# REPORT

## Policy paper: Resilience and vulnerability – Migration, ageing and technological change

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# Europe's challenges of population ageing: Are migration and automation possible solutions? FutuRes Deliverable 4.2 *

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**Abstract**

Contemporary Europe faces numerous economic challenges, some of which are linked to population ageing, migration, and job automation. These topics are important for the future of the economies in Europe and other advanced nations, and are clearly interlinked. Many countries face population ageing, with an increasing proportion of people in the older age groups relative to those of working age, and even greater to those actively participating in the labour market.

To boost a dwindling work force in the short term, one easy option would be to turn to immigration. However, the continuing supply of migrants is not guaranteed and may not be sufficient. An alternative for some industries is the automation of jobs, although despite the sometimes alarmist discourse about robots and artificial intelligence, at present only some jobs can be automated. There is a barrier to this for some countries due to the existing low level of automation capital and the perceived high cost of automation, which can be also a politically sensitive issue.

This policy paper provides an illustration of these challenges, and examines the effects and trade-offs of automation, migration, and labour market policies in the context of small open economy dynamic stochastic general equilibrium (DSGE) model which is calibrated to four of the EU27 countries with ageing populations.

**JEL Classification:** E32, E62, F22
**Keywords:** Job Automation, Migration, Population Ageing, DSGE Model, Small Open Economy

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# Contents

# 1 Introduction

This policy paper aims to analyse the challenges related to the interplay of demographic and labour force dynamics, migration and job automation in the context of population ageing in Europe. In particular, we aim to examine the effects and trade-offs of job automation, migration, and labour market policies through the lens of macroeconomic modelling. In the spirit of Barker and Bijak (2024*a*), we use dynamic stochastic general equilibrium (DSGE) models of small open economies calibrated to four EU27 countries with ageing populations – Germany, Italy, Poland and Sweden – characterised by different welfare regimes, demographic and migration characteristics and automation levels.

The report is split into two main parts. Section 2 provides the background analysis of the ageing population, labour force, and state of job automation across Europe. In Section 3, we apply the one-country DSGE models to the four selected European countries. We use the data presented in Section 2 to calibrate the models for policy analysis, and present the results of the impulse-response and steady-state analysis. Finally, Section 4 concludes the paper and offers policy insights, with focus on various policy solutions as to the trade-offs involved in the implementation.

# 2 Context: Macroeconomics, labour markets, ageing and robot adoption

We begin this report by discussing factors relevant for the challenges of ageing labour markets. In preliminary work (Barker and Bijak, 2024*a*), we have sought to answer the question on whether robots and migration could 'solve' the challenges posed by population ageing. The simple answer (for the near future) is negative: instead, a variety of policies would be required to re-activate large parts of the unemployed or inactive workforce in order to maintain the economic output. Specifying policies in exact terms was beyond the scope of the previous paper, but we referenced examples made by some governments. Further, robot adoption, which is increasing at significant rates, is characterised by high level of heterogeneity amongst even similarly developed countries. In Barker and Bijak (2024*a*), we have examined the interplay between migration and job automation in a two-country DSGE model which was calibrated to Germany (a country mainly receiving migrants, with a high rate of robot adoption) and Poland (until recently, a country predominantly sending migrants with a low rate of job automation).

Throughout this section, we present a series of summary statistics as a background for the topic and to compare the countries in Europe for which data are available. Table 1 provides a macroeconomic summary of potential countries, and is adapted from Barker and Bijak (2024*b*). Table 2 presents robots per 10,000 workers[1] and some further statistics on demographic factors including fertility rate and old-age dependency ratios. Table 3 presents net migration statistics, while Table 4 provides the breakdown of education levels, using the ISCED groupings, of 15–64 and 65–74 year olds to show the approximation of skill levels in each country. Finally, Table 5 shows participation and unemployment rates with particular focus on the 65–74 age group.

## 2.1 Macroeconomies of Europe: A brief introduction

Macroeconomics, and by extension the labour market conditions, encompass some of the key drivers of migration. People often search for jobs internationally in hope of improving their employment prospects, standard of living, or filling labour gaps in the destination country's labour market. A poorly performing economy incentivises emigration to a better one. Different labour markets may also offer the opportunities for workers that come from comparable countries, for example from France to Germany and vice versa.

Table 1 presents the net migration 'rates' (per 1,000 people) and selected macroeconomic and labour market indicators, expressed as averages for 2002 to 2019 and the 2019 values[2]. These statistics help to provide an insight to the potential macroeconomic drivers including migration 'push factors' (such as high unemployment and low wages) and 'pull factors' (high wages and high employment). The wages and real GDP per capita figures can be somewhat misleading for countries such as Norway and Switzerland which are known to have relatively high costs of living, however, they do have high living standards, which are seen as attractive to would-be migrants[3].

[1] A standard international comparison measure to evaluate the use of robots in a country. Statistics are not available for all countries.

[2] We use 'rates' for net migration in inverted commas, to indicate that the migration numbers do not correspond to correct populations at risk.

[3] We use this data form, as it is available at a quarterly frequency, alongside other components of the national accounts, whereas the purchasing-power data is available only at an annual basis.

Including the 2019 values alongside the 2002–19 averages illustrates the recent attractiveness of a country in addition to longer-term trends. Two of the most notable differences between averages and 2019 values are observed for Greece and Slovenia. Greece, by most measures, has a positive net migration over the total sample but this hides the fact that it has experienced large outflows of people in the 2010s. Since 2002, Slovenia has also overtaken Greece on many economic measures and has become comparable with other Southern European Countries. For each indicator presented, Slovenia has been recently on an upward trajectory, while Greece has mostly exhibited downward ones.

Focusing on GDP per capita is not the best measure when studying migration flows, which can be highly distorted by outside factors. This is part of the reason we include two forms of wage and salaries analysis. Reliable data by income groups are not always available, which precludes accounting for the wealth distribution or income inequalities, such as those measured by the Gini coefficient[4]. The values for GDP and wages are presented in real terms, so they are comparable across the time sample.

Figure 1 shows, for selected European countries, calculated average real wages and salaries per employee on the vertical axis, and the corresponding values of the Gini coefficient for 2019 (2018 for the UK) on the horizontal one. The graph shows that there is an inconsistent relationship between the two variables. It is arguable that there is a form of trend line, such that Gini decreases with a rise in wages and salaries but there are countries that are far from a 'trendline' per se, such as Switzerland (CHE) and Luxembourg (LUX) for the high-income segment. At the same time, Czechia (CZE), Slovakia (SVK) and Slovenia (SVN) have the lowest values of the Gini coefficient, and relatively lower wages. As the cost of living in these countries is lower than the EU15, from a domestic perspective or purchase power parity, the value of these wages could be higher, though. Unsurprisingly, the Nordic countries are considered to be European leaders in terms of a balance between the highly desired high-income and low Gini coefficients.

[4] In some countries, this can be distorted by a high proportion of high earners, such as the UK, with its high Gini coefficient, indicating high income inequality. For explanation on the Gini coefficient, see Hasell (2023). For a comparison with other OECD countries using the average household disposable income, see Figure 71 (pp268) Resolution Foundation & Centre for Economic Performance, LSE (2023).

Table 1: Selected Summary Statistics for Selected European Countries

| Country | Net Migration Rate | | Real GDP pc (1000€s) | | Wages (1000€s) | | EU-15 Wage Premium | | Unemp Rate% | | Emp Rate% | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Avg. | 2019 | Avg. | 2019 | Avg. | 2019 | Avg. | 2019 | Avg. | 2019 | Avg. | 2019 |
| *Northern European Countries* | | | | | | | | | | | | |
| **DNK** | 3.10 | 2.81 | 69.39 | 76.75 | 44.41 | 47.59 | 1.61 | 1.63 | 5.77 | 5.00 | 73.9 | 75.0 |
| **FIN** | 3.99 | 5.02 | 53.96 | 60.17 | 32.44 | 33.38 | 1.18 | 1.15 | 8.12 | 6.70 | 69.5 | 72.9 |
| **IRL** | 1.09 | 1.96 | 72.60 | 106.75 | 33.76 | 35.48 | 1.23 | 1.22 | 8.62 | 4.95 | 65.5 | 69.5 |
| **NOR** | 9.83 | 9.05 | 109.21 | 99.41 | 46.07 | 50.09 | 1.67 | 1.72 | 3.63 | 3.65 | 75.5 | 75.3 |
| **SWE** | 10.36 | 11.95 | 68.30 | 68.55 | 34.91 | 38.23 | 1.27 | 1.31 | 7.07 | 6.85 | 74.3 | 77.1 |
| **UK** | 6.35 | 9.72 | 55.58 | 53.75 | 34.03 | 34.73 | 1.24 | 1.19 | 5.73 | 3.75 | 71.8 | 75.2 |
| *Western European Countries* | | | | | | | | | | | | |
| **AUT** | 7.98 | 10.49 | 58.27 | 63.46 | 30.96 | 32.93 | 1.13 | 1.13 | 5.05 | 4.53 | 70.3 | 73.6 |
| **BEL** | 5.13 | 6.84 | 55.16 | 60.39 | 32.31 | 33.33 | 1.17 | 1.15 | 7.67 | 5.40 | 61.9 | 65.3 |
| **CHE** | 6.55 | 5.69 | 92.37 | 119.71 | 60.48 | 65.06 | 2.20 | 2.24 | 4.61 | 4.43 | 78.7 | 80.5 |
| **DEU** | 3.32 | 6.43 | 53.46 | 60.45 | 28.64 | 31.37 | 1.04 | 1.08 | 6.81 | 3.15 | 71.0 | 76.7 |
| **FRA** | 3.66 | 4.81 | 50.47 | 55.60 | 29.77 | 31.79 | 1.08 | 1.09 | 8.77 | 8.13 | 64.1 | 65.6 |
| **LUX** | 12.68 | 16.36 | 116.25 | 120.91 | 55.51 | 56.40 | 2.02 | 1.94 | 5.07 | 5.63 | 65.0 | 67.9 |
| *Southern European Countries* | | | | | | | | | | | | |
| **ESP** | 4.10 | 3.14 | 34.32 | 39.17 | 20.29 | 21.22 | 0.74 | 0.73 | 16.32 | 14.08 | 60.4 | 63.3 |
| **GRC** | 0.64 | -1.81 | 27.85 | 26.69 | 12.60 | 12.18 | 0.46 | 0.42 | 16.19 | 17.28 | 56.1 | 56.5 |
| **ITA** | 4.99 | 3.28 | 44.04 | 44.69 | 19.61 | 19.89 | 0.71 | 0.68 | 9.37 | 9.90 | 57.2 | 59.0 |
| **PRT** | 0.43 | 2.55 | 25.68 | 29.38 | 13.63 | 14.23 | 0.50 | 0.49 | 9.76 | 6.53 | 66.2 | 70.5 |
| *Eastern European Countries* | | | | | | | | | | | | |
| **BGR** | -7.83 | -10.76 | 8.69 | 11.73 | 3.82 | 5.44 | 0.14 | 0.19 | 9.61 | 4.25 | 60.6 | 70.1 |
| **CZE** | -0.13 | 1.46 | 20.57 | 27.60 | 9.76 | 12.22 | 0.35 | 0.42 | 5.84 | 2.00 | 67.9 | 75.1 |
| **EST** | -3.61 | 11.81 | 22.04 | 28.96 | 10.98 | 13.48 | 0.40 | 0.46 | 8.49 | 4.45 | 67.9 | 74.8 |
| **HUN** | -1.98 | -2.94 | 12.35 | 13.87 | 8.97 | 9.93 | 0.33 | 0.34 | 7.33 | 3.43 | 59.9 | 70.1 |
| **LTU** | -13.79 | -5.23 | 16.67 | 24.21 | 8.35 | 13.99 | 0.30 | 0.48 | 10.05 | 6.28 | 64.6 | 73.0 |
| **LVA** | -5.04 | -5.90 | 16.43 | 22.28 | 8.98 | 12.14 | 0.32 | 0.42 | 11.10 | 6.33 | 65.0 | 72.3 |
| **POL** | -3.73 | -2.53 | 14.07 | 18.47 | 7.96 | 10.61 | 0.29 | 0.36 | 10.54 | 3.30 | 59.2 | 68.2 |
| **ROU** | -7.89 | -7.72 | 9.87 | 12.58 | 4.97 | 8.39 | 0.18 | 0.29 | 6.53 | 3.93 | 60.4 | 65.8 |
| **SVK** | 0.64 | 1.85 | 19.52 | 25.50 | 9.13 | 11.84 | 0.33 | 0.41 | 12.65 | 5.78 | 61.1 | 68.4 |
| **SVN** | 5.29 | 10.16 | 25.08 | 30.22 | 16.99 | 18.87 | 0.62 | 0.65 | 6.91 | 4.45 | 66.3 | 71.8 |

