# Automation, Skill and Job Creation *

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**Abstract**

This paper explores heterogeneous effects of automation technologies on employment rate across regions from different income groups, and investigates mechanisms through proportion of skilled workers. Automation, measured by both robotic penetration and ICT trade volumes, is replacing US labour force. Exploiting variations across US commuting zones with different income levels, I find insignificant employment response in high income areas, while the magnitudes of employment reductions are more sizeable and significant in low and middle income areas. Leveraging shift-share IV strategies and generalised model specifications, further evidence supports that these patterns can be explained by a simple net job creation channel, as displacement effects outweigh productivity effects in low income CZs with lower proportion of skilled labour, and job creations are complementing job destructions in high income CZs with higher skill shares. Such technical changes are more pronounced for manufacturing sectors.

*JEL classification*: E24, J24; O14; O33.

**Keywords:** Automation; Displacement effects; Productivity effects; Net job creations; Skill shares.

# 1 Introduction

In recent years, development economists have regarded automation technologies as another source for persistent economic growth (PwC, 2018), and automation adoption could lead to positive employment effects. But on the other hand, a substantial body of evidence raised widespread concerns about technological unemployment, which is defined as job losses within industries due to adoption of automation technologies (Autor, 2014, 2015; Brynjolfsson and Mitchell, 2017; Dauth et al., 2021; Graetz and Michaels, 2017; PwC, 2018; Sachs and Kotlikoff, 2012; Mitchell and Brynjolfsson, 2017). Therefore, understanding impacts of automation technologies on labour market outcome at all levels of analysis, including skill group, metropolitan area, and country, is important.

Despite extensive research, the impacts of technological updating on labour market outcomes remain debated (Aghion et al., 2017; Autor and Salomons, 2018; Machin and Reenen, 1998), and little is known about heterogeneous effects with respect to proportion of skilled workers, reflected by regions from different income groups. In this paper, I leverage comprehensive macro and micro dataset across US commuting zones spanning the period of 2000 to 2019, to explore the impacts of automation technologies on employment rate, from the perspective of advanced economies.

In this research, I employ two complementary measures of automation technologies, namely robotic density and ICT (Information and Communication Technologies) intensity, based on dataset from International Federation of Robotics (2021), United Nations (2021) and The Conference Board (2021). Automation technologies are defined as ”any technology that enables machines, algorithms, capital to perform tasks previously allocated to humans” (Acemoglu and Restrepo, 2021b). Generally speaking, they are comprised of three components, including numerical controlled machinery, industrial robots, and specialised software. For industrial robots, they refer to “an automatically controlled, reprogrammable, and multipurpose machine” (International Federation of Robotics, 2021), which could cover automation technologies that do not require human instructions and can automatically operate based on programmed codes (Acemoglu and Restrepo, 2020). While for ICT investments, they refer to ”acquisition of equipment and computer software that is used in production for more than one year” (OECD, 2020). In other words, ICT investments include information technology equipment, communications equipment, and software, which have substantial overlaps with automation technologies that still require human corporations.

The conceptual framework builds on the theory of task-based framework (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019a). Following Acemoglu and Autor (2011), technological changes can sometimes do harm to labours, and sometimes benefit labour market outcomes, as degrees of substitutability vary across tasks and economic activities.

In this article, I advance the hypothesis that impacts of automation adoption on employment are determined by net job creations between displacement effects and productivity effects. For regions from low and middle income groups, it is discovered that job losses induced by technological advances are far more than new job vacancies in other sectors, implying displacement effects outweigh productivity effects. While for high income areas, productivity effects may contribute to job creations in both existing and new occupations, which could complement job destructions from displacement effects, leading to non-decreasing employment rate.

This research is related to several empirical studies on the effects of technological adoption on labour market outcomes. The first main contribution is to explore the heterogeneous effects across regions from different income groups. Early work focusing on general measures of technological updating such as TFP (total factor productivity) growth and patent awards across different types of countries (Autor and Salomons, 2018) are closely related, but I use two complementary indicators, namely robotic density and ICT intensity. Therefore, such specifications would make it plausible to distinguish between productivity growth originated from automated and non-automated sectors both within and across countries.

In the second main contribution, this paper complements studies of the role of skill shares and industrial structures on net job creation, causing heterogeneous effects from automation technologies on employment rate. Recent work by Acemoglu and Restrepo (2021a) estimated the impacts of educational upgrading on the adoption of automation, reflecting the fact that growing educational attainment could result in scarcity of production workers in blue collar jobs. The rising wages for manufacturing workers along with decline of participation rate will finally provide great opportunities for automation. This paper differs from those literature since, rather than workers with low education attainments, I show that the channel for high skilled labour force could be different. With intensive growth of high educated workers, supply effect appears to act as main driver of rising employment, and the effects are more pronounced in manufacturing industries.

For the third main contribution, this paper sheds light on the fact that net employment effects are mainly caused by differentials in productivity effects measured by job creations, and job destructions, a good proxy of displacement effects, are prevalent across regions.

In terms of mechanisms, I complement Acemoglu and Restrepo (2020, 2021b), Bonfiglioli et al. (2021), Dauth et al. (2021), and confirm that job creations usually occur for high skilled workers completing university education, while welfare deteriorations from unemployment are concentrated in labour force from low skilled groups.

The remainder of the paper is as follows. Section 2 presents conceptual framework. Section 3 describes data sources and stylised facts. Section 4 constructs empirical models, presents regression results under US evidence, and employs IV approach to tackle identification threats. Section 5 investigates mechanisms through job creations and job destructions. Section 6 discusses general results across countries. Section 7 concludes.

# 2 Conceptual Framework

According to task-based framework developed by Acemoglu and Autor (2011), welfare effects of automation may vary across occupations with different task contents. In this section, I illustrate conceptual framework relating productivity effects and displacement effects from automation technologies, and provide guidance for empirical results.

Firstly, automation does indeed substitute labour, especially for occupations whose tasks can easily be codified by computer programming (Acemoglu and Restrepo, 2020; Autor, 2013, 2015; Beaudry et al., 2016; Brynjolfsson and Mitchell, 2017; Mitchell and Brynjolfsson, 2017; Sachs et al., 2015). Compared with conventional labour force, automation technologies, represented by robots, have relatively lower price than ordinary wages, thus firm owners prefer to use robots. The adoption of new technologies could promote reallocation between capital and labour within tasks, and accelerate the progress where tasks previously conducted by labour are gradually taken over by capital, which is called displacement effect.

The phenomenon of job replacement is pervasive across regions with different income levels. For advanced economies, the positive association between education attainments and wage levels could provide great opportunities for the adoption of automation technologies (Acemoglu and Restrepo, 2021a)[1]. But those who are suitable for analytical or interpersonal tasks covers the majority of skilled labours, and such non-routine tasks cannot be easily codified by computer programming, making machines less capable of substituting

[1]Recent articles such as Acemoglu and Restrepo (2021b) also examined widening wage inequalities driven by automation, and highlighted that high skilled workers without job replacement will enjoy wage gains. Therefore, the firm owners would make further decisions based on rising wages for high skilled labour and relatively low price of machines.

workers (Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Agrawal et al., 2019). Meanwhile, it is noticed that those high skilled production workers are forced to spend substantially longer time on transition to other jobs after replacement, resulting in possibly low growth of jobless recoveries across developed countries. Hence such labour market frictions make it less probable for high skilled labour to lose their jobs.

Alternatively, for emerging market and developing economies, extensive use of cheap labour suggests higher likelihood of enormous job losses for workers engaged in human-performed tasks, as such routine tasks could also be performed by other computerised equipments (Agrawal et al., 2019). Facing exposure to automation technologies, low skilled workers who are still productive elsewhere could easily switch to other occupations, while those with limited alternative use are unable to conduct other tasks. In order to stay in original labour force, they tend to accept relatively lower reservation wage (Jackson and Kanik, 2019). Compared with workers in high income areas, who are endowed with alternative labour use, those in low income regions have no choice but to become "re-employed" with lower wage levels, offering less opportunities for the adoption of automation technologies (Acemoglu and Restrepo, 2021a), as economic cost cannot be ignored even when the technological feasibility could support automation of specific tasks (Autor, 2013). As a consequence, the narrowed gap of job losses induced by more substantial "re-employed" workers in low income areas, makes the displacement effects pervasive between two regions.

Secondly, automation could also complement labour, and generate several countervailing forces (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a; Autor, 2015). On the one hand, the adoption of automation technologies could reduce production costs where tasks can easily be automated, leading to overall economic expansion and thus rising labour demand especially in other non-automated sectors, which is called productivity effects (Acemoglu and Restrepo, 2018a, 2019b). For instance, smart machines are usually designed and enhanced by skilled workers (Sachs and Kotlikoff, 2012), and they could create substantial amounts of labour saving jobs, thus leading to surging labour demand in other relevant areas. Considering an economy with multiple industries, the development of automation technologies could also affect aggregate labour demand through composition effect, as improved efficiency in some tasks could affect demand for downstream products (Agrawal et al., 2019; Jackson and Kanik, 2019). Induced by general equilibrium effects, other industries with complementary inputs and tasks on the production steps will also witness an increase of labour demand (Dauth et al., 2021).

On the other hand, technological updating creates new tasks where labour has comparative advantages (Acemoglu and Restrepo, 2019b; PwC, 2018), and raises corresponding labour demand with the help of emerging AI platforms, which is called reinstatement effect. For example, by reducing uncertainties of predictions, artificial intelligence could reduce searching and production costs, hence increase relative returns of decision tasks and boosts labour demand for those specialised in new communication tasks (Agrawal et al., 2019; Brynjolfsson et al., 2019). The impacts on equilibrium wage are ambiguous, which are thought to be determined by trade-offs between productivity improvement and shrinking labour input (Acemoglu and Restrepo, 2018b; Jackson and Kanik, 2019).

Among those countervailing forces, this paper mainly focuses on productivity effects, namely rising high skilled labour demand in other non-automated sectors. This pattern of response is supposed to be more pronounced in high income economies, as there is a rapid takeoff in labour demand for high skilled occupations, triggered by rising consumer demand for final products (Acemoglu et al., 2020; Akerman et al., 2015; Webb, 2019), together with increasing amount of skilled labour supply. In contrast, insufficient supply of such skilled labour force in less developing economies makes automation technologies not capable of creating such vacancies.

Furthermore, as Figure A1 in the Appendix shows, the widening gap of skill shares across economies from different income groups, measured by proportion of skilled workers with tertiary education, reveals that equilibrium employment would be lower for less developing areas, and strong productivity effects in economically advanced areas may reduce the likelihood of welfare deterioration.

