] | [0.008] | [0.006] | [0.008] | [0.007] | [0.006] |
| Observations | 1415 | 1417 | 1408 | 1415 | 1417 | 1408 | 1415 | 1417 | 1408 |
| $R^2$ | -0.0536 | 0.0119 | -0.0496 | -0.0832 | 0.00880 | -0.0751 | -0.0261 | 0.0166 | -0.0325 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMI}$ | 0.00153 | 0.0339 | 0.377 | | | | | | |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{ROBOTS}$ | 0.00000677 | 0.000982 | 0.507 | | | | | | |
| F-test $H_0$: $\beta_{OFF\_LMI} = \beta_{ROBOTS}$ | 0.160 | 0.503 | 0.527 | | | | | | |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_LMInC}$ | | | | 0.0556 | 0.0673 | 0.890 | | | |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{ROBOTS}$ | | | | 0.0000329 | 0.00124 | 0.721 | | | |
| F-test $H_0$: $\beta_{OFF\_LMInC} = \beta_{ROBOTS}$ | | | | 0.440 | 0.402 | 0.805 | | | |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{OFF\_CHN}$ | | | | | | | 0.00207 | 0.238 | 0.0246 |
| F-test $H_0$: $\beta_{OFF\_HI} = \beta_{ROBOTS}$ | | | | | | | 0.000355 | 0.00706 | 0.788 |
| F-test $H_0$: $\beta_{OFF\_CHN} = \beta_{ROBOTS}$ | | | | | | | 0.0235 | 0.607 | 0.0412 |
| Kleibergen-Paap rk LM | 104.6 | 104.7 | 103.8 | 105.5 | 105.6 | 104.7 | 106.7 | 106.8 | 106.2 |
| Kleibergen-Paap rk LM (p-value) | 1.04e-21 | 9.99e-22 | 1.51e-21 | 6.76e-22 | 6.42e-22 | 9.77e-22 | 3.64e-22 | 3.48e-22 | 4.71e-22 |
| Kleibergen-Paap Wald rk F | 21.40 | 21.44 | 21.14 | 21.21 | 21.25 | 20.94 | 21.84 | 21.88 | 21.64 |
| Hansen J | 0.924 | 3.220 | 3.143 | 0.849 | 2.862 | 4.739 | 1.199 | 3.513 | 2.136 |
| Hansen J (p-value) | 0.820 | 0.359 | 0.370 | 0.838 | 0.413 | 0.192 | 0.753 | 0.319 | 0.545 |
| IV strategy | ln Y and K treated as exogenous; Offshoring intensities instrumented with their first and second lags; Imports of industrial robots instrumented with the first and second lags of the robot exposure variable | | | | | | | | |

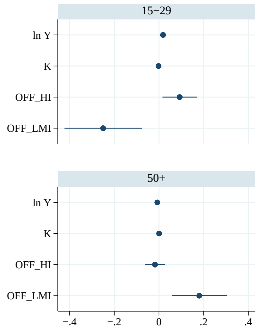
*Notes:* 2SLS estimations with robust standard errors in all columns. Country-industry and country-year fixed effects are included in the equations. The equations are weighted by the share of each industry's employment in total employment of the manufacturing and service industries examined in 1995. Asterisks denote significance at 1% (***), 5% (**), and 10% (*). For the description of the variables, see Table B4.