Adapted from Barker and Bijak (2024*b*). Average (Avg) uses values for 2002:2019, with the values for 2019 either annual or averaged over Q1:Q4. The values for real GDP per capita and wages are in 1000s of euro. Unemployment rate is for 15-64 year olds. Source: Authors' calculations using data from Eurostat, IMEM database, QuantMig Estimates, OECD, and national statistical institutes.

## 2.2 Ageing populations and migration

Table 2 presents the average total fertility rates for 2010–21, the average old-age dependency ratios (OADR) for 2011–22, 2023 and the forecasts for 2050. The European fertility rates average between 1.29 to 1.93, with the lowest values found in southern Europe: Spain, Portugal, Italy and Greece. These same four countries exhibit the four highest OADR values predicted for 2050. Notably, all fertility rates are *below* the replacement rate (2.1). Generally, and unsurprisingly, the higher the current fertility rate, the lower the predicted OADR, although this relationship may be mitigated somewhat by other factors, such as migration.

Current fertility rates feed into the old age dependency ratio within 15 years as that is the point that they join the notionally economically active age group (15–64). Fertility

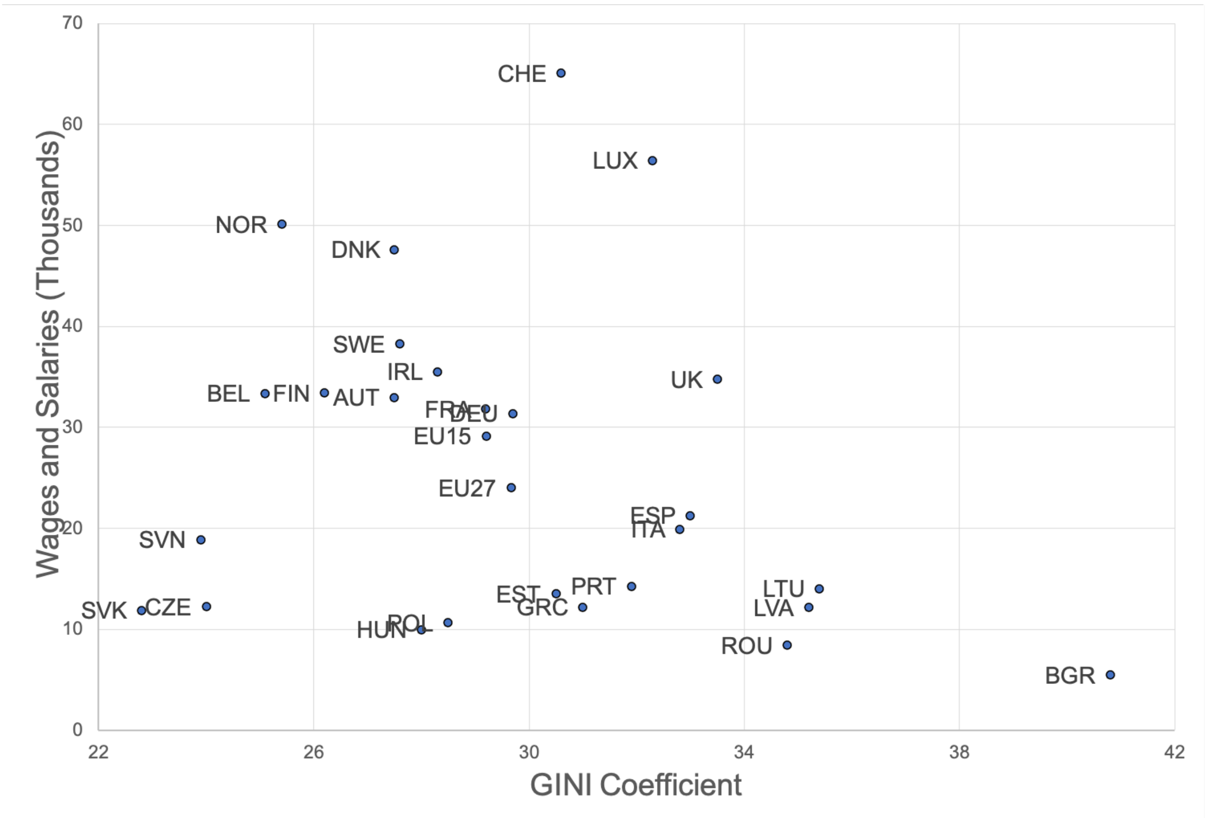



Figure 1: Wages and Salaries vs Gini Coefficient for selected European countries

The vertical axis shows real wages and salaries per employee in thousands of Euros. The horizontal axis shows the Gini coefficient value. The higher a Gini coefficient value, the more income inequality there is. The values are for 2019, though the UK's Gini coefficient is for 2018. Statistically, the values range between 0-100(%) for the Gini coefficient but for most countries the range is 22 to 60. Each mark on the graph is labelled with the respective three-letter code (except for the average values for EU15 and EU27 (post 2020)).

rates dropped below the replacement rate in the 1970s for most countries and have not recovered since. People born in that period are now not far from retirement, following in the footsteps of the already largely retired 'baby boom' generation[5]. In some ways, the current period and the next 10–15 years are going to see some of the greatest shifts in the numbers of retirees, given the size of the 'baby boom' cohorts. For 2023, in the EU27 it is estimated that there are more over 65s (95.9 million) than there are under 20s (91.5 million)[6].

Table 3 provides the net migration 'rates' for working-age people, and for all ages,

[5]The 'baby boom' generation is considered to be person born in the 20 years post World War II, approximately 1946–66. For fertility trends, see e.g. the Eurostat Table demo_frate

[6]Source Eurostat Table: proj_23np

Table 2: Demography Statistics for Selected European Countries

| Country | Robots per 10,000 wrks 2021 | Wages € Avg. 2019 | Wage Pre to EU15 | Fert Rate 1000s€ 2010-21 | OADR Avg. 2011-22 | OADR 2023 | OADR 2050 |
|---|---|---|---|---|---|---|---|
| *Northern European Countries* | | | | | | | |
| **DNK** | 234 | 47.59 | 1.82 | 1.73 | 29.3 | 32.3 | 42.1 |
| **FIN** | 161 | 33.38 | 1.25 | 1.61 | 32.5 | 37.5 | 46.1 |
| **IRL** | 54 | 35.48 | 1.13 | 1.85 | 20.3 | 23.2 | 43.2 |
| **NOR** | 88 | 50.09 | 2.00 | 1.70 | 25.3 | 28.5 | 41.0 |
| **SWE** | 321 | 38.23 | 1.37 | 1.82 | 31.1 | 32.7 | 38.5 |
| **UK** | 111 | 34.73 | 1.07 | 1.82 | 27.5 | 29.2 | 36.1 |
| *Western European Countries* | | | | | | | |
| **AUT** | 196 | 32.93 | 1.20 | 1.47 | 27.7 | 29.8 | 46.4 |
| **BEL** | 198 | 33.33 | 1.07 | 1.70 | 28.4 | 30.9 | 42.3 |
| **CHE** | 240 | 65.06 | 2.68 | 1.52 | 26.9 | 29.3 | 45.6 |
| **DEU** | 397 | 31.37 | 1.22 | 1.50 | 32.6 | 34.7 | 45.7 |
| **FRA** | 163 | 31.79 | 1.03 | 1.93 | 30.3 | 34.5 | 48.0 |
| **LUX** | 198 | 56.40 | 2.80 | 1.46 | 20.6 | 21.5 | 36.1 |
| *Southern European Countries* | | | | | | | |
| **ESP** | 167 | 21.22 | 0.64 | 1.29 | 28.2 | 30.8 | 59.0 |
| **GRC** | | 12.60 | 0.37 | 1.37 | 33.0 | 36.0 | 67.9 |
| **ITA** | 217 | 19.89 | 0.64 | 1.35 | 34.5 | 37.8 | 61.3 |
| **PRT** | 81 | 14.23 | 0.45 | 1.34 | 32.2 | 37.7 | 62.9 |
| *Eastern European Countries* | | | | | | | |
| **BGR** | 23 | 5.44 | 0.17 | 1.54 | 31.1 | 33.8 | 53.4 |
| **CZE** | 168 | 12.22 | 0.41 | 1.60 | 27.8 | 31.8 | 47.2 |
| **EST** | 34 | 13.48 | 0.43 | 1.60 | 29.4 | 31.9 | 46.2 |
| **HUN** | 115 | 9.93 | 0.31 | 1.45 | 27.7 | 31.9 | 45.5 |
| **LTU** | 30 | 13.99 | 0.34 | 1.58 | 28.9 | 30.7 | 53.4 |
| **LVA** | | 6.7 | 12.14 | 1.56 | 30.3 | 33.1 | 53.6 |
| **POL** | 63 | 10.61 | 0.27 | 1.37 | 23.9 | 29.7 | 50.5 |
| **ROU** | 33 | 8.39 | 0.19 | 1.65 | 26.5 | 30.9 | 50.2 |
| **SVK** | 143 | 11.84 | 0.34 | 1.47 | 21.4 | 26.7 | 49.7 |
| **SVN** | 249 | 18.87 | 0.60 | 1.59 | 28.2 | 33.8 | 53.7 |

Old age dependency ratio is defined as the ratio of people aged 65 plus relative to the population of 15-64 year olds. OADR sourced from Eurostat Table demo_pjanind and for the UK, ONS for years 2020 onward Eurostat, IMEM database, QuantMig Estimates OECD, and national statistical institutes. Robots per 10,000 workers is sourced from the International Federation of Robotics. Belgium and Luxembourg are grouped together.

both for migration within the EU+ system (32 countries: the EU, EFTA and the UK), or for all countries, for 2002-2019. The final two columns of the table report the foreign-born and foreign-national populations as percentages of the total. These values are for 2023, except for the UK (2019). For historical reasons, Czechia, Estonia and Latvia are the only countries where the share of foreign citizens is greater than the foreign-born population: for Czechia this is due to the sizeable Slovak population, and for the Baltic states to the presence of ethnic Russian minority who do not hold the citizenship of their countries of residence. Other than that, the share of foreign citizens is typically smaller than foreign-born, as migrants often naturalise in their host countries.