In summary, it is discovered that heterogeneous impacts of automation adoption on employment are determined by net job creations between displacement effects and productivity effects. With growing proportion of high skilled labour, productivity effects tend to become more pronounced and could contribute to job creations in high income regions, indicating that new job vacancies could complement job destructions from displacement effects. While such non-negative employment effects are less likely to be observed in regions from low and middle income groups, induced by strong displacement effects by lower percentage of high skilled labours.

# 3 Data and Stylised Facts

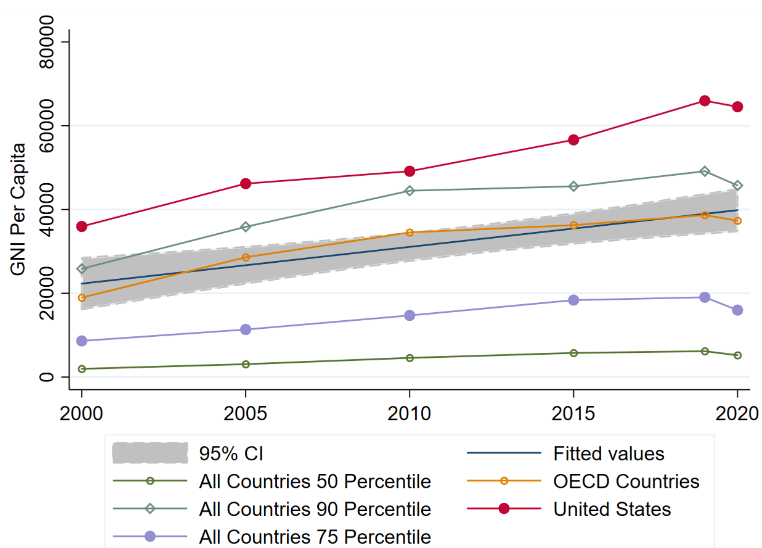
In this section, I present data sources and describe stylised facts.

## 3.1 Labour Market Outcomes

To relate automation technologies with employment and job creation across US local labour markets, I follow Acemoglu and Restrepo (2020, 2021a), Autor et al. (2013), Bonfiglioli et al. (2021), and identify US local labour markets based on the concept of commuting zones (CZs). Introduced by Tolbert and Sizer (1996), 722 commuting zones covering the US continental territory could better describe strong commuting ties within CZs and weak commuting ties among them.

In the main analysis, I collect county-level data about employment rate and other demographic characteristics for the period 2000-2019 from Bureau of Economic Analysis (2021), and aggregate to CZ level. Employment rate is measured as the ratio of employed workers to whole population with the age of 15 and above. The cutoff of 15 years of age is motivated by definition of working-age labour force (Acemoglu and Restrepo, 2021a). To further investigate the determinants of labour market outcomes, I also leverage data on employment ratio by education and industry groups. Other demographic controls include total population, proportion of age, gender, race, education, and Census Divisions [2].

FIGURE 1: Income Level Across Countries, 2000-2020




Notes:
The graph presents trends of GNI per capita for countries from different income groups, and advanced economies - using data from World Bank (2021).

[2]Based on geographic locations, the US states are grouped into 4 regions (Northeast, Midwest, South, West) and 9 divisions (New England Division, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific).

For baseline regression, classification of regions for high, middle and low income groups are based on personal income per capita, and is comparable to the income percentile of OECD countries around the world. Figure 1 unpacks the overall trend in GNI per capita across countries in different income groups, together with US and OECD countries. Two main facts emerge from the aggregate trends. First, income growth in advanced economies are substantially higher than that in developing countries. Second, most of the OECD countries are located around 80 percentiles of the overall income distribution across countries. Hence, I define CZs from high income group as those which are above 80 percentile of the whole income distribution, low income CZs as the bottom quintile by personal income per capita, and the rest are treated as middle income regions.

Besides arbitrary classification of income groups, in a more general model, I also explore the impacts of the interaction between automation technologies and income level, to investigate smooth changes of the employment effects.

To support the hypothesis that the heterogeneous impacts of automation technologies on employment are determined by the net job creations, I construct CZ-level measures of job destruction rates and job creation rates, based on Business Dynamics Statistics (US Census Bureau, 2021). For each CZs, I observe job destructions, job creations, number of firms and employees, and detailed industry codes. The change of net job creation rate for CZ $i$ over period $t$ is then computed as follows:

$$\Delta Net\,Job\,Creation\,Rate_{it} = \frac{\Delta Job\,Creation_{it} - \Delta Job\,Destruction_{it}}{N(Employees)_{it}} \tag{1}$$

For cross country analysis, detailed information of macro economic indicators on 216 countries stems from World Bank (2021) for the period 1993-2019. Based on GNI per capita in current USD, the world's main economies are assigned to four income groups, including low, lower middle, upper middle, and high income countries [3], which provide a subjective classification to investigate heterogeneous effects behind different income groups. For each country, I observe employment rate along with gender and industry composition, GDP per capita, total population, total labour force, proportion of adults and female workers, fertility rates, and regions [4].

[3] The calculation of GNI per capita is based on the World Bank Atlas method (World Bank, 2021). For instance, the GNI per capita threshold for low and lower middle income economies in 2020 is $1,045, and the threshold between lower and upper middle income economies is $4,095; economies with a GNI per capita above $12,696 are defined as high income economies.

[4] Based on geographic locations, the sample countries are grouped into 7 groups, including East Asia & Pacific, Europe & Central Asia, Latin America & Carribean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa.

## 3.2 Automation Technologies

I combine the comprehensive labour market dataset with several sources of data on automation technologies, namely robotic usage and ICT intensity.

The main source of data on robotic usage is International Federation of Robotics (2021), containing counts of operational stocks and installations of robots for each industry over 72 countries between 1993 and 2019, based on yearly surveys of global robot manufacturers. For empirical analysis, the main explanatory variable is computed using operational stocks of robots per thousand labour force. Since International Federation of Robotics (IFR) does not report data on industry breakdowns regarding robot stocks until 2004 (Acemoglu and Restrepo, 2020), unclassified components are re-allocated to each industry according to share of robotic stocks.

The second measure of automation technologies, namely ICT intensity, is motivated by Acemoglu and Restrepo (2021a), Graetz and Michaels (2017, 2018), Michaels et al. (2014), Kim et al. (2021), which emphasises the substitutability between ICT and low skilled workers. Bearing this motivation in mind, I complement the IFR data with US ICT import and export obtained from bilateral trade statistics of Comtrade database (United Nations, 2021). Trade volumes of re-export are subtracted from final calculations. To address robustness of the findings, results based on overall import and export of automation technologies will also be provided.

Since IFR data on operational stocks of robots, and Comtrade data on trade volumes are available only at the country-by-industry level, I follow Acemoglu and Restrepo (2020), Bonfiglioli et al. (2021), Dauth et al. (2021), and use a shift share design to allocate robotic adoptions and ICT trade volumes to each CZs according to their initial employment ratios, and construct exposure to automation as follows.

$$\Delta AutomationExposure_{it} = \frac{\Delta Automation_t^{US}}{Labour_t^{US}} \times \frac{Employed_{it_0}}{Employed_{t_0}^{US}} \tag{2}$$

The term $\frac{\Delta Automation_t^{US}}{Labour_t^{US}}$ is five year equivalent changes in robotic density and ICT trade volume for US over period $t$, and $\frac{Employed_{it_0}}{Employed_{t_0}^{US}}$ is share of industrial employment of CZ $i$ at year 2000.

In some of the specifications, I instrument the adoption of automation technologies using Bartik IV based on average robotic density in other European countries with similar industrial composition and trade structure. Following Acemoglu and Restrepo (2020), Benmelech and Zator (2022), Bonfiglioli et al. (2021), eight European countries are comprised of: Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland. Different constructions using other country combinations are also provided as robustness checks. The instrument is computed as follows:

$$\Delta AutomationIV_{it} = \frac{1}{8} \times (\Sigma_j^J \frac{\Delta Automation_t^j}{Labour_t^j}) \times \frac{Employed_{it_0}}{Employed_{t_0}^{US}} \tag{3}$$

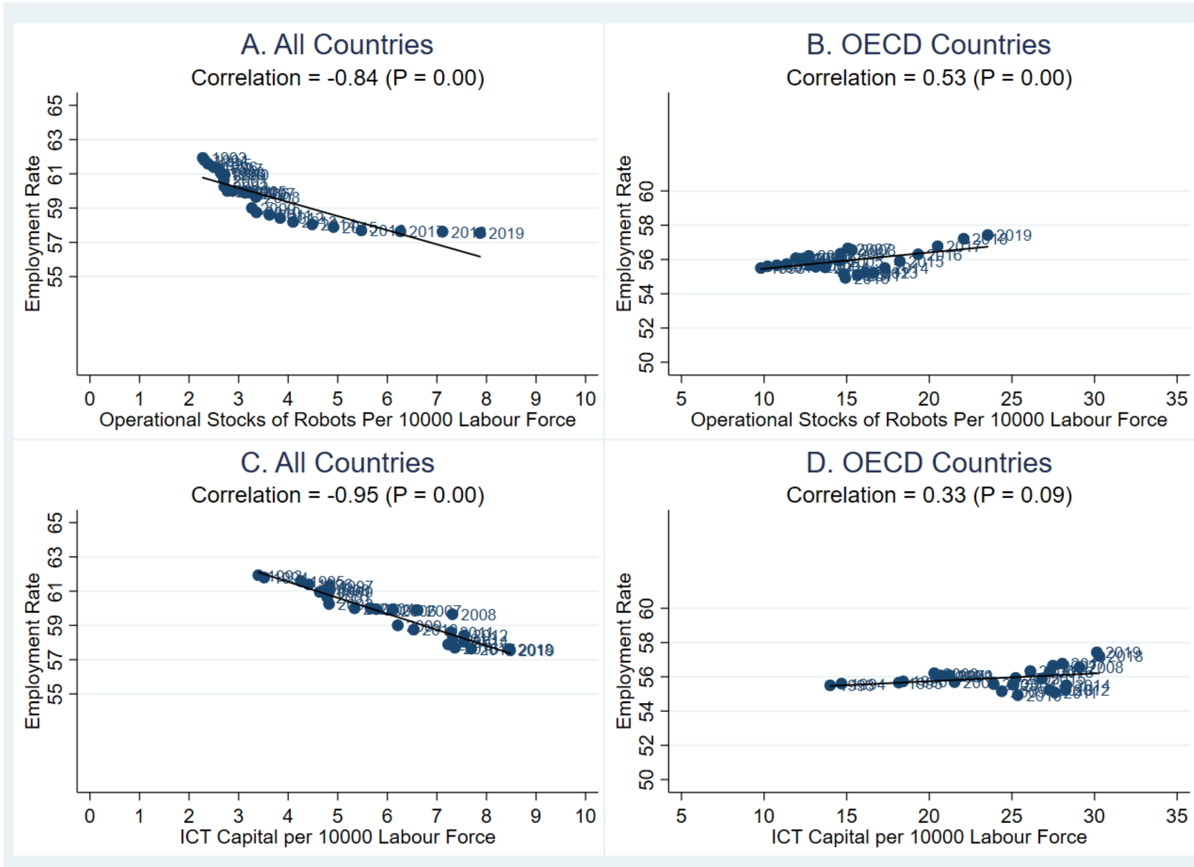
Similarly, $\frac{\Delta Automation_t^j}{Labour_t^j}$ is five year equivalent changes in robotic density and ICT trade volume for European country $j$ over period $t$.