Table B4: Description of variables

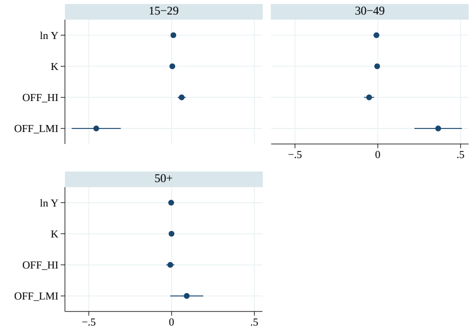
| Variable | Description | Source |
|---|---|---|
| $\text{Wsh}^{15-29}$ | Wage bill share of workers aged 15–29 | EU KLEMS |
| $\text{Wsh}^{30-49}$ | Wage bill share of workers aged 30–49 | EU KLEMS |
| $\text{Wsh}^{50+}$ | Wage bill share of workers aged 50+ | EU KLEMS |
| $\text{Wsh}^{15-29,HS}$ | Wage bill share of high-skilled workers aged 15–29 | EU KLEMS |
| $\text{Wsh}^{15-29,LS}$ | Wage bill share of less (i.e., medium- and low-) skilled workers aged 15–29 | EU KLEMS |
| $\text{Wsh}^{30-49,HS}$ | Wage bill share of high-skilled workers aged 30–49 | EU KLEMS |
| $\text{Wsh}^{30-49,LS}$ | Wage bill share of less (i.e., medium- and low-) skilled workers aged 30–49 | EU KLEMS |
| $\text{Wsh}^{50+,HS}$ | Wage bill share of high-skilled workers aged 50+ | EU KLEMS |
| $\text{Wsh}^{50+,LS}$ | Wage bill share of less (i.e., medium- and low-) skilled workers aged 50+ | EU KLEMS |
| $\text{W}^{15-29}$ | Relative real hourly wage of workers aged 15–29 | EU KLEMS |
| $\text{W}^{30-49}$ | Relative real hourly wage of workers aged 30–49 | EU KLEMS |
| $\text{W}^{50+}$ | Relative real hourly wage of workers aged 50+ | EU KLEMS |
| Y | Real gross value-added | EU KLEMS |
| K | Aggregate capital stock to value-added | EU KLEMS |
| OFF | Imported inputs from all countries available to value-added | WIOD and EU KLEMS |
| OFF_HI | Imported inputs from high-income countries to value-added | WIOD and EU KLEMS |
| OFF_LMI | Imported inputs from lower-income countries to value-added | WIOD and EU KLEMS |
| OFF_LMInC | Imported inputs from lower-income countries excluding China to value-added | WIOD and EU KLEMS |
| OFF_CHN | Imported inputs from China to value-added | WIOD and EU KLEMS |
| OFF_HECI | Imported inputs from countries with high economic complexity to value-added | WIOD, EU KLEMS, ATLAS of ECI |
| OFF_LECI | Imported inputs from countries with lower economic complexity to value-added | WIOD, EU KLEMS, ATLAS of ECI |
| OFF_HHC | Imported inputs from countries with high human capital abundance to value-added | WIOD, EU KLEMS, PWT |
| OFF_LHC | Imported inputs from countries with lower human capital abundance to value-added | WIOD, EU KLEMS, PWT |
| ROBOTS | Total value of imported industrial robots (HS 1996 code(s): 847950) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| DEDIC. MACH. | Total value of imported dedicated machinery, including industrial robots, (HS 1996 code(s): 847989) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| 3-D PRINT | Total value of imported 3-D printing machines (HS 1996 code(s): 847780) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| DATA PROC. | Total value of imported automatic data processing machines (HS 1996 code(s): 8471, 847330) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| CONVEYORS | Total value of imported automatic conveyors (HS 1996 code(s): 8428) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| REGUL. INSTR. | Total value of imported automatic regulating instruments (HS 1996 code(s): 9032) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| CALC. MACH. | Total value of imported electronic calculating machines (HS 1996 code(s): 8470, 847321) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| MACH. TOOLS | Total value of imported automatic machine tools (HS 1996 code(s): 8456, 8457, 8468) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| WELD. MACH. | Total value of imported automatic welding machines (HS 1996 code(s): 8515) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| TEXT. MACH. | Total value of imported automatic textile, knitting and weaving machines (HS 1996 code(s): 8444, 8445, 8446, 8447, 8448) of a country normalised by its value in the initial year (1996) | UN COMTRADE |
| RSH | Industry-level share of routine tasks in 1980 | D. H. Autor et al. (2003) |
| CEL | Mobile cellular subscriptions per 100 people | World Bank WDI |

*Notes*: Author's notation.

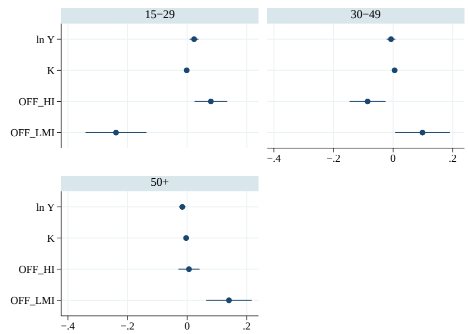
Figure B1: Offshoring and wage bill shares by age, robustness