The different net migration figures help isolate anomalies within each of the four country groups, based on the UN classification[7]. For the Northern countries, Ireland has on average a significantly lower net migration than the others. This is due to large net emigration in 2009–15 following the financial crisis. Denmark and Finland have a significantly lower rate than either Norway and Sweden, and less so the UK. Even though Denmark and Finland have high wage premiums relative to the EU-15, they are not as attractive destination for migrants as macroeconomic indicators would suggest.

For the Western countries, Luxembourg stands out across all measures, due to its unique position within the EU and small size. Germany's net migration indicators are lower than could be expected for the largest EU economy, but still strongly positive. A similar observation holds for France: both countries have high numbers of migrants but relatively lower net migration 'rates'.

There is great variation in the Southern European countries. Greece, Portugal and Spain all experience negative net migration averages within the EU+, while Italy's is barely positive. Since the financial crisis, Greece's migration has struggled to recover, and remains largely negative. Portugal's total net migration 'rates' are small yet positive. Italy and Spain have significantly positive averages, but the reliance on non-EU+ migration is evident. Germany, France and the UK, the three countries with the largest populations in the EU+, all have positive averages net migration indicators, both within Europe and overall, but the differences between them are not so stark.

The former socialist countries of Eastern Europe (technically, Central and Eastern) exhibit a variety of migration patterns. The 2002–19 averages do not necessarily reflect the transition towards positive net migration, happening at a different pace across the region. Three groups of countries can be distinguished. The first one is characterised by negative net migration throughout the sample and are likely to experience for the considerable future. These include Bulgaria, Hungary, Latvia, Lithuania, and Romania. Hungary's net negative migration average is low, but this is driven by low levels of overall flows in both directions. The second group comprises Estonia, and Poland: for these countries, while the 2002–19 averages were negative, there were clear upward trend of net migration. Poland is a special case here, with around a million people moving to

[7] UN Standard M49, https://unstats.un.org/unsd/methodology/m49/, as of 1 October 2024.

the country since the Russian invasion of Ukraine in 2022, according to Eurostat data[8]. The third group includes Czechia, Slovakia and Slovenia. They all experience positive net migration overall, and negative for EU+ but with upwards trends (Slovakia being a borderline case).

Table 3: Migration Statistics for Selected European Countries

| Country | NM Rate WA All | NM Rate All All | NM Rate WA EU+ | NM Rate All EU+ | For. Born Pop % | Foreign Citizenship % |
|---|---|---|---|---|---|---|
| *Northern European Countries* | | | | | | |
| **DNK** | 2.50 | 3.10 | 1.24 | 1.41 | 13.6 | 10.5 |
| **FIN** | 3.14 | 3.99 | 0.75 | 0.98 | 8.3 | 5.8 |
| **IRL** | 0.68 | 1.09 | 3.00 | 3.52 | 21.8 | 14.4 |
| **NOR** | 8.21 | 9.83 | 4.17 | 4.65 | 17.6 | 11.1 |
| **SWE** | 8.17 | 10.36 | 1.92 | 2.25 | 20.4 | 8.1 |
| **UK** | 5.64 | 6.35 | 2.22 | 2.45 | 14.2 | 9.3 |
| *Western European Countries* | | | | | | |
| **AUT** | 6.72 | 7.98 | 4.37 | 5.00 | 21.6 | 18.8 |
| **BEL** | 3.94 | 5.13 | 2.09 | 2.64 | 19.1 | 13.5 |
| **CHE** | 5.66 | 6.55 | 5.52 | 6.23 | 30.2 | 26.0 |
| **DEU** | 2.74 | 3.32 | 1.35 | 1.55 | 19.5 | 14.6 |
| **FRA** | 2.76 | 3.66 | 0.55 | 0.72 | 13.1 | 8.2 |
| **LUX** | 11.59 | 12.68 | 10.32 | 11.14 | 50.4 | 47.4 |
| *Southern European Countries* | | | | | | |
| **ESP** | 3.21 | 4.10 | -0.25 | -0.29 | 17.1 | 12.7 |
| **GRC** | 0.38 | 0.64 | -1.07 | -1.27 | 11.3 | 7.3 |
| **ITA** | 4.22 | 4.99 | 0.07 | 0.01 | 10.9 | 8.7 |
| **PRT** | 0.33 | 0.43 | -1.72 | -2.07 | 16.1 | 7.0 |
| *Eastern European Countries* | | | | | | |
| **BGR** | -7.08 | -7.83 | -8.24 | -9.20 | 2.6 | 1.3 |
| **CZE** | 0.01 | -0.13 | -0.37 | -0.67 | 7.1 | 7.9 |
| **EST** | -3.07 | -3.61 | -4.11 | -4.84 | 17.2 | 17.3 |
| **HUN** | -1.80 | -1.98 | -2.31 | -2.62 | 6.7 | 2.4 |
| **LTU** | -11.86 | -13.79 | -11.08 | -12.85 | 8.1 | 3.4 |
| **LVA** | -4.31 | -5.04 | -4.70 | -5.44 | 12.8 | 13.9 |
| **POL** | -3.44 | -3.73 | -3.34 | -3.67 | 2.5 | 1.2 |
| **ROU** | -6.84 | -7.89 | -7.38 | -8.46 | 2.8 | 1.1 |
| **SVK** | -0.33 | 0.64 | -0.94 | -0.13 | 3.9 | 1.1 |
| **SVN** | 4.29 | 5.29 | -1.33 | -1.53 | 14.6 | 9.0 |

The average net migration 'rates' (net migration per 1000 people) for 2002:2019. The net migration values are all ages (All) or working age (WA), with the partner region all countries (All) or EU+. The first line in the title identifies age, and the second one, location. Sources: IMEM database, QuantMig Estimates OECD, and national statistical institutes. Foreign-born population and foreign citizenship are values for 2023 (except the UK which is 2019). Authors' calculations using Eurostat tables tps00001 (total population), tps00157 (foreign-born population), and tps00158 (population without the citizenship of the reporting country).

## 2.3 An ageing work force

In Section 2.2, we presented statistics on the ageing population, whereas in this section we focus on the retirees in the workforce. In a previous study (Barker and Bijak, 2024*a*),

[8]See e.g. monthly statistics on temporary protection for persons fleeing Ukraine, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Temporary_protection_for_persons_fleeing_Ukraine_-_monthly_statistics, as of 1 October 2024.

we discussed some of the existing policies used by governments to reactivate the people aged 65-74 into the work force. One unsurprising finding was that neither migration nor job automation on there own were able to address the challenges of ageing fully, and it was important to increase economic activity in all age groups.

Data provided by Eurostat does not produce an estimate of the unemployment rate for the age group 65–74, however, we provide an estimate using the best available information. For brevity, we report only the total for the countries in this section. Table 4 shows the breakdown for the 15–74 year olds, or the potential work force, by age and education level with the final column giving the percentage of 15–64 year olds in the total population.

Table 4: Population shares of 15-74 year olds by (ISCED) education levels

| **Country** | **Total** | | **ISCED 0-2** | | **ISCED 3-4** | | **ISCED 5-8** | | |
|---|---|---|---|---|---|---|---|---|---|
| | 15-64 | 65-74 | 15-64 | 65-74 | 15-64 | 65-74 | 15-64 | 65-74 | |
| **EU27** | 85.1 | 14.9 | 21.3 | 5.6 | 38.5 | 6.3 | 25.3 | 3.0 | 63.9 |
| *Northern European Countries* | | | | | | | | | |
| **DNK** | 85.2 | 14.8 | 21.6 | 4.4 | 33.9 | 6.4 | 29.7 | 4.0 | 63.5 |
| **FIN** | 82.8 | 17.2 | 15.1 | 5.2 | 38.3 | 6.9 | 29.4 | 5.1 | 61.6 |
| **IRL** | 88.5 | 11.5 | 15.6 | 4.7 | 32.8 | 3.7 | 40.1 | 3.1 | 65.4 |
| **NOR** | 86.6 | 13.4 | 21.4 | 2.4 | 30.1 | 6.6 | 35.2 | 4.4 | 64.9 |
| **SWE** | 85.6 | 14.4 | 17.2 | 3.6 | 34.4 | 5.9 | 34.0 | 4.9 | 62.1 |
| *Western European Countries* | | | | | | | | | |
| **AUT** | 87.0 | 13.0 | 16.1 | 3.4 | 43.3 | 6.9 | 27.7 | 2.7 | 66.2 |
| **BEL** | 86.1 | 13.9 | 19.5 | 5.4 | 32.4 | 4.8 | 34.2 | 3.7 | 63.8 |
| **CHE** | 87.1 | 12.9 | 15.2 | 2.4 | 37.8 | 6.8 | 34.2 | 3.7 | 65.9 |
| **DEU** | 85.3 | 14.7 | 18.8 | 2.7 | 42.6 | 7.9 | 23.9 | 4.0 | 63.9 |
| **FRA** | 84.4 | 15.6 | 18.6 | 5.9 | 35.2 | 6.2 | 30.6 | 3.5 | 61.6 |
| **LUX** | 90.0 | 10.0 | 22.6 | 3.4 | 27.4 | 3.9 | 40.1 | 2.7 | 69.3 |
| *Southern European Countries* | | | | | | | | | |
| **ESP** | 86.7 | 13.3 | 32.8 | 8.6 | 22.2 | 1.9 | 31.6 | 2.8 | 66.2 |
| **GRC** | 84.9 | 15.1 | 20.0 | 8.2 | 39.4 | 3.9 | 25.5 | 2.9 | 63.6 |
| **ITA** | 84.5 | 15.5 | 33.2 | 9.8 | 36.3 | 4.1 | 15.1 | 1.6 | 63.5 |
| **PRT** | 84.7 | 15.3 | 34.2 | 11.9 | 26.6 | 1.4 | 24.0 | 2.0 | 63.3 |
| *Eastern European Countries* | | | | | | | | | |
| **BGR** | 83.4 | 16.6 | 17.4 | 4.2 | 44.4 | 9.1 | 21.6 | 3.3 | 62.4 |
| **CZE** | 84.1 | 15.9 | 10.1 | 2.1 | 54.3 | 11.7 | 19.7 | 2.2 | 63.3 |
| **EST** | 85.3 | 14.7 | 14.2 | 2.4 | 40.4 | 7.1 | 30.7 | 5.2 | 63.2 |
| **HUN** | 84.3 | 15.7 | 16.2 | 3.3 | 46.7 | 9.2 | 21.4 | 3.2 | 65.1 |
| **LTU** | 86.3 | 13.7 | 9.4 | 0.9 | 42.6 | 8.7 | 34.3 | 4.1 | 65.1 |
| **LVA** | 85.2 | 14.8 | 12.1 | 1.6 | 43.9 | 9.4 | 29.1 | 3.9 | 63.1 |
| **POL** | 83.6 | 16.4 | 10.9 | 2.9 | 48.4 | 10.9 | 24.3 | 2.5 | 65.1 |
| **ROU** | 85.1 | 14.9 | 18.3 | 5.9 | 52.8 | 8.0 | 13.9 | 1.1 | 64.3 |
| **SVK** | 86.3 | 13.7 | 11.4 | 2.1 | 53.6 | 9.4 | 21.4 | 2.2 | 66.6 |
| **SVN** | 84.8 | 15.2 | 11.2 | 3.6 | 43.6 | 8.4 | 30.0 | 3.3 | 63.8 |