For cross country analysis, I utilise ICT capital data from Total Economy Database of The Conference Board (2021), which could provide share of ICT capital compensation in GDP over 125 countries during the period from 1993 to 2019. To attain data on actual amount of ICT capital, I multiply percentage of ICT capital compensation by GDP. The ICT intensity is measured by ICT capital values per thousand workers.

## 3.3 Stylised facts

Now I present a number of facts regarding labour market outcomes and technological changes across countries over the period of analysis.

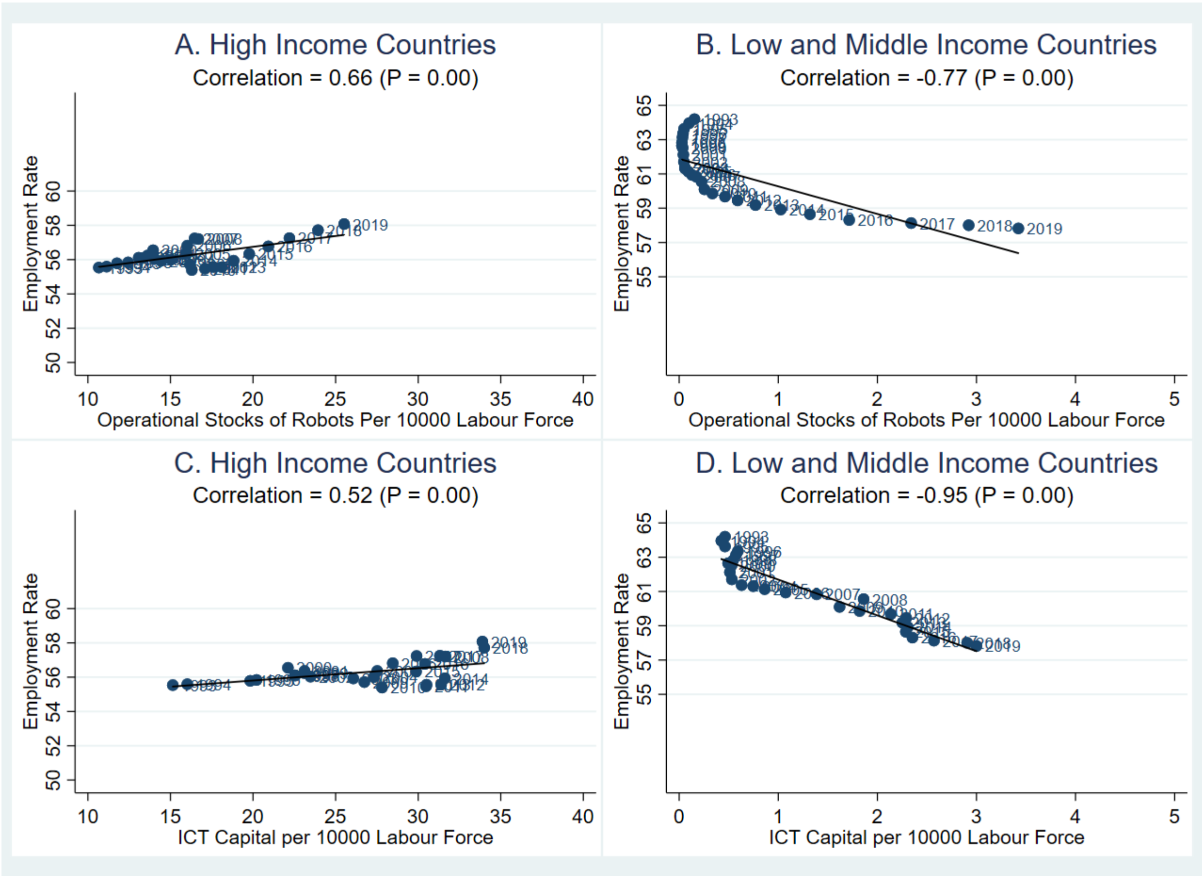
Figure 2: Automation Technologies and Employment Rate for All Countries and OECD Countries, 1993-2019




Notes:

The employment rate, defined as the ratio of employed people and total population who are above 15 years old, is from World Bank (2021). Robot density refers to operational stock of robots per 10000 labour force, and data about robotic stocks is from International Federation of Robotics (2021). ICT intensity, defined as ICT capital per 10000 labour force, is from The Conference Board (2021). ICT capital is calculated based on ICT capital share and GDP measured by constant US dollars. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020).

Figure 3: Automation Technologies and Employment Rate for High and Low Income Economies, 1993-2019




Notes:

The employment rate, defined as the ratio of employed people and total population who are above 15 years old, is from World Bank (2021). Robot density refers to operational stock of robots per 10000 labour force, and data about robotic stocks is from International Federation of Robotics (2021). ICT intensity, defined as ICT capital per 10000 labour force, is from The Conference Board (2021). ICT capital is calculated based on ICT capital share and GDP measured by constant US dollars. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020).

The relationship between adoption of automation technologies and employment for all countries are presented in Figure 2. It is clear that both robotic density and ICT intensity [5] are economically significant and negatively correlated with employment rate, implying that growth of automation technologies is killing the employment across countries. While evidence from the sample of OECD countries displayed in Panel B and Panel D reveals positive correlation between automation technologies and employment rate, highlighting the fact that automation technologies are replacing labour force does not seem to work in developed countries [6], and productivity effects are probably dominating the process across rich countries.

Figure 3 turns to unpack the association for areas among different income groups. For advanced economies, the relationship between robotic density and employment rate is significantly positive, though the magnitudes of the slope between ICT intensity and employment rate are slightly lower, implying less complementarity between ICT investments and labour inputs. Therefore, expanding automation adoption may complement human labours to some extent, and does not necessarily lead to employment reductions.

While for countries from low and middle income groups exhibited in Panels B and Panel D of Figure 3, I find employment rate is negatively associated with automation technologies, and the coefficients are statistically significant [7]. These results are consistent with the hypothesis that job destructions have outweighed job creations in low and middle income countries.

[5] Due to large magnitudes for country level robotic data, here the denominator of robotic density is 10 thousand total labour force, while for cross country analysis in Section 6, the denominator becomes 1 thousand working population. ICT intensity is computed following the same procedure.

[6] According to polarisation evidence in the context of EU and US (Michaels et al., 2014), countries and industries with fast ICT growth are likely to witness demand shifts from workers with intermediate education level to college educated workers, and have no clear effects on the least educated groups, causing less job displacement. Moreover, ICT's overall contribution to productivity growth is higher relative to robots (Graetz and Michaels, 2018), implying less labour inputs required for the same amount of output. In other words, adoption of conventional ICT appears to boost economy through rising TFP instead of job creations. Driven by low levels of substitutability and complementarity, the graph for OECD countries reveals a less significant relationship between ICT intensity and employment rate.

[7] One concern which may lead to measurement errors is informal employment. As suggested by Elgin et al. (2021), workers in informal sectors constitute about 70 percent of total employment in emerging market and developing economies. I also present evidence for formal and informal sectors in Figures A2 and A3. The results showed slightly positive relationship with respect to employment in formal sectors, which specialise in more capital intensive tasks, and overall negative relationship for emerging market and developing economies is mainly driven by employment responses from informal sectors.

# 4 Empirical Framework and Results

In this section, I establish the first empirical implication, and present econometric results about heterogeneous effects of automation technologies on employment across US commuting zones from different income groups. Then I describe identification issues and IV approach, along with results from alternative automation technologies. Building on this evidence, I finally investigate the key role of net job creations behind displacement effects and productivity effects in the next section.

## 4.1 Regression Model

In the regression analysis, the main specification relating automation technologies and employment rate is constructed as follows:

$$\Delta Employment_{it} = \beta_0 + \beta_1 \Delta AutomationExposure_{it} + \delta X_i + \alpha_i + \varepsilon_{it} \tag{4}$$

Following Acemoglu and Restrepo (2020), Bonfiglioli et al. (2021), Dauth et al. (2021), I estimate Equation 4 by stacking five-year equivalent first differences for four time periods: 2000-2005, 2005-2010, 2010-2015, 2015-2019. Here, $\Delta Employment_{it}$ is the changes in employment rate for CZ $i$ in over period $t$, measured by the changes in ratio of employment to working age population. $\Delta AutomationExposure_{it}$ is some proxies of CZ-level exposure to automation technologies, as defined in Equation 2. Some of the specifications include $X_i$, which are geographic fixed effects represented by as region dummies and Census Divisions, and demographic characteristics such as total population, proportion of age, gender, race, education. Finally, $\varepsilon_{it}$ is a heteroscedastic error term.

All the estimates reported in this article, unless noted otherwise, are weighted by the amount of total labour force in 2000, the initial year covered in the sample data, to avoid endogenous changes in employment. The primary interest is $\beta_1$, which captures the link between dynamics of automation technologies and employment rate. It is expected that $\beta_1$ could be significantly negative for low and middle income CZs, and significantly positive or insignificant for CZs in high income group. Overall, the development of automation technologies corresponds to declining employment to population ratio, with slightly lower magnitudes, as suggested in Figure 2.

## 4.2 Baseline Results

Table 1 presents results for robotic density. Columns 1-5 are regressions of full sample. Column 1 provides the most parsimonious specification only including year dummies to account for macro shocks. Column 2 adds baseline demographics $X_i$. Column 3 also considers geographic dummies as covariates for regional specific characteristics. Column 4 additionally controls the interactions between state FE and year FE to account for time varying policy changes across states. To examine the sensitivity of estimates, Column 5 exhibits results using adjusted penetration to robots, taking gross economic expansion across all sectors into considerations [8], and Column 6 displays results excluding the period 2015-2019. Heterogeneous effects in regions across different income groups are presented in Columns 7-9.

In all nine columns of Table 1, it is observed that robotic adoption is negatively correlated with employment responses. All estimates are statistically significant and sizeable. For the preferred specification in Column 4, the estimated coefficient in robotic density is -0.705, implying one additional robot per thousand workers tends to reduce employment rate by 0.71 percentage points.

These findings support the evidence presented in Section 3.3 that displacement effects may outweigh productivity effects from the perspective of all CZs. Because the amounts of less developing CZs are substantially higher than that for high income areas, new vacancies induced by rising high skilled labour demand in non-automated sectors in advanced economies are not capable of absorbing replaced workers and new entrants across US.