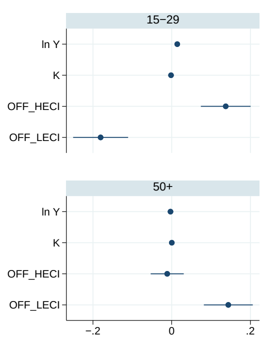

(a) Long differences, OLS



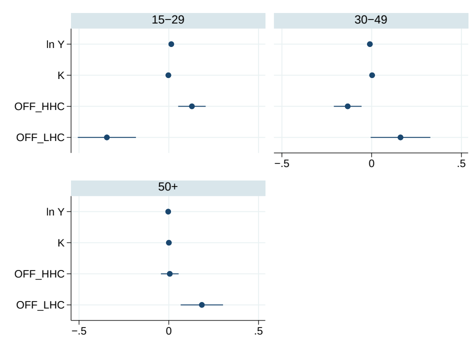

(b) Country-year and industry-year fixed effects, 2SLS, main IV




(c) Relative wages, 2SLS, main IV



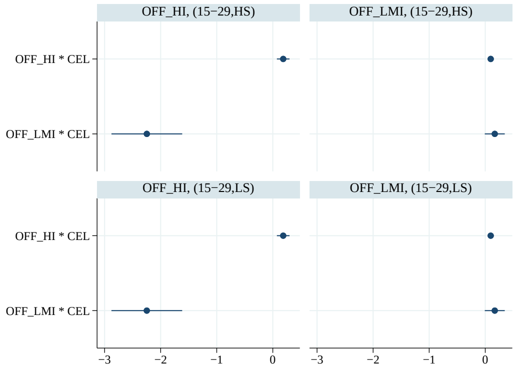

(d) High Vs low economic complexity of offshoring destination countries, 2SLS, main IV



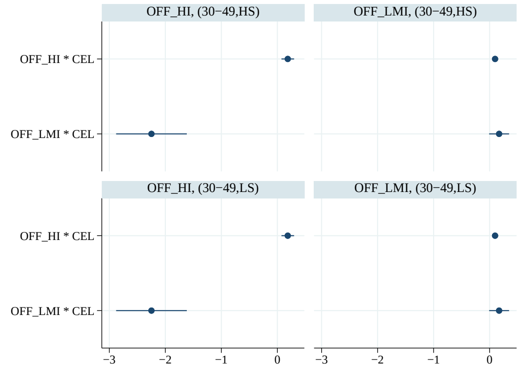

(e) High Vs low human capital abundance of offshoring destination countries, 2SLS, main IV

*Notes*: OLS estimations with long-differenced variables, year fixed effects and robust standard errors in Panel (a). 2SLS estimations with country-year and industry-year fixed effects and robust standard errors in Panel (b). 2SLS estimations with log of relative wages, country-industry fixed effects, year fixed effects and robust standard errors in Panel (c). 2SLS estimations with country-industry and country-year fixed effects and robust standard errors in Panels (d) and (e). In Panels (b), (d) and (e), offshoring intensities are instrumented with their first and second lags, while the log of value-added and aggregate capital intensity are not instrumented (main IV). In Panel (c), the explanatory variables, including the logs of relative wages, log of value-added and aggregate capital intensity, are instrumented with their first and second lags. The coefficient estimates of the logs of relative wages are not disclosed for the sake of exposition. In all panels, the equations are weighted by the share of each industry's employment in total employment of the manufacturing and service industries examined in 1995. For the description of the variables, see Table B4.

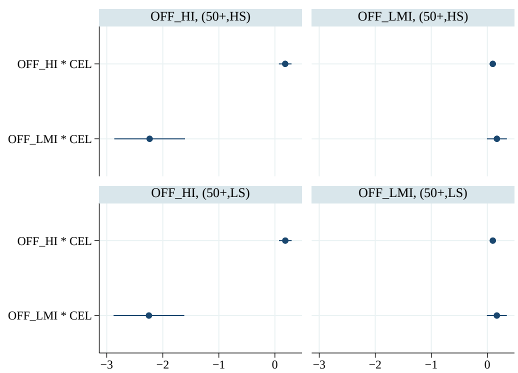
Figure B2: First stages of 2SLS in Table 4




(a) Columns (1)–(2)