The share of population by education level and age group. ISCED levels include 0–2: primary education, 3–4: secondary, and 5–8 tertiary. The final column gives the total percentage of 15-64 year olds in the total population. Source: Eurostat Table lfsa_pganedm and demo_pjanbroad and authors' own calculations

Table 5 presents the labour force participation (or activity) rates and estimated (only approximately) unemployment rates for the 65–74 age group. As unemployment rates for the 65–74 age groups are notoriously difficult to calculate, we focus our analysis on the participation rates. In isolation, both economic activity and unemployment rates for this age group seem low: as is expected, they are significantly lower than for younger ages. This is especially true for people with lower levels of education (ISCED 0-2), with a clear educational gradient for both age groups.

The participation rates also vary between the EU+ countries. In the 65–74 group, the highest participation rate can be seen for Iceland (32.7%) with Romania the lowest (3.4%). Across the countries under study, the 'Northern' countries average the highest, both across education levels, and in total. The other three regions vary, with Western European rates tending to be the lowest, and Southern and Eastern being in the middle. From a labour market point of view, with economies short on workers, reactivating people in the 65–74 age group, or dissuading the soon to be retirees from exiting the labour market at 65, appears to be a prime opportunity to increase the workforce without depending on immigration. Further options to increase the overall participation rate remain beyond the scope of this paper.

## 2.4 Robot adoption

Figure 2 and Table 2 show the recent (2016 and 2021) numbers of robots per 10,000 workers in selected EU countries, plus the United Kingdom, which show a great variation. Stereotypically, it can be thought that there should be more robots in more advanced economies due to the high cost of automation. However, this is not necessarily the case. Major industries vary across the EU+: for example, Norway has a significant source of GDP from gas and oil, but some European countries have hardly any mining or equivalent industries. The notable variance of robot density especially in the CEE countries can be attributed to differences in the industrial structure and the presence of large firms, and in particular, automotive and electronics.

There are some stark contrasts between the countries in terms of the robot adoption. Despite the advances in robotics in the last 10–15 years, Southern European economies have been held back following the financial crisis, with the predictable lack of investment in robotics compared to Northern Europe. The main exception here is Italy, with a car industry and a large presence of the packaging industry.[9]

[9]Source: HowToRobot First Accessed 22 April 2024.

Table 5: Ages 65-74 Participation Rates Selected European Countries

| **Country** | **Partic Rates** | | | |
|---|---|---|---|---|
| | **Total** | **ISCED** | **ISCED** | **ISCED** |
| | **Total** | **0-2** | **3-4** | **5-8** |
| *Northern European Countries* | | | | |
| **DNK** | 17.9 | 15.2 | 16.8 | 21.6 |
| **FIN** | 13.9 | 9.9 | 13.2 | 17.7 |
| **IRL** | 20.1 | 15.7 | 21.7 | 25.5 |
| **NOR** | 22.0 | 15.6 | 19.4 | 30.0 |
| **SWE** | 20.0 | 15.9 | 18.3 | 25.5 |
| *Western European Countries* | | | | |
| **AUT** | 8.7 | 5.4 | 7.3 | 15.5 |
| **BEL** | 5.6 | 2.7 | 4.2 | 10.1 |
| **CHE** | 16.7 | 8.5 | 15.1 | 25.5 |
| **DEU** | 14.2 | 10.8 | 12.3 | 20.3 |
| **FRA** | 6.6 | 4.9 | 5.6 | 11.3 |
| **LUX** | 5.6 | 2.1 | 4.7 | 9.9 |
| *Southern European Countries* | | | | |
| **ESP** | 6.4 | 4.2 | 8.5 | 11.7 |
| **GRC** | 9.5 | 8.3 | 8.1 | 14.5 |
| **ITA** | 9.4 | 6.0 | 11.5 | 23.2 |
| **PRT** | 14.8 | 11.5 | 21.4 | 30.6 |
| *Eastern European Countries* | | | | |
| **BGR** | 11.2 | 5.0 | 10.6 | 19.4 |
| **CZE** | 10.4 | 3.9 | 8.5 | 27.0 |
| **EST** | 28.2 | 14.5 | 24.7 | 39.2 |
| **HUN** | 9.4 | 3.8 | 8.4 | 19.1 |
| **LTU** | 20.5 | 2.8 | 16.7 | 30.4 |
| **LVA** | 22.9 | 8.6 | 21.3 | 30.3 |
| **POL** | 9.1 | 3.2 | 8.0 | 19.7 |
| **ROU** | 3.4 | 3.4 | 2.8 | 7.4 |
| **SVK** | 7.3 | 5.4 | 6.2 | 13.7 |
| **SVN** | 6.9 | 3.2 | 5.1 | 19.5 |

Participation rates for people aged 65-74 in selected European case studies in 2022. These figures are approximations from authors' calculations. Figures are available for 15-64 and 15-74. The Eurostat tables used have options for sex, age, migration status, citizenship and educational attainment level. ISCED Education levels for 0-2 are 'Less than primary, primary and lower secondary education'. Levels 3-4 are 'upper secondary and post-secondary non-tertiary education'. Levels 5-8 are 'tertiary education'. For later in this model we apply migration status (foreign born vs native-born and citizenship (total). The specific tables are Employment (lfsa_egaisedm), Employment Rates (lfsa_erganedm), Unemployment (lfsa_urganedm), and Population (lfsa_pganedm).

As for Eastern Europe, Czechia, Slovakia, and Slovenia are outliers, *especially* Slovenia. At 249 robots per 10,000 workers in 2021, this ranks them third in the reporting European countries[10] behind only Germany and Sweden. Slovenia's adoption of the Euro in 2007 has been macroeconomically beneficial as it has allowed using a relatively stable currency, and easier trading with other Eurozone members, providing more stability for importers and exporters. Progress is not only seen in robots, but the wage premium and wages and salaries which puts these countries on a par or ahead with the Southern European economies. Czechia and Slovakia both have rates which reflect the advancements

[10]The Netherlands, which due to its migratory data is not included in this analysis, has 224, placing it sixth on this list.

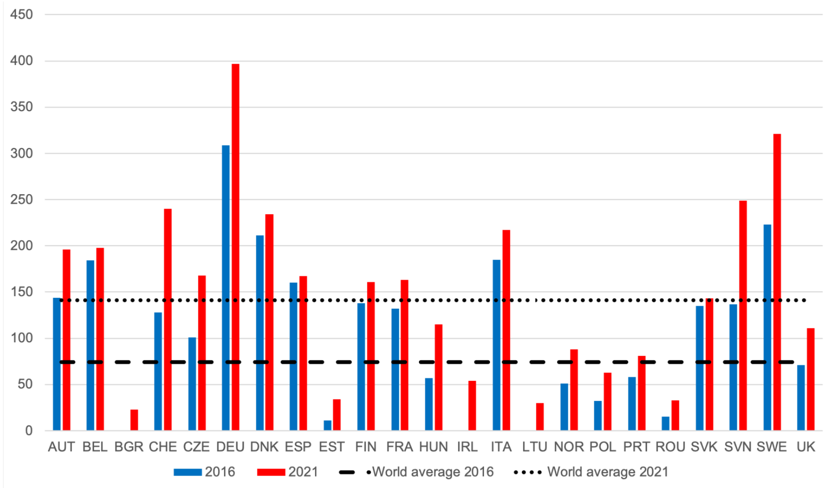



Figure 2: Robots per 10,000 workers in selected EU countries and the UK, 2016 and 2021

The blue bars give the values for 2016 (where available), with the red bars the values for 2021. The dashed and dotted horizontal lines are the global averages for these respective years. Source: International Federation of Robotics (IFR). Barker and Bijak (2024*a*)

in their manufacturing industry.[11] The only other Eastern European countries to exceed 50 robots per 10,000 workers are Hungary (115) and Poland (63). The corresponding indicators for Bulgaria, Estonia, Lithuania and Romania are tiny.

## 2.5 Country selection

In Section 2, we have so far set out the background to the situation on the labour markets and robot adoption status across Europe. To make a comparison between groups of countries within the four broad European regions (Northern, Eastern, Southern and Western), here we present a selection of 'typical' countries as case studies. The selection is based (predominantly) on macroeconomic profiles, with the aim of identifying countries that exhibit relatively low macroeconomic volatility for the respective regions, are representative for the regions, and give some meaningful analysis through contrast to other selected countries.

### 2.5.1 Northern Europe

In this group, we include the Nordic countries, the UK, and Ireland. Within this group, there is a large disparity in terms of the socio-economic and labour market conditions.

[11] A lot of this can be attributed to the car industry, as Czechia and Slovakia rank second and first in car production per 1000 people. Source: Helgi Library.

In terms of selecting the case study country, we exclude the UK, as it is no longer part of the EU, which makes data evaluation trickier as many data not reported to Eurostat. Ireland has had a rather volatile migratory profile. This leaves the selection to the Nordic Europe: Denmark, Finland, Iceland, Norway, and Sweden. Iceland has a small population and data availability issues, whilst Norway's economy is largely oil-driven which makes it not easily comparable with other economic models[12] Of the three remaining countries, Sweden has the largest population, and an economy that does not risk the distortions of the pharmaceutical industry that Denmark potentially faces[13] or Finland's historic link with Nokia[14]. At the same time, Sweden is a relative leader in the robot adoption in Europe. For that reason, we select **Sweden** as the case study country to represent Northern Europe.