[8] Following Acemoglu and Restrepo (2020), the adjusted penetration of robots is computed as

$$\Delta AdjustedRoboticExposure_{it} = (\frac{\Delta Automation_t^{US}}{Labour_t^{US}} - \eta_{it} \times \frac{Automation_{t0}^{US}}{Labour_t^{US}}) \times \frac{Employed_{it}}{Employed_t^{US}} \quad (5)$$

where $\eta_{it}$ measures growth rate of overall value added in commuting zone $i$ over period $t$.

Table 1: Regression of Employment Rate on Robotic Penetration for US, 2000-2019

| | Total | | | | | | High Income CZs | Middle Income CZs | Low Income CZs |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Robotic Penetration | -0.522*** | -0.241** | -0.248** | -0.705*** | | -0.675*** | 0.016 | -1.306*** | -1.014*** |
| | (0.117) | (0.098) | (0.099) | (0.213) | | (0.246) | (0.209) | (0.154) | (0.215) |
| Adjusted Robotic Penetration | | | | | -0.203*** | | | | |
| | | | | | (0.017) | | | | |
| Year FE | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| Demographics | | √ | √ | √ | √ | √ | √ | √ | √ |
| Geographic FE | | | √ | √ | √ | √ | √ | √ | √ |
| State × Year FE | | | | √ | √ | √ | √ | √ | √ |
| Time Period | 2000-2019 | 2000-2019 | 2000-2019 | 2000-2019 | 2000-2019 | 2000-2015 | 2000-2019 | 2000-2019 | 2000-2019 |
| $R^2$ | 0.583 | 0.635 | 0.635 | 0.770 | 0.810 | 0.782 | 0.817 | 0.796 | 0.640 |
| $N$ of Commuting Zones | 722 | 722 | 722 | 722 | 722 | 722 | 143 | 424 | 155 |
| $N$ of Observations | 2890 | 2888 | 2888 | 2888 | 2888 | 2166 | 572 | 1696 | 620 |

*Notes*: The table presents within group estimates of the effects of robotic penetration on employment rate. Explanatory variable is changes in robotic density. Other demographics include population, age, gender, race and education. Geographic FE refers to Census Divisions. The regressions are weighted by total labour force in 2000.

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

Columns 7-9 turn to results across different income groups. In response to extensive adoption of automation technologies, I find that employment rate did not experience significant changes in high income CZs, implying that new job creations are complementing employment losses, thus lowering the probability of welfare deteriorations. The estimates from middle and low income CZs indicate sizeable and robust negative impacts of robotic density on employment rate. It is observed that 1000 unit increase in robotic stocks per worker will lead to a drop of 1.31 percentage points in employment rate for middle income CZs, and that in low income counterparts could generate a displacement effect of 1.01 percentage points. The substantial magnitudes suggest that negative employment effects are mainly driven by displacement forces from low and middle income CZs.

## 4.3 Identification Issues

The evidence presented so far strongly suggest that the adoption of automation technologies, represented by exposure to robots, is killing the employment across US commuting zones, even after controlling for geographic variations and macro shocks. Such effects are more pronounced in low and middle income CZs, and insignificant for high income CZs. Nonetheless, it may not be sufficient to guarantee that the main results can avoid contamination by endogenous adjustment of local labour force. In this part, I address identification threats, and then implement a quasi-experimental shift share design to estimate the causal effects of automation technologies on US labour market outcomes.

There are several reasons why the development of automation technologies could be correlated with error terms in Equation 4. First, firm's decision to adopt automation may also be driven by other local industry specific changes, which could directly affect their labour demand. For example, consumers' demand shock could motivate firm owners to invest more capital and labour inputs to produce final goods, hence simultaneously rising automation and employment (Aghion et al., 2017; Webb, 2019). In addition, common trade shocks from emerging markets such as China and Mexico may drive the move towards automation (Bloom et al., 2015). Confronting with upward pressure of labour cost in high income countries, firms from labour intensive industries are inclined to use automation, making them vulnerable to international competition due to comparative advantages in labour inputs for emerging market and developing economies, and finally reduce manufacturing employment (Autor et al., 2013).

Second, any shocks from labour demand and market competition will affect industries' decisions to locate in specific areas Acemoglu and Restrepo (2020), and individual workers' adjustments across occupations and regions (Dauth et al., 2021). Affected workers from industries with high exposure of automation technologies tend to switch tasks within original establishments, or move to other firms, especially for young workers or those with higher education attainments (Dauth et al., 2021). Therefore, such spillover effects will lead to downward biased estimation of the quantitative magnitudes of both displacement effects and productivity effects.

Finally, I might worry about reverse causality, as industries with labour saving technologies and fast growing total factor productivity tend to invest more on automations, especially for those facing fierce competition and substantial amounts of robotic suppliers (Beaudry et al., 2016; Graetz and Michaels, 2018). Eventually, such firms are expected to experience another waves of labour substituting process (Jackson and Kanik, 2019).

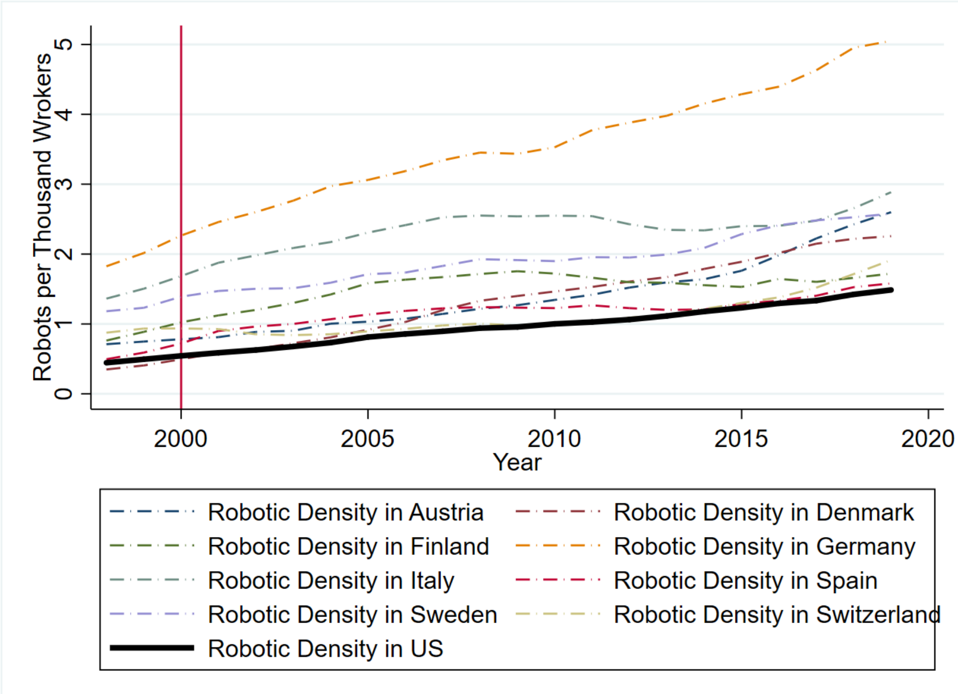
## 4.4 Shift Share IV Research Design

To alleviate potential concerns, I undertake a shift share design as instruments for exposure to automation technologies, which leverages two components: predetermined exposure shares and idiosyncratic shocks. This research design is motivated by several important papers from Acemoglu and Restrepo (2020), Aghion et al. (2017), Autor et al. (2013), Bartik (1991), Bonfiglioli et al. (2021), Bound and Holzer (2000), Dauth et al. (2021), based on the fact that local labour markets differ markedly in their industry specialisations and employment concentrations, due to differential endowments and comparative advantages.

The shifts are obtained from the supply shocks of robotic usage in other European countries, which can be regarded as an exogenous driver of automation in US (Autor et al., 2013; Bonfiglioli et al., 2021), as they are unlikely to be intervened by government policies in the short run. As reflected in Figure 4, the robotic densities across eight European countries are higher than those in US, implying that European countries, especially those which are specialised in manufacturing industries like Germany, are technologically more advanced than US in robotic development (Acemoglu and Restrepo, 2021b), thus the robotic density in Europe could only affect US labour market exclusively through robotic adoption in US due to similar industrial structures, as revealed by the parallel pre-trends before 2000 [9] (Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018). The shift share design combines these sets of shocks with variation in the CZ level of employment shares, and is constructed as Equation 3.

[9] It is observed that there is a widening gap between robotic density in US and Germany, and sensitivity checks excluding Germany in Table 4 also show consistent results.

Figure 4: Robotic Density Across Countries, 1998-2019




Notes:
The graph presents trends of robotic density for European countries and US - using data from International Federation of Robotics (2021) and World Bank (2021). Robot density refers to operational stock of robots per 10000 labour force. The 8 European countries include Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland.

Such supply driven components are not liable to reverse casualty (Bound and Holzer, 2000; Graetz and Michaels, 2018). Further, it shuts down unobserved changes in decision making by firms and workers, implying that it can only influence employment rate through the channel of the adoption of automation without spillover effects. As for common trade shocks, I ran regressions of constructed IV on trade volumes and other country level demographics such as age, gender and fertility rates, and displayed the relationship between predicted outcomes and import and export volumes [10] in Figure A4 in the Appendix. The t-statistics from both two regressions suggest insignificant association between constructed IV and trade shocks. Consequently, this instrumental variable approach makes this identification highly plausible.

Following Acemoglu et al. (2001, 2019); Aghion et al. (2017), I report the results of shift share IV design for seven specifications with the same sets of controls $X_i$ in Table

[10]Motivated by Autor et al. (2013); Bonfiglioli et al. (2021), I select China and Mexico as countries which have great import competitions with US, and choose Germany, Japan and South Korea as economies which accounting for large proportion of US export volumes.

2. The first specification repeats within group estimate for panel data regression with full controls. The second specification constructs reduced form equation to examine the correlation between the instrument and outcome variable. The third specification is to check whether the IV satisfy the condition for relevance through first stage regression. The final specification reports IV structural estimates.

Table 2 contains IV results for the impacts of robotic penetration on employment. Column 2 displays reduced form outcomes of the effect of European robotic usage on US employment rate. The significantly negative estimates show a dramatic reduction in employment, driven by spillover effects of European robotic technologies from the supply side, with quantitatively large magnitudes.

Column 3 displays the results for first stage equation of the instrument on robotic density, which reveals substantial explanatory power of predicted automation exposure for robotic density. The coefficient in Column 3 suggests that 1000 unit increase in operational stocks of robots per worker in those European counties corresponds to 1.41 unit increase in US robotic penetrations, with high F-statistics on the excluded instrument, implying no weak instrument problems.