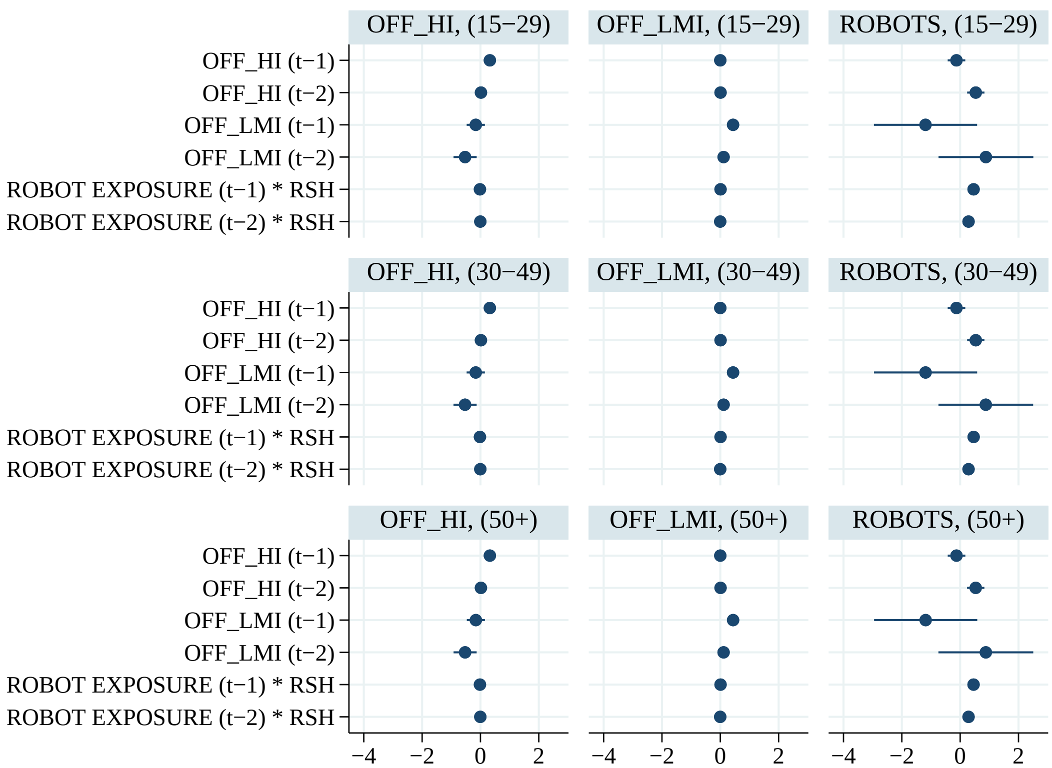

(b) Columns (3)–(4)




(c) Columns (5)–(6)

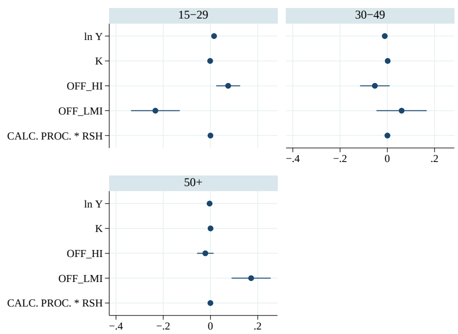
*Notes*: For the description of the variables, see Table B4.

Figure B3: First stages of 2SLS in Table 5

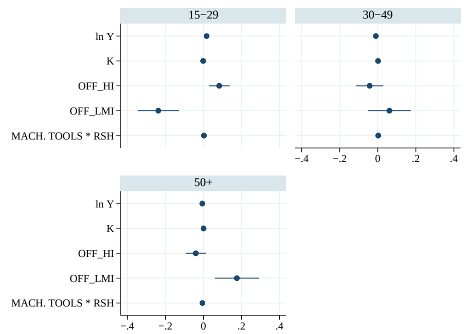



*Notes:* For the description of the variables, see Table B4.

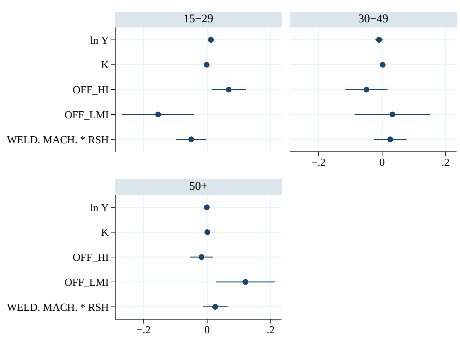
Figure B4: Offshoring, other automation technologies and labour demand by age, 1996–2005, 2SLS



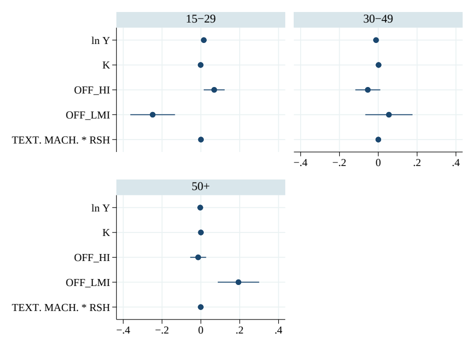

(a) Calculating machines




(b) Machine tools




(c) Welding machines




(d) Textile machines

*Notes*: 2SLS estimations with robust standard errors in all panels. Country-industry and country-year fixed effects are included in the equations. The equations are weighted by the share of each industry's employment in total employment of the manufacturing and service industries examined in 1996. For the description of the variables, see Table B4.