### 2.5.2 Western Europe

The group of Western EU+ countries include Austria, Belgium, France, Germany, Luxembourg, Liechtenstein, the Netherlands, and Switzerland. Luxembourg and Liechtenstein have populations that are too small to allow a meaningful analysis (661,000 and 40,000 people, respectively[15] respectively). Likewise, Austria, Belgium, the Netherlands and Switzerland have significantly smaller populations than either France or Germany. Between both these countries, we have the two largest economies in the EU+. As discussed in Section 2.4, Germany has the highest rate of robot adoption in Europe, experiences noted challenges with advanced ageing, and attempts to attract more migrants, particularly at the high end of the skills spectrum. For these reasons, we adopt **Germany** as

[12]Norway's oil industry is not privatised like the UK's or other countries, but all the profits go towards the Government Pension Fund which is meant to allow multiple generations to benefit from the oil wealth. Besides, oil prices can be highly volatile which makes Norway's GDP subject to fluctuation as well. Norwegian GDP is often reported by excluding oil revenues from offshore activities, as stated by Statistics Norway. As an example of how the oil revenues can change, in 2019 oil accounted for 14% of GDP, while in 2022 this was 35%. Source: Norwegian Ministry of Energy and Statistics Norway, *Macroeconomic indicators for the petroleum sector, 1971-2024*. Accessed 22 April 2024.

[13]The so-called Denmark's pharmaceutical problem: a leading company in this sector, Novo Nordisk, in 2024 had a higher market capitalisation than the annual GDP of Denmark. As of 19 April 2024, the market capitalisation of Novo Nordisk is 419.90 billion USD (source: Google Finance), while Denmark's GDP for 2023 was 405.2 billion USD (source: IMF Data Mapper. Such a great disparity, and potential overreliance on Novo Nordisk would provide a risky future should the status of Novo Nordisk collapse.

[14]Nokia, once one of the largest mobile phone producers, saw a vast drop in their revenue and market share with the launch of new generation of smartphones such as Apple's iPhone (Ali-Yrkkö et al., 2010).

[15]Source: Eurostat table *demo_gind*.

the case study country to represent Western Europe.

### 2.5.3 Southern Europe

In our taxonomy, Southern Europe encompasses the EU+ of the Iberian peninsula and the Mediterranean basin, including some of the most highly-indebted European economies, such as Greece, Italy, Portugal and Spain, plus Cyprus and Malta. Cyprus and Malta are relatively small and have data availability issues, so we exclude them from potential selection as case studies. Greece can be excluded based on its slow economic recovery from the global financial crisis of 2008–11, and its atypical migration pattern, with negative net migration overall. Italy is the third biggest economy in the Eurozone and the EU. Even though the country struggled a lot of during the financial crisis, net migration remained high. On these grounds, we proceed with the choice of **Italy** as a case study to represent Southern Europe.

### 2.5.4 Eastern Europe

Finally, for the Eastern Europe category, we consider current EU members *only*, including the A8 countries: Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia; A2 countries: Bulgaria and Romania; and Croatia. Within this group there are stark contrasts: Bulgaria and Romania are the two countries with the lowest GDP per capita, as well as wages and salaries in the EU (Table 1). They both have economies that heavily feature agriculture compared to other EU nations. At the other end of the scale, Slovenia, in 2019, had a EU15 wage premium of 0.65, which made it comparable with Italy, and exceeded the values for Greece and Portugal. The economic development of some A8 countries can be noted in Table 1. At the same time, especially Czechia, Slovakia and Slovenia have relatively high numbers of robots per 10,000 workers (Figure 2), reflecting the pace of their economic transition undergone since the 1990s. At the same time, Poland is the largest of these countries in terms of the population and economy, which even though in and of itself is not a driver of the selection, it adds parts to the analysis which make it more apparent. In addition, Poland is also lagging behind in terms of the number of robots per 10,000 workers, which on its own makes for an interesting case study. In this version of the paper, we propose to have net immigration shocks. This makes Poland, traditionally a net sender of migrants, a prime candidate, especially in wake of the Russian invasion of Ukraine, leading many Ukrainians to move to Poland. Hence, we proceed with the choice of **Poland** to represent Eastern Europe.

In summary, to represent Northern, Western, Southern and Eastern European countries, we select Sweden, Germany, Italy and Poland, respectively. The number of robots per capita, relative to the status of GDP per capita are similarly ranked, with Sweden being 'richer' than Germany, but Germany more advanced in terms of robotics.

# 3 Analysis: DSGE models, simulation results and policy scenarios

The dynamic stochastic general equilibrium (DSGE) model put forth in this section is based on the model in Barker and Bijak (2024*a*). The major change is that we now model one country at a time, and net migration is entirely exogenous. We apply the model to the countries selected in Section 2.5. In the first part of this section, we present a revised version of the model, followed by some notes on the calibration with data based on (and extending) the tables summarised in Section 2.

## 3.1 DSGE Model: Outline specification

Our model represents a small open economy that includes households, firms, and a fiscal authority. The households can be high- or low-skill. Households are first identified as *native* or *migrant*. *High*-skilled households are of ISCED levels 5–8, and are inter-temporal optimisers for consumption and employment, while *low*-skill households are of ISCED levels 0–4, with hand-to-mouth consumption, and are optimising their labour market status preference inter-temporally. The final identifier is whether the household members are of working-age (15–64) or early retirees (65–74). Thus, there are eight (2x2x2) households in this model.

In the modelled economies, the production of the final good uses both high- and low-skilled inputs. The high-skill input is the traditional form of physical capital, coupled with high-skill labour. The low-skill input is perfectly substitutable with the automation capital (robots) and low-skill labour as per Leduc and Liu (2020). Natives and migrants are modelled as perfect substitutes. A brief model description follows.

**Households** The households make choices based on individual preferences. We calibrate the values for each household, based on the existing labour market status, and share within the total population. Each household makes their own choices on labour market participation, hours worked, and consumption levels of the final good. For simplicity, we break the analysis down into the high and low-skilled households. Figure 3 shows the breakdown of the households in this model.

Natives and migrants, high-skill or low-skill, working-age or early retirees make their

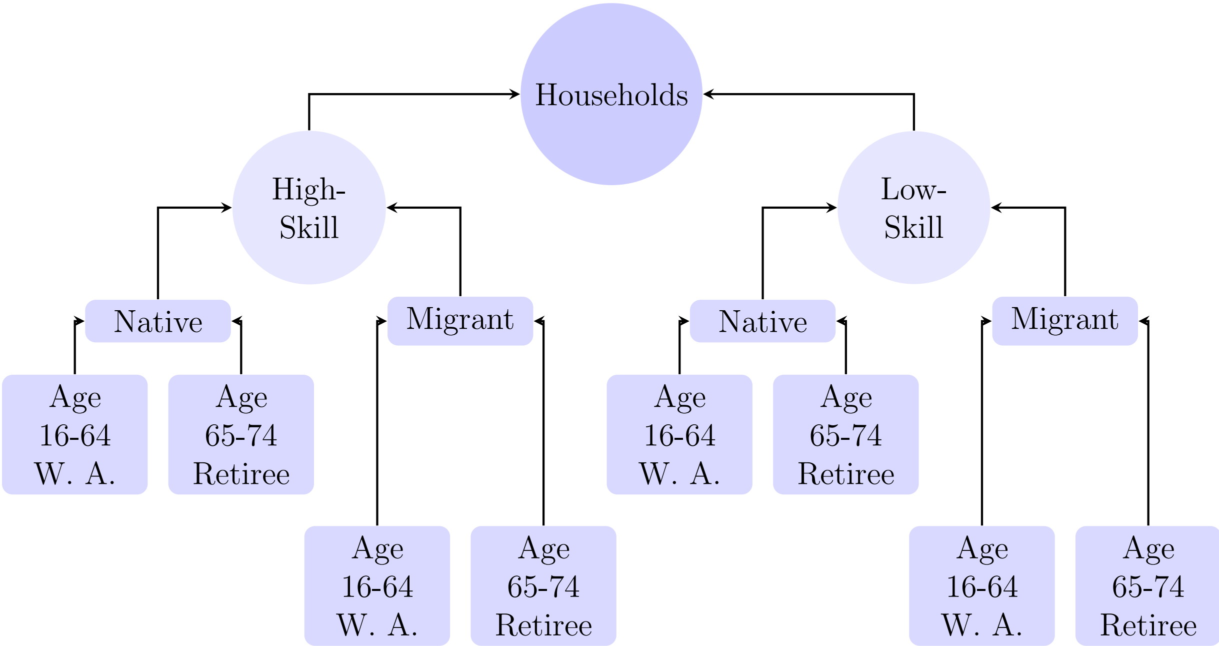



Figure 3: Household composition in DSGE model

The flow chart shows the sub-division of households within the DSGE model presented. Households are either high or low-skill. They are native or migrant (identified in the data as native born or foreign born, irrespective of citizenship. The final classification is the age group: aged 15-64 which is people of working-age (W.A.), or those at 65-74 who are of state retirement age that are would-be retirees.

choices but with marginally differing preferences due to weights based on existing labour market status, labour income, or existing consumption levels. For example, a native worker is likely to have more bargaining power over wages than a migrant using the Nash bargaining method for wages. As a result, they will place a different value on being active in the work force. While the productivity of native vs migrant counterparts is assumed to be the same, the native worker will have more bargaining power when it comes to wages resulting in the native premium. Would-be retirees have greater preferences to leave the labour market and become inactive. In Figure 4, we examine the decisions that the households make. There are two types of decisions: one involves optional expenditures, and the other is labour market status. The households decide on how much to consume, and the high-skill households are able to switch consumption to bond purchases that will be redeemed in the next period. Low-skilled households use their disposable income on consumption in that period. Taxes are compulsory, however, they influence how much of the final good that the household can consume.

The labour market uses search and matching frictions as per Merz (1995), with the extension of inactivity as used in Dolado et al. (2021). Households make decisions with regard to their labour status. All individuals have the choice to be active in the labour market as either employed or unemployed. The outside option is for individuals to be inactive. The employed people can only be employed or unemployed in the next period, while unemployed people can remain unemployed if they cannot find a job for the next period. If the unemployed people find a job, they become employed, and if they decide to exit the labour market they become inactive. For the inactive people, they can choose to remain inactive in the next period or become categorised as unemployed to search for work. Inactive people in the age group 65-74 age group can be considered retired, although this decision can be reversed at any time.