Lastly, Column 4 offers the IV estimates of the effects of robotic density on employment. Instrumenting with predicted robotic penetration, the coefficient of -4.82 indicates that 1000 unit exogenous rise in robotic stocks per worker is predicted to reduce overall employment by 4.82 percentage points. The relatively larger absolute magnitude on IV estimates is consistent with downward endogeneity bias (Acemoglu and Restrepo, 2020; Dauth et al., 2021), as reallocation forces by both industries and workers in response to robotic usage could hamper the welfare changes of displacement effects to some extent.

Table 2: IV Regression of Employment Rate on Robotic Penetration for US, 2000-2019

| | Within Group | Reduced Form | First Stage | IV Structural Form |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Robotic Penetration | -0.610*** | | | -4.820*** |
| | (0.180) | | | (1.799) |
| Robotic Penetration (Europe) | | -6.780*** | 1.407*** | |
| | | (1.192) | (0.479) | |
| Year FE | √ | √ | √ | √ |
| Demographics | √ | √ | √ | √ |
| Geographic FE | √ | √ | √ | √ |
| State × Year FE | √ | √ | √ | |
| F Statistics | | | 126.37 | |
| $N$ of Commuting Zones | 722 | 722 | 722 | 722 |
| $N$ of Observations | 2888 | 2888 | 2888 | 2888 |

*Notes*: The table presents within group and IV estimates of the relationship between robotic penetration and employment rate in US, where robotic penetration computed using operational stocks of robots from 8 European countries (Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland) is used as the instrument. The regressions are weighted by total labour force in 2000. Other demographics include population, age, gender, race and education. Geographic FE refers to Census Divisions.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Employment Effects of Robots and Income Level for US, 2000-2019

| | Within Group | | IV Structural Form | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Robotic Penetration | -0.610*** | -1.654*** | -4.820*** | -5.036*** |
| | (0.180) | (0.314) | (1.799) | (1.411) |
| Robotic Penetration×Income | | 0.239*** | | 0.904*** |
| | | (0.052) | | (0.303) |
| Year FE | √ | √ | √ | √ |
| Demographics | √ | √ | √ | √ |
| Geographic FE | √ | √ | √ | √ |
| State × Year FE | √ | √ | √ | √ |
| $N$ of Commuting Zones | 722 | 722 | 722 | 722 |
| $N$ of Observations | 2888 | 2888 | 2888 | 2888 |

*Notes*: The table presents within group and IV estimates of the relationship between robotic penetration and employment rate by income level in US, where robotic penetration from 8 European countries is used as the instrument. The regressions are weighted by total labour force in 2000. Other demographics include population, age, gender, race and education. Geographic FE refers to Census Divisions.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## 4.5 Robots and Employment by Income Level

To account for smooth changes of the employment effects, I also include interaction term between automation technologies and income level for IV estimation. The structural form is then estimated as follows:

$$\begin{aligned}\Delta Employment_{it} = \beta_0' &+ \beta_1' \Delta Autom\widehat{ationE}xposure_{it} \\ &+ \beta_2' \Delta Autom\widehat{ationE}xposure_{it} \times Income_{it} \\ &+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}\end{aligned} \tag{6}$$

where $Income_{it}$ is average value of personal income per capita in CZ $i$ at year t, and $\Delta Autom\widehat{ationE}xposure_{it}$ is predicted based on first stage estimation:

$$\Delta Autom\widehat{ationE}xposure_{it} = \pi_0 + \pi_1 \Delta AutomationIV_{it} + \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it} \tag{7}$$

Hence $\beta_1'$ from Equation 6 captures evolution of employment effects along with levels of income.

Table 3 presents within group and IV estimates based on Equations 4 and 6. Compared with baseline results displayed Column 1, Columns 2 turns to results using interactions between robotic exposure and continuous levels of income. More interestingly, the positive coefficient estimate of interaction term reveals that rising income level could slow down negative employment effects of robotic adoption. Instrumented with the shift share IV, Columns 4 indicates that 1 extra unit in robotic stocks per thousand workers tends to reduce employment rate by 5.04 percentage points. Further, the coefficient estimate for interaction term is 0.90, highlighting the flattening effects of regional economic growth. This reveals that a $5000 increase in personal income per capita, which is roughly the gap between the threshold of high income CZs ($30443) and low income CZs ($24868), will cause a decline of 0.45 percentage points of employment reductions in response to extensive robotic penetrations in high income CZs.

Table 4: Employment Effects of Robots and Income Level using Alternative IV, 2000-2019

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Robotic Penetration | -5.036*** | -3.705*** | -6.242*** | -7.370** | -3.815*** | -4.750*** |
| | (1.411) | (1.150) | (2.228) | (3.616) | (1.007) | (1.267) |
| Robotic Penetration × Income | 0.904*** | 0.630* | 1.098*** | 1.233** | 0.654** | 0.850*** |
| | (0.303) | (0.356) | (0.372) | (0.484) | (0.272) | (0.300) |
| Year FE | √ | √ | √ | √ | √ | √ |
| Demographics | √ | √ | √ | √ | √ | √ |
| Geographic FE | √ | √ | √ | √ | √ | √ |
| State × Year FE | √ | √ | √ | √ | √ | √ |
| $N$ of Commuting Zones | 722 | 722 | 722 | 722 | 722 | 722 |
| $N$ of Observations | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 |

*Notes*: The table presents IV estimates of the relationship between robotic penetration in US and employment rate, where robotic penetration computed using operational stocks of robots from European countries is used as the instrument. Column 1 is based on data from Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland; Column 2 is based on data from all European countries; Column 3 is based on data from Denmark, Finland, France, Italy, Sweden, Germany; Column 4 is based on data from Spain, Finland, France, Italy, Norway, Sweden, UK; Column 5 is based on data from Denmark, Netherlands, Italy, Sweden, UK; Column 6 is based on data from Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK. Other demographics include population, age, gender, race and education. Geographic FE refers to Census Divisions.

Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Taking the role of economic corporations and sectoral compositions among western countries into accounts, Table 4 presents sensitivity checks under different constructions, including specifications using all European countries, one using five European countries [11] (Acemoglu and Restrepo, 2020), and one also considering Spain and UK (Bonfiglioli et al., 2021) [12]. These do not qualitatively alter the results. The IV estimates indicate sizeable and robust negative impacts of robotic exposure on employment rate, and those negative employment effects will gradually diminish, confronted with rising levels of income.

## 4.6 Alternative Automation Technologies

In this subsection, I continue to investigate how exposure to other automation technologies has affected employment rate in CZs from different stages of economic growth. In order to gauge the robustness of the results, I estimate Equation 6 with trade volumes of goods containing ICT and overall automation technologies as dependent variables.

I present corresponding IV estimates of the impacts of ICT import and export under the same specifications in Table 5, respectively. All the estimates are strong and significant. Instrumented with predicted exposure of robotic usage, it is revealed in Columns 1 and 3 that 1000 dollars increase in ICT import exposures will lead to falling employment rate of 0.32 percentage points, and export counterparts could generate a displacement effect of 0.67 percentage points. The implications with regard to interactions of automation and income level do not qualitatively alter the results. Consistent with Subsection 4.4, the estimates for in Columns 2 and 4 are significantly positive, confirming flattening effects of economic development. The estimated quantitative magnitudes for trade volumes of ICT and the whole automated machines are similar to those exhibited so far.

Overall, these findings are broadly consistent with the stylised facts in Section 3.3, and support our empirical implications on the relationship between automation technologies and employment.

[11] The five European countries are Denmark, Finland, France, Italy, Sweden. As robotic density is more pronounced in Germany, which acted as a leading country in manufacturing and robotic usage (Dauth et al., 2021), so I exclude Germany.

[12] Taking trade structures into accounts, I also implement robustness checks based on Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK.

Table 5: Employment Effects of Other Automation and Income Level in US, 2000-2019

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| ICT Import | -0.317*** | -1.367*** | | | | | | |
| | (0.104) | (0.418) | | | | | | |
| ICT Export | | | -0.670*** | -2.103*** | | | | |
| | | | (0.184) | (0.499) | | | | |
| Automation Import | | | | | -0.199** | -1.686 | | |
| | | | | | (0.080) | (1.404) | | |
| Automation Export | | | | | | | -0.196*** | -0.664*** |
| | | | | | | | (0.054) | (0.162) |
| ICT Import × Income | | 0.262*** | | | | | | |
| | | (0.081) | | | | | | |
| ICT Export × Income | | | | 0.394*** | | | | |
| | | | | (0.095) | | | | |
| Automation Import × Income | | | | | | 0.329 | | |
| | | | | | | (0.276) | | |
| Automation Export× Income | | | | | | | | 0.126*** |
| | | | | | | | | (0.031) |
| Year FE | √ | √ | √ | √ | √ | √ | √ | √ |
| Demographics | √ | √ | √ | √ | √ | √ | √ | √ |
| Geographic FE | √ | √ | √ | √ | √ | √ | √ | √ |
| State × Year FE | √ | √ | √ | √ | √ | √ | √ | √ |
| $N$ of Commuting Zones | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 |
| $N$ of Observations | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 |

*Notes*: The table presents IV estimates of the relationship between ICT and automation trade volumes in US and employment rate, where robotic penetration computed using operational stocks of robots from 8 European countries (Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland) is used as the instrument. The regressions are weighted by total labour force in 2000. Other demographics include population, age, gender, race and education. Geographic FE refers to Census Divisions.

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

Table 6: Business Dynamics, Robotic Penetration and Income Level for US, 2000-2019

| | $\Delta$ Job Destruction Rate | | $\Delta$ Job Creation Rate | | $\Delta$ Net Job Creation Rate | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Robot Penetration | 1.374 | 1.495 | -2.864* | -3.170** | -4.238* | -4.665** |
| | (1.765) | (1.869) | (1.533) | (1.232) | (2.449) | (2.108) |
| Robot Penetration $\times$ Income | | -0.192 | | 0.484*** | | 0.676** |
| | | (0.267) | | (0.182) | | (0.306) |
| Year FE | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ |
| Demographics | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ |
| Geographic FE | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ |
| State $\times$ Year FE | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ |
| Firm Size $\times$ Year FE | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ | $\surd$ |
| $N$ of Commuting Zones | 722 | 722 | 722 | 722 | 722 | 722 |
| $N$ of Observations | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 |

*Notes*: The table presents IV estimates of the effects of robotic penetration on changes of job destruction rate, job creation rate and net job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

# 5 Mechanism

Having studied the heterogeneous effects of automation technologies on local labour market outcomes, I shift the focus to investigate the mechanisms behind the effects of technological changes.

As suggested in the Section 2, the phenomenon of job replacement is pervasive across regions with different income levels, while welfare improvements induced by productivity effects are more pronounced in high income regions, and could complement job losses by displacement effects. In this section, I utilise the availability of comprehensive panel data across US CZs, to explore the relationship between automation technologies and net job creations, and discover what kind of jobs could be created or replaced. For the remainder of this suction, I will on focus on IV estimates.