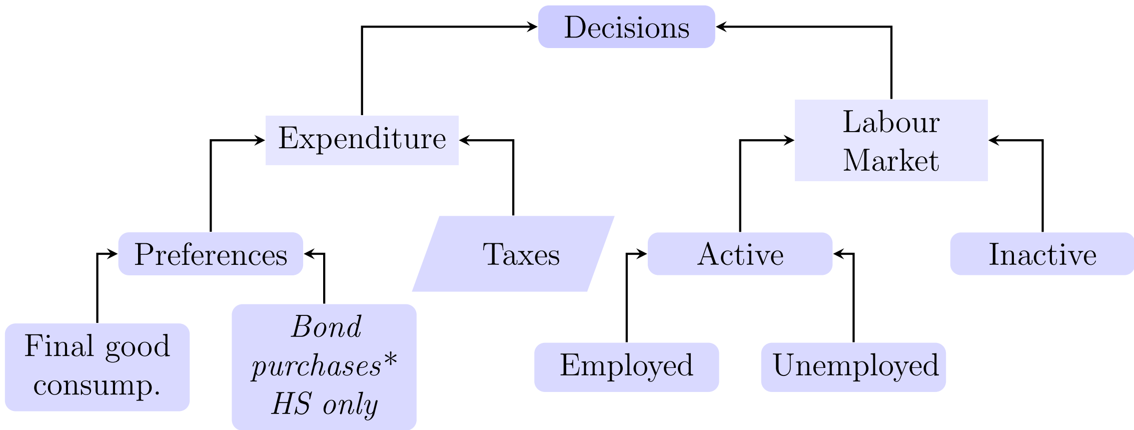



Figure 4: Household choices and sources of income and expenditure

The flow chart shows the choices made by households. Taxes are not a choice but lump-sum. Employment yields labour income, while unemployment (for working-age households) receives unemployment benefit. Only retirees receive a pension income for out of the labour market. Inactive working-age people receive no income. Bond purchases are for the high-skilled households only.

The high-skilled,native, working-age household owns the firms and make decisions over future investment plans. The other high-skilled households receive dividends from any profits but do not make operating decisions. The low-skilled households have no firm ownership so receive no dividends.

There exists a steady state, which evolves through calibrated variables such as the labour market status, and various macroeconomic substitutability factors. The substitutability can be easiest demonstrated in the production function, whereby there are differing preferences over the high-skill versus low-skill labour, and high-skill labour versus capital.

**Firms** There are perfectly competitive firms which share common features, where $i$ denotes the country specific values. Figure 5 summarises the inputs required for the final producing good. Firms employ a high-skill 'bundle' ($H_t^i$) comprised of the physical capital ($K_t^i$), which is complementary to high-skilled labour ($N_t^{H^i}$). The low-skilled 'bundle' ($L_t^i$) combines robots and low-skilled labour ($N_t^{L^i}$). The firms are subject to a series of shocks (exogenous increases) in: total factor productivity (TFP), $\psi_t^{a^i}$, labour productivity, automation productivity, and investment, $\psi_t^{x^i}$. The complementarity of the high-skill and low-skill inputs is given by $\Phi^i$, which is a function of the elasticity of substitution $\sigma_{H,L} = \alpha^i/(\alpha^i - 1)$. The final output production follows a capital-skill complementarity form, and is given by:

$$y_t^i = \psi_t^{a^i} p_{i_t}^i \left( e \left(H_t^i\right)^{\alpha^i} + (1-e) \left(L_t^i\right)^{\alpha^i} \right)^{\frac{1}{\alpha^i}} . \tag{1}$$

with $p_{i_t}^i$ denoting the relative price, and $\alpha^i$ identifies the complementarity between the high and low-skill inputs. The complementarity of capital and high-skill labour is given by $\Phi^i$, which is a function of the elasticity of substitution $\sigma_{K,N^{iH}} = \Phi^i/(\Phi^i - 1)$. The respective high-skill services and low-skill services are defined as follows:

$$H_t^i = \left[ \nu^i (K_{t-1}^i)^{\Phi^i} + (1-\nu^i)(N_t^{i^H} h_t^{i^H} \psi_{N_t}^{i^H})^{\Phi^i} \right]^{\frac{1}{\Phi^i}} \tag{2}$$

$$L_t^i = \left[ N_t^{L^i} h_t^{L^i} \psi_{N_t}^{L^i} + A_t^i \psi_t^{A^i} \right] \tag{3}$$

This model uses the automation dynamics put forth by Leduc and Liu (2019). Low-skill workers and robots (automated jobs) are perfect substitutes, so the firm must decide whether to post a vacancy (with the view to hiring a low-skill worker) or purchase a robot. As this is an applied policy paper, we have decided to limit the explanation to the main model features.

Figure 6 describes the decision process. The decision rests upon a threshold value $x_t^*$ relative to the fixed cost. If this threshold level is exceeded, the firm decides to invest in a robot and removes a vacancy. If the threshold value is below the fixed cost, the firm posts a vacancy. The threshold cost is entirely endogenous and is based on status of robots versus that of the labour market. If there is a low chance of filling a vacancy, the firm is more likely to choose a robot, but if there is a high chance of filling a vacancy

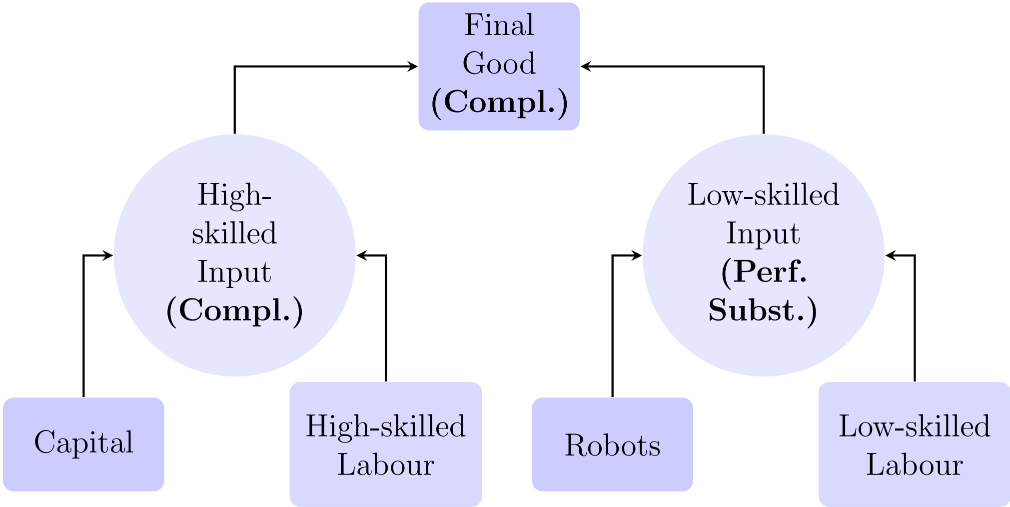



Figure 5: Overview of the Production Setup

The inputs to the final good production for the firms. In Germany, labour includes immigrants from Poland but in Poland, there the labour market is local. Natives and migrants are imperfect substitutes.

then the firm is more likely to proceed with employing workers.

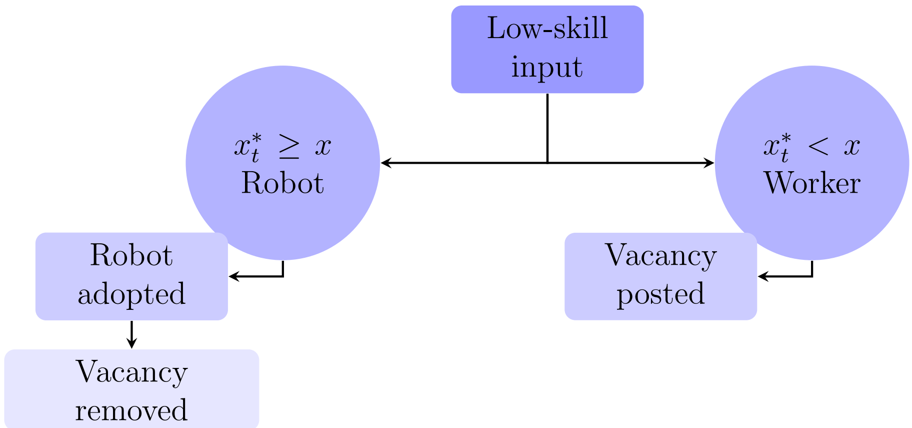



Figure 6: Overview of the Automation Decision

A robot is adopted when the threshold value of automation, $x_t^*$, equals or exceeds the fixed cost $x$. The threshold is the value of automation relative to value of a vacancy. Based on the automation dynamics in Leduc and Liu (2019).

A notable aspect of the assumptions is the increase in productivity that migrants can have. They can either bring new skills, or have a higher productivity level, (Huber et al., 2010; Kangasniemi et al., 2012) or be underemployed (brain waste) (Batalova et al., 2016; Barker, 2020) given their more vulnerable employment status.[16] The standard marginal product theory would posit, *ceteris paribus*, a decrease in marginal product given the

[16]Research has shown that migrants have more vulnerable employment status, and when redundancies are made they are likely be the first to be made redundant over natives (Dustmann et al., 2010).

increased employment levels or the same output produced by more workers. The changes in productivity can be on a larger or smaller scale, as many firms cannot follow the same production function. This topic is discussed in Australian Productivity Commission (2006) or Hierlaender et al. (2010). As an example, Kangasniemi et al. (2012) used a growth accounting analysis on a sectoral level showing a negative effect on Spain's labour productivity growth, while there is a negligible contribution for the UK's economy. This can be attributed to the fact that the UK has more highly skilled migrants than Spain receives. Nam and Portes (2023) focused on total productivity to the UK, given its positive non-EU net migration and a negative net migration within the EU. To account for this feature, we allow for a specific shock to labour productivity simultaneous to a migration shock.

**Fiscal policy** The government modelled in this paper is mostly exogenous. The expenditure decisions on government consumption are counter-cyclically related to the economy. As a proviso, we introduce government investment to focus solely on automation technologies rather than traditional physical capital. The role of this is to assess the implications that fiscal investment in robot technology can result in (Thuemmel, 2018). The steady state of this expenditure is set to zero. Unemployment insurance and pensions systems are not modelled here, they are simply given values based on replacement rates. There is no monetary policy as this is a real business cycle model. Two of the countries (Germany and Italy) are part of the European monetary union so do not have full control over interest rates, while Poland and Sweden are modelled as small open economies.

**Exogenous processes** Each model shock, or exogenous process, takes the same form.

$$X_t = \rho_X X_{t-1} + (1-\rho_X)\overline{X} + \varepsilon_t^X \qquad \varepsilon_t^X \sim \mathcal{N}(0, \sigma_X^2), \tag{4}$$

where $\rho_X \in (0,1)$ is the autoregressive parameter, $\overline{X}$ is the steady state value, and $\varepsilon_t^x$ is an i.i.d. shock with zero mean and a constant variance $\sigma_X^2$.

## 3.2 Notes on model calibration

The DSGE model put forth in this paper is a small open economy. The steady state is calculated in MATLAB, with the DSGE model specifically employing dynare (Adjemian et al., 2024). Due to the nature of this paper, we focus this section on the model calibration (aligning it with the available empirical data) directly related to the policy aims of this study. The model is individually calibrated to four case study countries with Bayesian estimation of model parameters, including those used for modelling exogenous model shocks.

The two aspects we are most interested in involve the labour market and robots, with the relevant data introduced in Section 2. The horizon for this model is a medium-run horizon of five years (20 quarters), as such, we do not change the relative household size related to the old-age dependency ratios.

To make the models more manageable, and focus on high- and low- skill jobs and workers, we combine ISCED levels 0–2 and 3–4 into a single group. Irrespective of migration status, this now makes the 'low-skill' group account for more than 50% of the population. Education level is not a perfect indicator of skill level for employment, particularly since there are always forms of underemployment. There is, however, no reliable measure that would allow us to classify and make approximations for skill-level employment to that level of detail. Table 6 shows the population shares, participation rate and unemployment rate for high- and low-skill populations, native and migrants, by age category, for the four countries under study. The table emphasises the distinctions made from the statistics presented in Section 2 regarding foreign-born status, education/skill level, and age. Sweden (39.1%) and Germany (28.8%) have a greater high-skill share than Poland (27.6%) and Italy (16.8%).

While discussing the skill-level may seem arbitrary, it has great relevance for policy. Robots and automative technologies are conventionally associated with low-skill occupations. This will have a greater impact on the labour market. The 2021 numbers of robots per 10,000 workers are: 321 in Sweden, 397 in Germany, 217 in Italy, and only 63 in Poland (see Figure 2). The substitutability of robots and workers can be contested, with some believing them to be perfect substitutes (as in this paper), while others suggest imperfect substitutes. For jobs with high-skill automation technologies are considered complementary. As listed in Table 6, migrants make up 23.7% of the Swedish population aged 15-74, of which 40.0% are high-skilled. The corresponding figures for Germany are 21.3%, of whom 24.9% are high-skilled. For Italy, there are 12.53% migrants in the 15-74 age category, of which 12.45% high-skilled, and for Poland, 0.74% of the population aged 15-74 are migrants, with half of them high-skilled.

The high and low-skill inputs exhibit different elasticities of substitution with automation capital (robots) - the elasticities are approximated to target the wage skill premium and international premium. For the countries with more advanced existing robots per 10,000, there is greater probability of robot adoption because the relative costs are lower. Consequently, there is a lower elasticity of substitution.

The data series are taken from the national accounts, converted to *per capita* real terms, and log-transformed. We use GDP for the total factor productivity (TFP), private consumption for consumption preferences, productivity of intellectual property assets for robot productivity, the investment for intellectual property is for robot investment, government consumption, GDP of the USA for foreign TFP, while migration is taken from IMEM/QuantMig estimates[17]. These variables are reported to Eurostat as part of the national accounts collection, which allows for making international comparisons.

We estimate the parameters for the main shocks to the DSGE model by using the data discussed above. Table 7 shows the priors used for all countries, and the posterior means for individual countries. Many posterior means do not differ significantly from the prior ones, which suggests that the data does not provide much information for estimating the parameters of such complex models. In particular, the means of the autoregressive parameters do not deviate largely from the priors, which suggest that the model is not learning much from the data and cannot be identified from the available data alone.

## 3.3 Modelling results: Responses to shocks

Using the results from the estimation, we present a series of policy related scenarios. The responses allow policy makers to evaluate the knock-on effects and trade-offs so that policy changes can be made and solutions fine-tuned accordingly.

[17]QuantMig Migration Estimates Explorer, `https://bit.ly/quantmig-estimates`

Table 6: Calibration variables: Demographics and labour market

| Country | Skill level | | Natives | | Migrants | |
|---|---|---|---|---|---|---|
| | | | *WA* | *65–74* | *WA* | *65–74* |
| *Germany* | | | | | | |
| | High-skill | | | | | |
| | | Population share | 19.23 | 3.61 | 4.90 | 0.54 |
| | | Participation rate | 92.68 | 19.86 | 82.55 | 22.11 |
| | | Unemployment rate | 1.50 | 0.00 | 4.80 | 1.32 |
| | Low-skill | | | | | |
| | | Population share | 46.46 | 8.83 | 14.53 | 1.89 |
| | | Participation rate | 76.46 | 12.19 | 71.00 | 11.78 |
| | | Unemployment rate | 3.11 | 2.02 | 5.87 | 3.71 |
| *Sweden* | | | | | | |
| | High-skill | | | | | |
| | | Population share | 26.41 | 4.00 | 8.84 | 0.64 |
| | | Participation rate | 93.25 | 25.95 | 90.38 | 21.87 |
| | | Unemployment rate | 1.90 | 4.37 | 7.70 | 13.50 |
| | Low-skill | | | | | |
| | | Population share | 37.76 | 8.13 | 12.84 | 1.37 |
| | | Participation rate | 77.43 | 17.52 | 76.33 | 16.14 |
| | | Unemployment rate | 7.05 | 3.53 | 23.20 | 5.09 |
| *Italy* | | | | | | |
| | High-skill | | | | | |
| | | Population share | 13.84 | 1.43 | 1.45 | 0.11 |
| | | Participation rate | 84.96 | 22.59 | 75.94 | 30.60 |
| | | Unemployment rate | 3.80 | 0.06 | 8.40 | 5.15 |
| | Low-skill | | | | | |
| | | Population share | 58.76 | 13.43 | 10.40 | 0.57 |
| | | Participation rate | 60.05 | 7.12 | 69.17 | 21.68 |
| | | Unemployment rate | 9.04 | 3.35 | 11.37 | 8.49 |
| *Poland* | | | | | | |
| | High-skill | | | | | |
| | | Population share | 24.74 | 2.49 | 0.36 | 0.02 |
| | | Participation rate | 91.65 | 20.55 | 84.97 | 35.34 |
| | | Unemployment rate | 1.30 | 1.30 | 1.30 | 1.30 |
| | Low-skill | | | | | |
| | | Population share | 58.17 | 13.87 | 0.33 | 0.04 |
| | | Participation rate | 65.90 | 7.04 | 69.40 | 4.87 |
| | | Unemployment rate | 3.84 | 3.63 | 3.63 | 3.71 |

Source: Authors' own calculation based on Eurostat data. WA denotes the main working age (15–64). High-skill is defined as ISCED 5-8, with low-skill values corresponding to ISCED 0-2 and 3-4. Participation (activity) rates and unemployment rates for people aged 65-74 in selected European case studies in 2022. These figures are approximations from authors' calculations. Figures are available for 15-64 and 15-74. The Eurostat tables used have options for sex, age, migration status, citizenship and educational attainment level. We apply migration status to foreign born vs native-born and set citizenship to total. The specific tables are Employment (`lfsa_egaisedm`), Employment Rates (`lfsa_erganedm`), Unemployment (`lfsa_urganedm`), and Population (`lfsa_pganedm`).

Throughout this section, unless stated otherwise, we present responses to 'shocks' in the form of one standard-deviation increases of individual variables. The variables such as

Table 7: Bayesian Estimation: Prior summaries and posterior means

| **Description** | **Prior mean** | **Prior s.d.** | **DEU** | **SWE** | **ITA** | **POL** | **PDF** |
|---|---|---|---|---|---|---|---|
| *Autoregressive Parameters* | | | | | | | |
| TFP | 0.70 | 0.6983 | 0.7019 | 0.6911 | 0.6953 | $\beta$ | 0.10 |
| Cons. Pref. | 0.70 | 0.6985 | 0.6996 | 0.6911 | 0.7030 | $\beta$ | 0.10 |
| Investment | 0.70 | 0.7003 | 0.7000 | 0.6998 | 0.7015 | $\beta$ | 0.10 |
| Robot Prod. | 0.70 | 0.6966 | 0.6991 | 0.7112 | 0.7001 | $\beta$ | 0.10 |
| Gov Cons. | 0.70 | 0.6981 | 0.6995 | 0.7067 | 0.6997 | $\beta$ | 0.10 |
| Foreign TFP | 0.70 | 0.7005 | 0.7023 | 0.7032 | 0.7036 | $\beta$ | 0.10 |
| Migration | 0.70 | 0.6972 | 0.6973 | 0.6903 | 0.6990 | $\beta$ | 0.10 |
| IP Invest | 0.70 | 0.7002 | 0.7028 | 0.6923 | 0.6986 | $\beta$ | 0.10 |
| *Model Parameters* | | | | | | | |
| | 1.00 | 0.9988 | 0.9989 | 1 | 0.9983 | $\Gamma$ | 0.05 |
| | 1.50 | 1.4991 | 1.5003 | 1.5093 | 1.5028 | $\Gamma$ | 0.05 |
| | 0.01 | 0.0100 | 0.0100 | 0.0100 | 0.0100 | $\beta$ | 0.0001 |
| *Standard deviation of shocks* | | | | | | | |
| TFP | 0.10 | 0.0279 | 0.0271 | 0.0392 | 0.0291 | $\Gamma^{-1}$ | 0.05 |
| Cons. Pref. | 0.10 | 0.0566 | 0.0831 | 0.8173 | 0.1185 | $\Gamma^{-1}$ | 0.05 |
| Investment | 0.10 | 0.0364 | 0.0890 | 0.0546 | 0.1026 | $\Gamma^{-1}$ | 0.05 |
| Robot Prod. | 0.10 | 0.0322 | 0.0327 | 0.0478 | 0.0409 | $\Gamma^{-1}$ | 0.05 |
| Gov Cons. | 0.10 | 0.0239 | 0.0987 | 0.0238 | 0.0245 | $\Gamma^{-1}$ | 0.05 |
| IP Invest | 0.10 | 0.0473 | 1.5317 | 0.024 | 2.2891 | $\Gamma^{-1}$ | 0.05 |
| Foreign TFP | 0.10 | 0.0238 | 0.0238 | 0.0237 | 0.0238 | $\Gamma^{-1}$ | 0.05 |
| Migration | 0.10 | 0.0268 | 0.0735 | 0.055 | 0.0653 | $\Gamma^{-1}$ | 0.05 |

Results from the Bayesian estimation after 300,000 MCMC iterations. The first columns list the estimated parameters, the second and third columns give the prior means and standard deviations, with the fourth to seventh column giving the posterior means for the individual countries. The eighth column shows the assumed distributions ($\beta$: Beta, $\Gamma$: Gamma, $\Gamma^{-1}$: Inverse Gamma). TFP = Total Factor Productivity.

output (GDP) are in **per-capita** terms. The responses are reported as percentage change from steady state, and their development over time (for 20 successive quarters since the shock) is presented as **impulse-response functions** (IRF). The IRF is a plot of the path that endogenous variables (such as GDP or employment) take following this shock or exogenous increase for another variable (such as labour productivity, investment or migration). For some shocks we provide intra-country comparison where appropriate (for example, concerning different population groups). We posit that the results of the analysis are not limited to the specific case studies, but can be broadly extended, at least in the qualitative sense, to countries with similar labour markets or activity characteristics.