## 5.1 Automation and Reduced Job Creation

As a starting point, I provide several pieces of evidence linking adoption of automation technologies, with changes in job destruction rate, job creation creation rate and net job creation rate, and estimate the equation of the following form.

$$\begin{aligned}\Delta Job_{it} = \gamma_0 &+ \gamma_1 \Delta AutomationExposure_{it} \\ &+ \gamma_2 \Delta AutomationExposure_{it} \times Income_{it} + \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}\end{aligned} \tag{8}$$

Contrary to Equation 6, the left hand side variable $\Delta Job_{it}$ of Equation 8 denotes changes in job destruction rate, job creation rate and net job creation rate in for CZ $i$ over period $t$, where the denominator is the overall number of employees for 2000, the initial year of analysis. Other variables of this five-year stacked first difference model share the same specifications as described in Section 4.4. Specifically, I also control for interactions between year fixed effects and firm quartiles, to account for evolution of establishments affiliated with different firm sizes.

Table 6 reports results of Equation 8, where exposure to automation technologies, represented by US robotic penetrations, is instrumented by European counterparts. Conceptually, I distinguish between job destructions and job creations, and characterise the consequences of both displacement effects and productivity effects.

As displayed in Columns 1-2, the insignificant estimates for the impacts of robotic density on changes of job destruction rate across CZs reveal that technological job losses are pervasive across regions with different income levels. These results confirm that automation technologies could replace production workers irrespective of stages of economic growth, proxied by personal income per capita. Columns 3-4 document the impacts on job creations. The point estimate for all CZs is statistically significant at 10 percent with a coefficient of -2.86, implying a rise of robotic stocks per thousand workers could lower job creation rate by 2.86 percentage points. The positive coefficient for interaction with income level, displayed in Column 4, suggests that new vacancies created by productivity effects could gradually complement technological job losses, especially for economically advanced areas. Furthermore, the coefficients for net job creations in Columns 5-6 are substantially larger in absolute magnitude, which bolster the interpretation that displacement effects of automation technologies in low income CZs could act as key drivers for overall decline of net job creation rate. Meanwhile, stronger productivity effects in high income CZs cause slightly weaker power of job replacement.

All columns in Table 7 turn to only focus on changes of net job creation rate, which present results for ICT import and export, and automation trade volumes as alternative measures of automation technologies. Though less precisely estimated, I also find more pronounced reduction of job creation rate for low income CZs relative to other regions, and the phenomenon of job losses diminishes with rising income level, which robustly support the hypothesis before.

In summary, these results indicate that displacement effects are pervasive across areas, and final employment outcomes are determined by differentials in productivity effects, proxied by job creations. I next turn to a detailed investigation of other empirical implications with respect to skill composition.

TABLE 7: Net Job creation Dynamics, Other Automation Technologies and Income Level for US, 2000-2019

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| ICT Import | -0.083** | -1.116*** | | | | | | |
| | (0.036) | (0.409) | | | | | | |
| ICT Export | | | -0.203** | -1.681*** | | | | |
| | | | (0.089) | (0.590) | | | | |
| Automation Import | | | | | -0.042** | -1.156 | | |
| | | | | | (0.019) | (0.714) | | |
| Automation Export | | | | | | | -0.059** | -0.528*** |
| | | | | | | | (0.026) | (0.186) |
| ICT Import × Income | | 0.207*** | | | | | | |
| | | (0.077) | | | | | | |
| ICT Export × Income | | | | 0.316*** | | | | |
| | | | | (0.112) | | | | |
| Automation Import × Income | | | | | | 0.207 | | |
| | | | | | | (0.130) | | |
| Automation Export × Income | | | | | | | | 0.100*** |
| | | | | | | | | (0.035) |
| Year FE | √ | √ | √ | √ | √ | √ | √ | √ |
| Demographics | √ | √ | √ | √ | √ | √ | √ | √ |
| Geographic FE | √ | √ | √ | √ | √ | √ | √ | √ |
| State × Year FE | √ | √ | √ | √ | √ | √ | √ | √ |
| Firm Size × Year FE | √ | √ | √ | √ | √ | √ | √ | √ |
| *N* of Commuting Zones | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 |
| *N* of Observations | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 |

*Notes*: The table presents IV estimates of the effects of other automation technologies on changes of net job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include importation and exportation of ICT equipments and automation technologies. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions.

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

## 5.2 Skill Upgrading and Net Job Creation

I have documented the presence of net job creations behind the employment effects of automation technologies. In this subsection, I present additional results, highlighting what kind of jobs could be created (replaced) by automation technologies. Since regressions adopting alternative measures such as ICT and automation trade volumes also generate similar results, I will only focus on the impacts from robotic usage. Table 8 estimates the following regression model, where I interact robotic penetration with skill shares and personal income per capita:

$$\begin{aligned}\Delta Job_{it} = \gamma_0' &+ \gamma_1' \Delta RobotExposure_{it} + \gamma_2' \Delta RobotExposure_{it} \times SkillShare_{it} \\ &+ \gamma_3' \Delta RobotExposure_{it} \times SkillShare_{it} \times Income_{it} \\ &+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}\end{aligned} \tag{9}$$

where $\Delta RobotExposure_{it}$ is CZ-level exposure to robotic usage. I use $SkillShare_{it}$, measured by the proportion of workers who received university or high school education, to describe geographic disparities of skill upgrading across US CZs. Therefore, $\gamma_2'$ can be interpreted as the mitigating effects of skill share, during the dynamics of net job creations induced by robotic penetration, and $\gamma_3'$ depicts the evolving forces of skill upgrading along with economic development.

The results for both university and high school educated workers are reported in Table 8. Column 1 replicates IV estimates of robotic exposure on employment. Columns 2-3 include the interaction of robotic usage and skill shares. The point estimates for interaction with proportion of both two types of skilled labour are statistically significant at 5 percent with a coefficient of 0.01, implying a rise of percentage of high school and university educated workers could mitigate decline of net job creation rate by 0.01 percentage points. The evidence is also consistent with the hypothesis before, as productivity effects induced by high skilled labour tend to become more powerful, and could complement job losses by displacement effects.

In Columns 4-5, I continue to examine the heterogeneity across CZs at different stages of economic development. Strikingly, the negative coefficients for interactions with both skill share and income level exhibit that the importance of mitigation effects from skill shares are diminishing. This pattern is consistent with rule of diminishing marginal returns, as for economically more advanced areas, capabilities of learning by doing and labour market experience could play a relatively more substantial role for high-skill tasks, compared with human capital accumulation (Stinebrickner et al., 2019).

Table 8: Net Job creation Dynamics and Robots by Skill Share for US, 2000-2019

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Robotic Penetration | -4.238* | -4.614** | -3.398** | -11.941* | -3.668* |
| | (2.449) | (2.114) | (1.543) | (7.158) | (2.121) |
| Robotic Penetration | | 0.007** | | 0.072* | |
| × %High School Educated Worker | | (0.003) | | (0.042) | |
| Robotic Penetration | | | 0.012** | | 0.069* |
| × %University Educated Workers | | | (0.005) | | (0.037) |
| Robotic Penetration × Income | | | | -0.009* | |
| × %High School Educated Workers | | | | (0.005) | |
| Robotic Penetration × Income | | | | | -0.009* |
| × %University Educated Workers | | | | | (0.005) |
| Year FE | √ | √ | √ | √ | √ |
| Demographics | √ | √ | √ | √ | √ |
| Geographic FE | √ | √ | √ | √ | √ |
| State × Year FE | √ | √ | √ | √ | √ |
| Firm Size × Year FE | √ | √ | √ | √ | √ |
| $N$ of Commuting Zones | 722 | 722 | 722 | 722 | 722 |
| $N$ of Observations | 2888 | 2888 | 2888 | 2888 | 2888 |

*Notes*: The table presents IV estimates of the effects of robotic penetration on changes of net job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions.
Robust standard errors in parentheses.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The findings reflect the fact that automation technologies are killing low skilled employment for workers without high school degrees, and bring welfare improvements for high skilled workers with tertiary and university education. Coupled with detailed investigation of the role of income level, it is recognised that the slowdown effects of net job creation reductions are more pronounced for CZs with high percentage of university educated workers, illuminating that new occupations are mainly created for high skilled workers.

## 5.3 Structural Change and Net Job Creation

Lastly I go one step further, and discover various patterns of employment effects of automation technologies across six broad sectors. In contrast to Equation 9, I modify the econometric model as follows:

$$
\begin{aligned}
\Delta Job_{it} = \gamma_0'' &+ \gamma_1'' \Delta RobotExposure_{it} \\
&+ \gamma_2'' \Delta RobotExposure_{it} \times Industry\,Share_{it} \\
&+ \gamma_3'' \Delta RobotExposure_{it} \times Industry\,Share_{it} \times Income_{it} \\
&+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}
\end{aligned}
\tag{10}
$$

where $Industry\,Share_{it}$ is defined as the ratio of value added for a given sector and overall GDP. Based on IFR classifications (International Federation of Robotics, 2021), those six broad sectors include manufacturing, agriculture, mining, utility, construction and R&D activities.

Table 9 displays the estimation results. As reflected in Columns 1-2, increases in robotic density are systematically associated with declining net job creation rate given GDP share of manufacturing. With a rise of percentage of manufacturing GDP, the displacement effects of robots on net job creations would be mitigated by 0.02 percentage points, and the absolute magnitudes of marginal effect are diminishing along with personal income per capita. Surprisingly, estimates for other sectors in remaining columns are insignificant. This evidence indicates that new vacancies created by productivity effects could absorb production workers from manufacturing industries, and high income CZs with growing high skilled task requirements would experience a slowdown of net job creations.

In all cases, the results confirm that net job creations play a key role in heterogeneous effects of automation technologies on labour market outcomes, and technical updating is biased against unskilled workers and those in manufacturing industries.

Table 9: Net Job creation Dynamics and Robotic Penetration by Industry for US, 2000-2019

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Robot Penetration | -4.238* | -4.613** | -4.841** | -4.678** | -4.729** | -5.948* | -4.171** |
| | (2.449) | (2.128) | (2.274) | (2.126) | (2.147) | (3.349) | (1.983) |
| Robot Penetration | | 0.022* | | | | | |
| $\times$ %Manufacturing GDP | | (0.012) | | | | | |
| Robot Penetration$\times$ | | | -0.005 | | | | |
| %Agriculture GDP | | | (0.005) | | | | |
| Robot Penetration | | | | 0.002 | | | |
| $\times$ %Mining GDP | | | | (0.003) | | | |
| Robot Penetration | | | | | 0.003 | | |
| $\times$ %Utility GDP | | | | | (0.007) | | |
| Robot Penetration | | | | | | 0.034 | |
| $\times$ %Construction GDP | | | | | | (0.033) | |
| Robot Penetration | | | | | | | 0.151 |
| $\times$ %R&D GDP | | | | | | | (0.098) |
| Robot Penetration$\times$ Income | | -0.004* | | | | | |
| $\times$ %Manufacturing GDP | | (0.002) | | | | | |
| Robot Penetration $\times$ Income | | | 0.001 | | | | |
| $\times$ %Agriculture GDP | | | (0.001) | | | | |
| Robot Penetration $\times$ Income | | | | -0.000 | | | |
| $\times$ %Mining GDP | | | | (0.001) | | | |
| Robot Penetration $\times$ Income | | | | | -0.001 | | |
| $\times$ %Utility GDP | | | | | (0.001) | | |
| Robot Penetration $\times$ Income | | | | | | -0.006 | |
| $\times$ %Construction GDP | | | | | | (0.006) | |
| Robot Penetration $\times$ Income | | | | | | | -0.028 |
| $\times$ %R&D GDP | | | | | | | (0.018) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Geographic FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State $\times$ Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Firm Size $\times$ Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N$ of Commuting Zones | 722 | 722 | 722 | 722 | 722 | 722 | 722 |
| $N$ of Observations | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 | 2888 |

*Notes*: The table presents IV estimates of the effects of robotic penetration on interactions between changes of net job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

# 6 Further Discussion

So far, I have looked at the employment effects and net job creations of automation technologies across US CZs. In the final step of analysis, I discuss implications for cross country evidence.

The specification relating automation technologies and employment rate is constructed as follows:

$$\begin{aligned} Employment_{it} = \beta_0'' &+ \beta_1'' AutomationExposure_{it} \\ &+ \beta_1'' AutomationExposure_{it} \times Income_{it} \\ &+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it} \end{aligned} \tag{11}$$

Here, $Employment_{it}$ is employment rate for country $i$ in year $t$. $AutomationExposure_{it}$ is some proxies of automation exposures, including robotic density calculated by operational stocks of robots per thousand workforce, and ICT intensity calculated by ICT capital values per thousands of full time workers. $Income_{it}$ is GNI per capita in country $i$ at year 2019 [13]. Regressions are weighted by initial amount of total labour force. Other covariates $X_i$ capture geographic fixed effects represented by region dummies, and demographic characteristics such as population and GDP. $\varepsilon_{it}$ is a heteroscedastic error term.

Table 10 presents main results for robotic density and ICT intensity with full controls. Column 1 indicates that robotic density is negatively correlated with employment rate. All estimates are statistically significant and sizeable. The coefficient estimate in robotic density is -0.454, implying one more robot per thousand workers tends to reduce employment rate by 0.45 percentage points. While Column 2 suggests that 1 extra dollar in GNI per capita could mitigate employment reductions 0.07 percentage, indicating that the negative employment responses induced by robotic adoptions tend to be more pronounced in low income countries, and with growing GNI per capita, employment rate in high income countries rises sharply in response to extensive adoption of automation technologies. The estimates for ICT intensities displayed in Columns 3-4 are comparable to the direction of those for robotic densities [14].

In summary, the fact that automation technologies are killing the employment still holds

[13] I use GNI per capita in 2019 as there are missing values in previous years. Regression results based on income level in 1993 are also consistent with Table 10.

[14] The reason about small magnitudes of employment effects from ICT intensities are described in footnotes of Section 3.3.

for cross country analysis. I find that productivity effects are more pronounced for developed countries with high income levels. In contrast, negative employment effects are much stronger in low and middle income countries, as rising demand of high skilled labour in other non-automated sectors is not capable of compensating job losses induced by automation technologies.

Table 10: Employment Rate and Automation Across Countries, 1993-2019

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Robotic Density | -0.454** | -1.423*** | | |
| | (0.210) | (0.189) | | |
| Robotic Density × Income | | 0.068*** | | |
| | | (0.007) | | |
| ICT Intensity | | | -0.013*** | -0.011*** |
| | | | (0.004) | (0.004) |
| ICT Intensity × Income | | | | 0.028*** |
| | | | | (0.005) |
| $R^2$ | 0.673 | 0.789 | 0.497 | 0.579 |
| $N$ of Countries | 64 | 64 | 107 | 107 |
| $N$ of Observations | 1686 | 1686 | 2866 | 2866 |
| Geographic FE | √ | √ | √ | √ |
| Year FE | √ | √ | √ | √ |
| Geographic × Year FE | √ | √ | √ | √ |
| Demographics | √ | √ | √ | √ |

*Notes*: The regressions are weighted by total labour force in 1993. Independent variables are robotic density and ICT intensity. Other baseline controls include country level demographics such as population and GDP. Geographic FE refers to region dummies.
Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Overall, these findings are broadly consistent with US evidence. Nonetheless, lack of identification strategies is potentially puzzling, making it hard to disentangle spillover effects and other endogenous factors. A more in-depth research uncovering exogenous variation of penetration to automation technologies across countries is a promising direction for future empirical implications.

# 7 Conclusion

Automation seems to influence differently employment depending on the income level of each country or region. This paper leverages comprehensive CZ level data to provide a unified analysis regarding the impacts of automation technologies on employment rate in US, and investigates mechanisms based on responses of workers with different skill levels and industries under forces of displacement effects and productivity effects.

The article focuses on US evidence. I find that rising penetration of automation technologies, including industrial robots and ICT trade volumes, corresponds to reductions in employment rate across all commuting zones. The magnitudes of negative employment response are more sizeable and significant in low and middle income areas, implying that displacement effects are dominating the process of technology updating. While mitigating effects of income level suggest that productivity effects may flatten welfare deteriorations by displacement effects.

Motivated by the conceptual framework, these patterns can be explained by a simple net job creation channel. After adopting automation technologies, it is witnessed that job replacement occurs across all regions. For high income CZs, new vacancies are created in other non-automated sectors, where high skilled labour forces are required in most cases, and higher proportion of skilled workers with university education raises the possibility of successful matches. Nonetheless, relatively lower percentage of skilled workers in low and middle CZs could not provide great opportunities for such job creations, leading to substantial employment losses. As a consequence, growing income level could depress the absolute magnitudes of negative employment effects, and reduce the welfare deterioration to some extent. Encouragingly, the analysis reveals that such technological change is biased against low skilled workers (Graetz and Michaels, 2018), and causes welfare improvement for high skilled workers, as new occupations are mainly created among labour force completing university matriculation. Taking structural change into accounts, it is uncovered that areas with large proportions of manufacturing GDP could benefit from productivity effects.

Moreover, regression results from cross country analysis point out the potential to generalise the implications for worldwide economic growth. With novel datasets and appropriate identification strategies, I believe both empirical studies exploring heterogeneous effects under other institutional settings, and theoretical models incorporating roles of skill upgrading, would therefore be a promising direction for future research.

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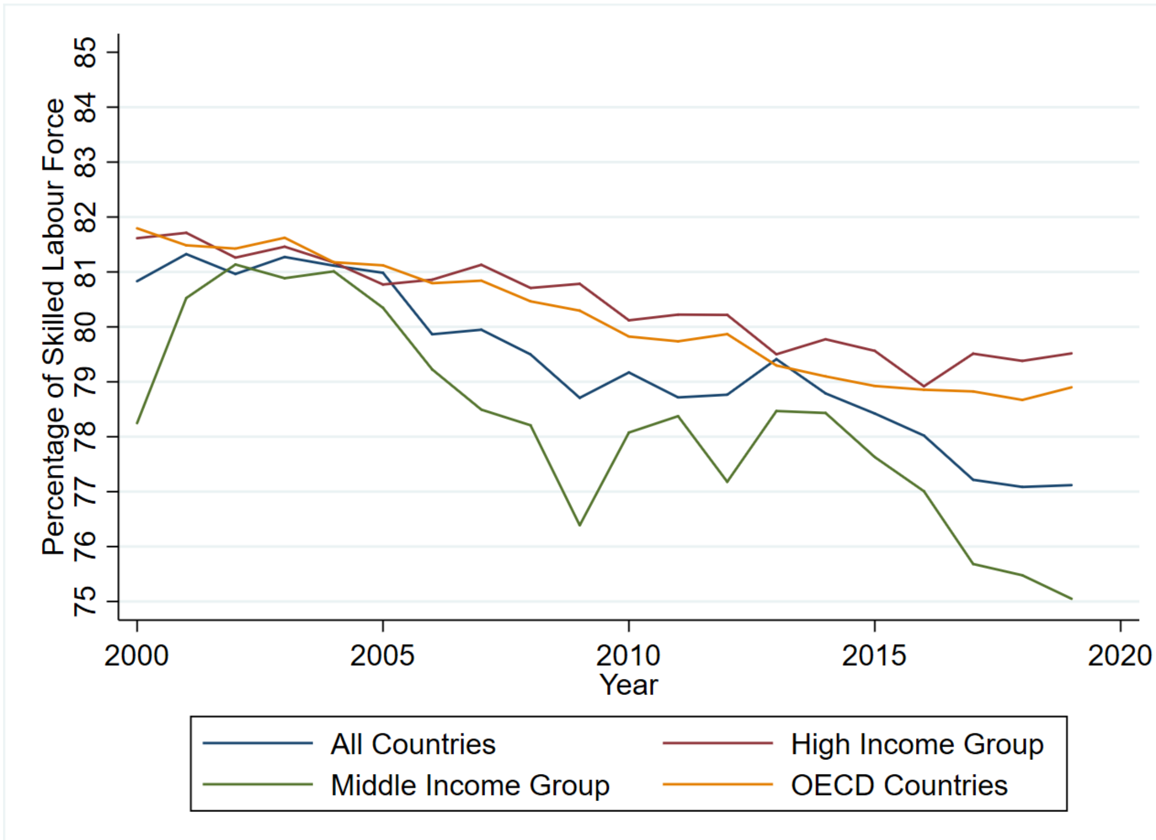
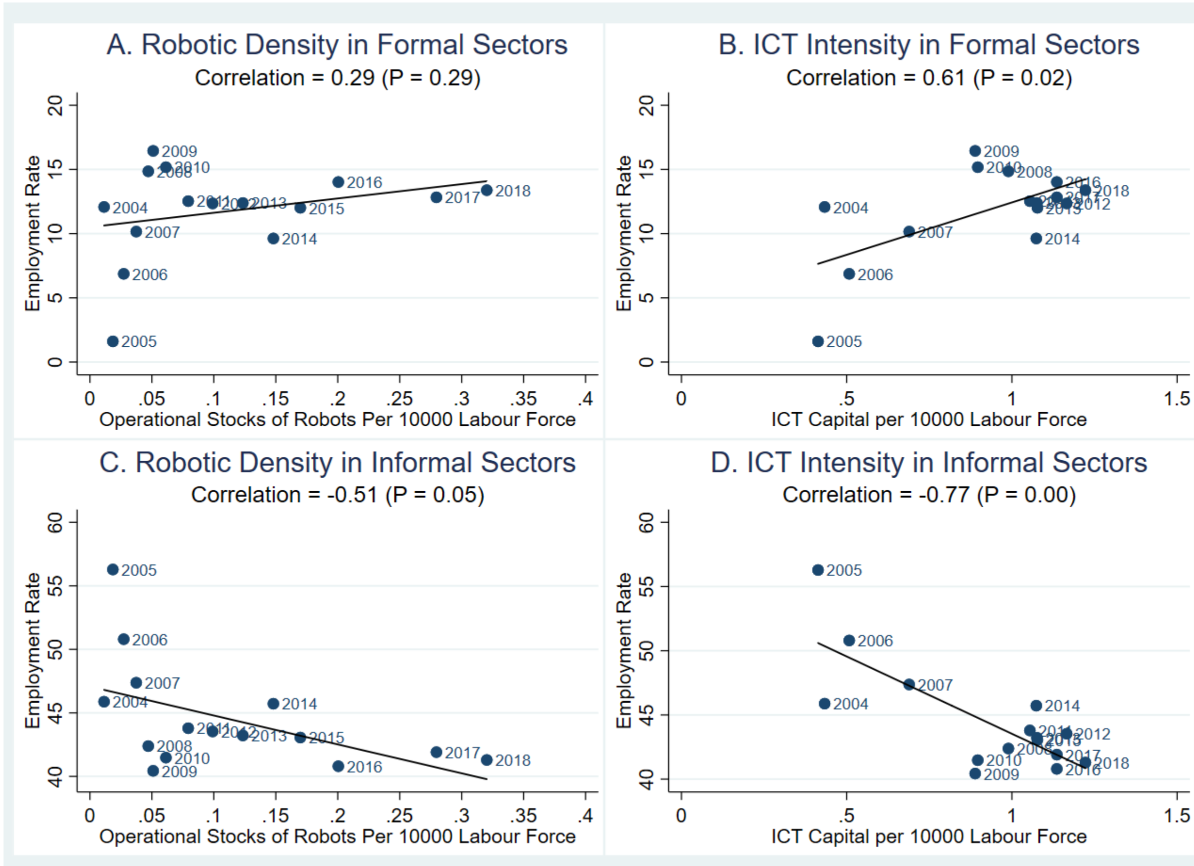
# Appendix

Figure A1: Evolution of Labour Force with Advanced Education, 2000-2019



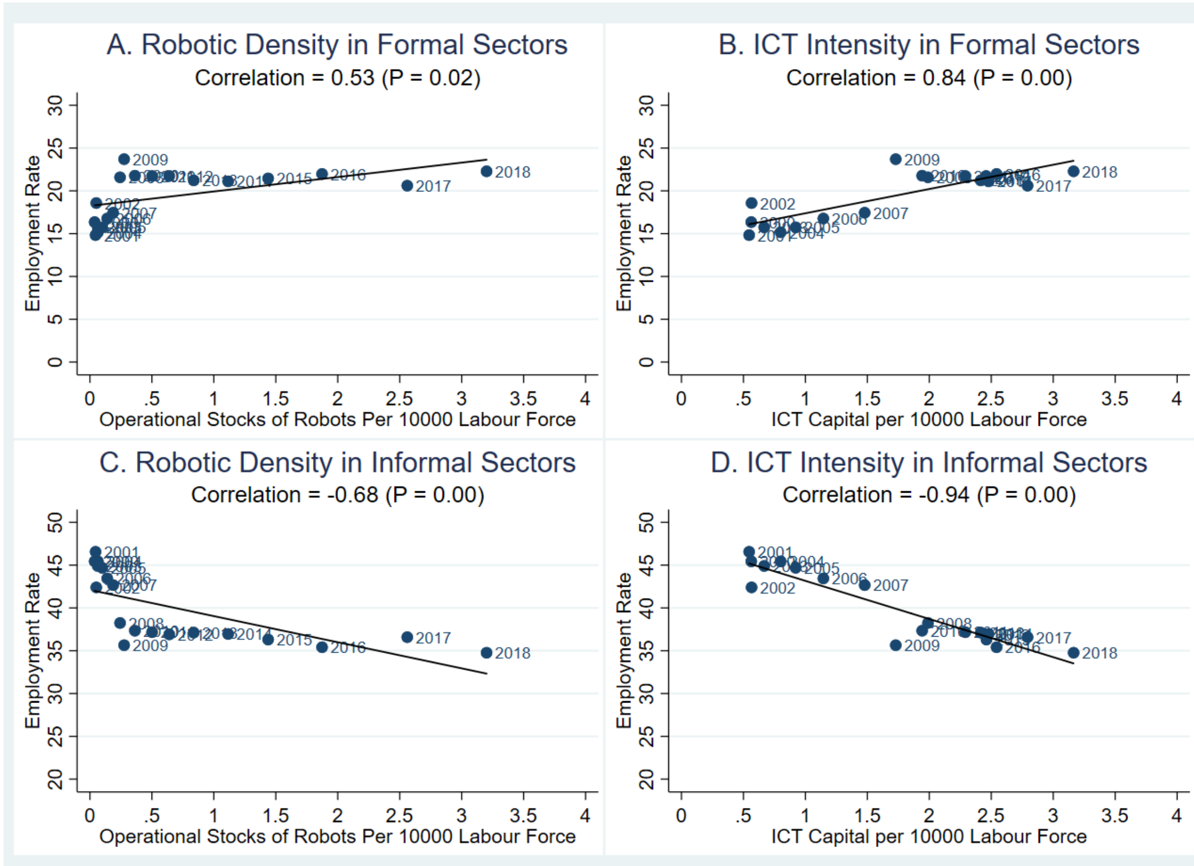

Notes:
The graph presents proportion of skilled labour force, defined as those who received tertiary education, for countries from different income groups - using data from World Bank (2021).

Figure A2: Automation Technologies and Informal Employment for Low and Lower Middle Income Group, 1993-2019



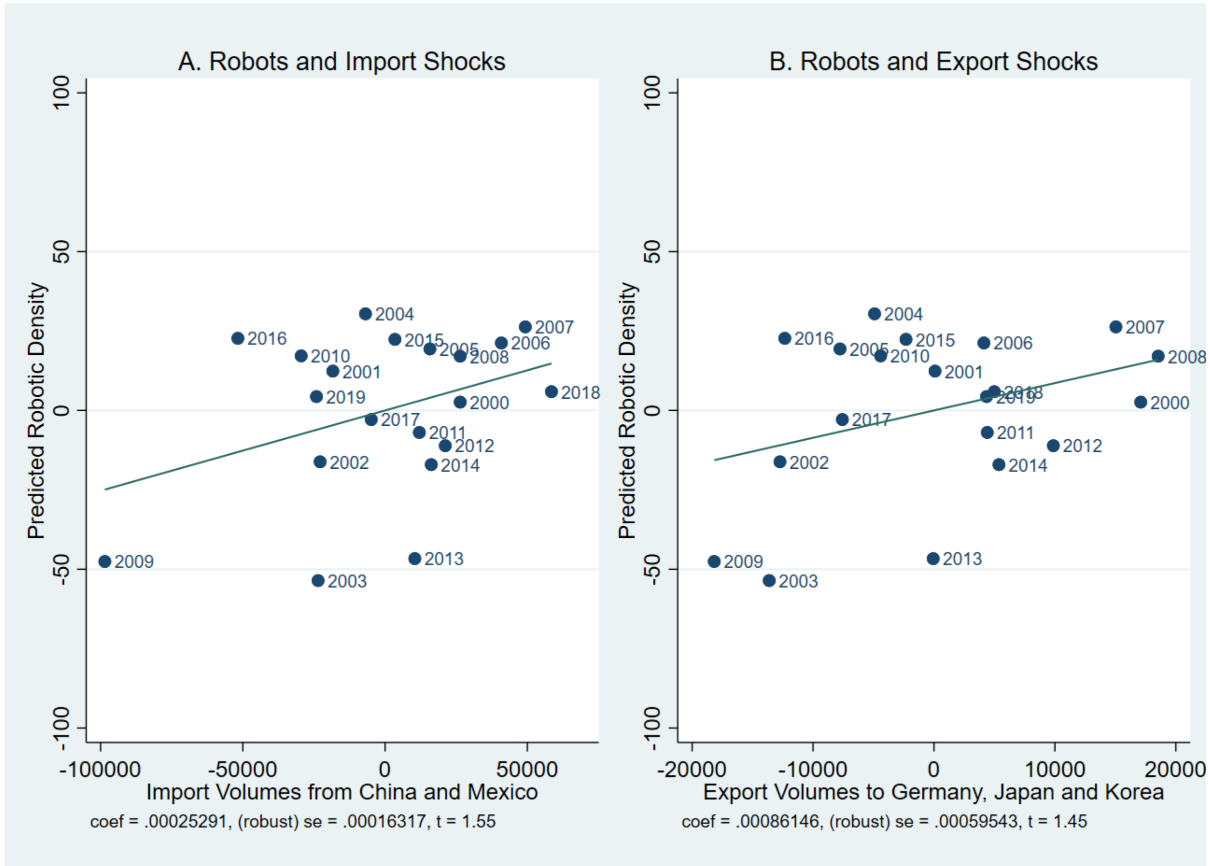

Notes:
The employment rate for formal and informal sectors are from Elgin et al. (2021). The operational stock of robots is based on International Federation of Robotics (2021), and ICT intensity is from The Conference Board (2021). Employment rate is the ratio of employed people and total population who are above 15 years old. Robot density refers to operational stock of robots per 10000 labour force. ICT intensity refers to ICT capital per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020).

Figure A3: Automation Technologies and Informal Employment for Middle Income Group, 1993-2019




Notes:
The employment rate for formal and informal sectors are from Elgin et al. (2021). The operational stock of robots is based on International Federation of Robotics (2021), and ICT intensity is from The Conference Board (2021). Employment rate is the ratio of employed people and total population who are above 15 years old. Robot density refers to operational stock of robots per 10000 labour force. ICT intensity refers to ICT capital per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020).

Figure A4: Predicted Robotic Density and Trade Volumes, 2000-2019




Notes:
The graph presents relationship between predicted robotic density and trade volumes - using data from International Federation of Robotics (2021), World Bank (2021) and United Nations (2021). The predicted robotic density is obtained based on regression of European robotic adoption on trade volumes and country level demographics. European robotic adoption is computed using ratio operational stocks of robots from 8 European countries (Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland) and total labour force. Import volumes from China and Mexico, and export volumes to Germany, Japan and South Korea are measured in million USD.