### 3.3.1 Endogenous and exogenous automation changes

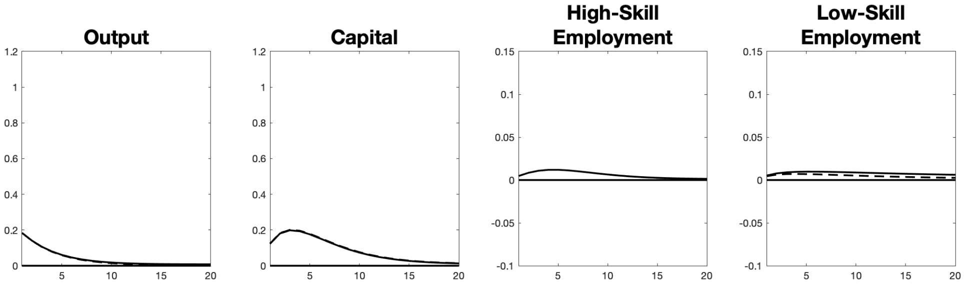
Here we present two scenarios: (i) the decision of automation is fully endogenous and (ii) automation levels remaining at their steady state level. We compare the response of the standard real business cycle (RBC) shock of a total factor productivity (TFP), $Y_t = \psi_t^A f(K_t, A_t, L_t^H, L_t^L)$, where $\psi_t^A$ is the TFP shock, $K_t$ is the physical capital, $A_t$ is the automation capital, which is at its steady-state level, while $L_t^H$ and $L_t^L$ are the high-skill and low-skill labour inputs, respectively. A TFP shock is a baseline shock used in macroeconomics that allows to model a general increase of a range of economic parameters rather than a targeted variable such as labour.

Figures 7 and 8 show the responses to a TFP shock without endogenous automation decisions. Some of the response size can be attributed to the different magnitudes of TFP shocks between countries. We focus on the differences between endogenous automation decisions (solid lines) and automation at steady-state levels (dashed lines). The differences for Germany and Sweden are smaller than those for Italy or Poland. There is a larger increase to output when automation levels change which is replicated across employment decisions. The increase for low-skill employment is actually larger with automation. This is not a persistent effect for Poland as the initial increase swaps after eight quarters. From Figure 8, the differences are small, and for Poland they still suggests some idiosyncrasies, such as a small dip in wages shortly after the TFP shock, which is unexpected but on the whole insignificant. With focus on the contrast between endogenous and exogenous automation, the results show marginal gains from endogenous increases.

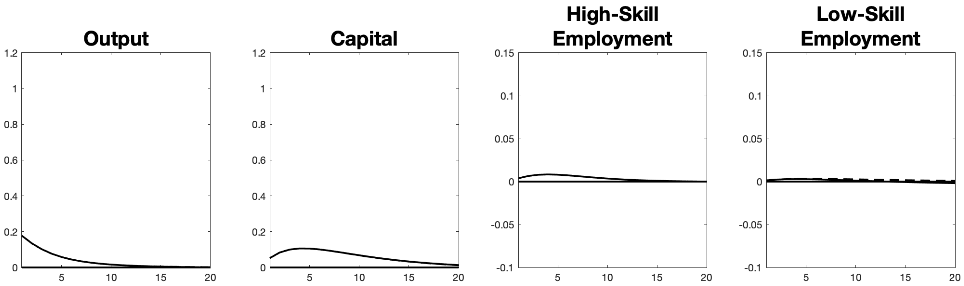
### 3.3.2 Automation productivity

Having shown the impacts of no increases to automation levels, we now show the response to a one standard deviation change in productivity. A realistic example of this could be an advancement in technology, such as a new machine that increases output per hour. A permanent change would require that this level of advancement to increases permanently, so for the new technology not only to be adopted, but embedded in the business-as-usual practice, which is entirely independent of low-skill labour productivity.

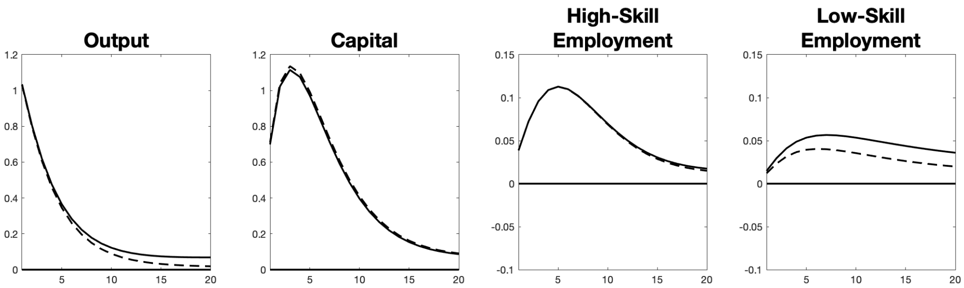
Figures 9 and 10 shows the responses to an estimated 1SD temporary shock to the productivity of robots. Figure 9 shows the responses of output, physical capital, the number of robots and wages for the high- and low-skill working-age natives. The estimated shocks are relatively greater in terms of magnitude for Italy and Poland which partially explains the larger responses. The increase in productivity results in a small economic



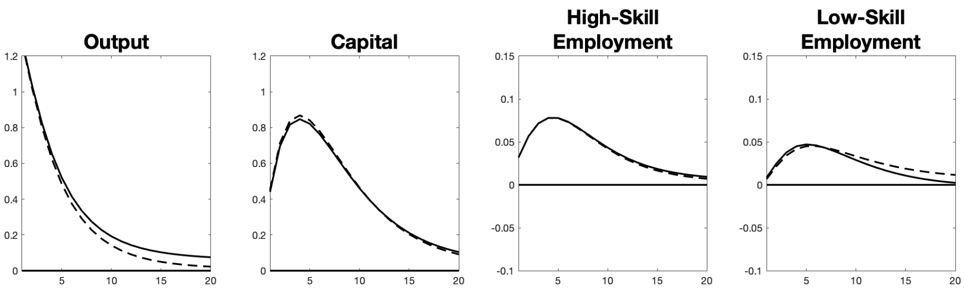

(a) Germany




(b) Sweden




(c) Italy

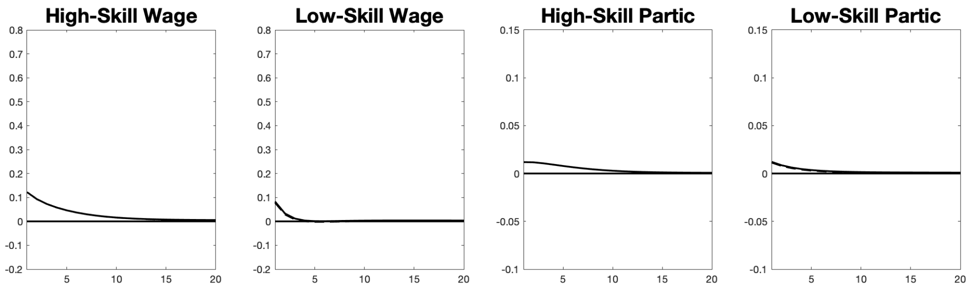



(d) Poland

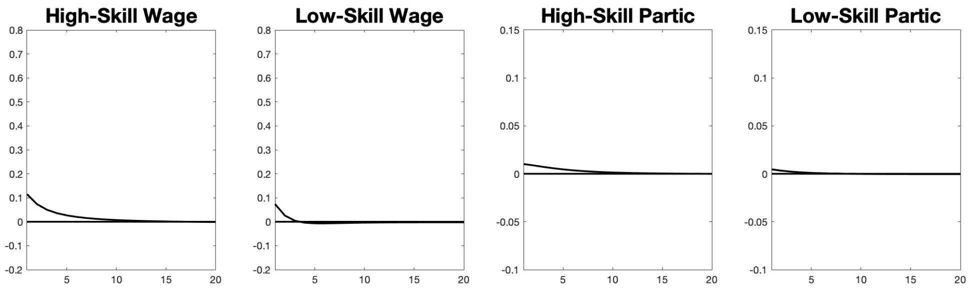
Figure 7: Exogenous and Endogenous Automation Decisions (1)

The figure shows the impulse response functions to output, capital, high-skill and low-skill employment following an exogenous increase total productivity when automation levels remain at the steady state. The axes are normalised across response variable. The solid line identifies endogenous decision of automation, with the dashed line with automation set to its steady-state trajectory.

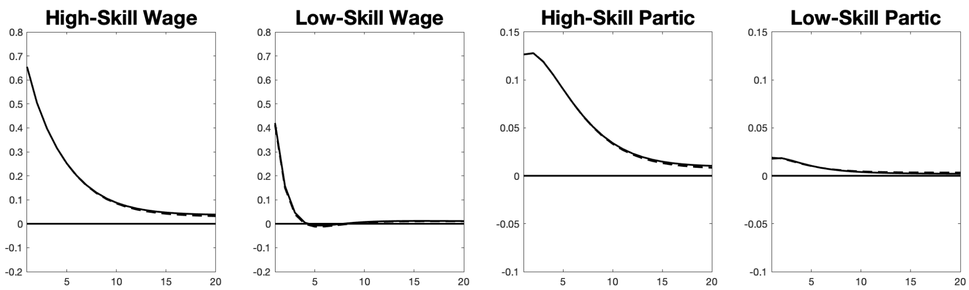
expansion that is relatively long-lasting. Both types of capital increase, though traditional physical capital increases more than the automation capital (robots). However,



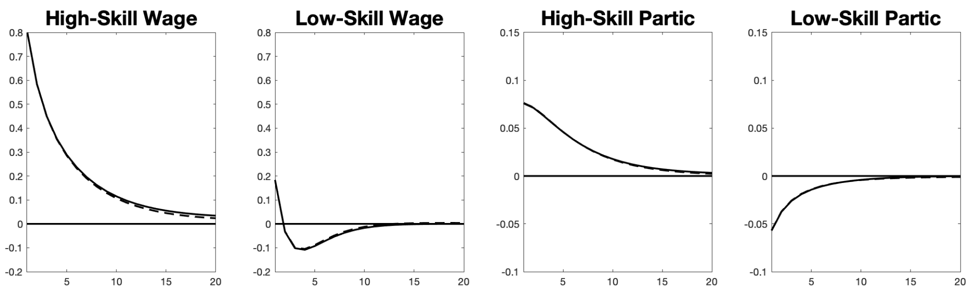

(a) Germany




(b) Sweden




(c) Italy




(d) Poland

Figure 8: Exogenous and Endogenous Automation Decisions (2)

The figure shows the impulse response functions to aggregate high-skill and low-skill wages, and participation rates for each household following an increase in TFP when automation levels remain at the steady state. The axes are normalised across response variable. The solid line identifies endogenous decision of automation, with the dashed line with automation set to its steady-state trajectory.

the number of robots is not required to boost output as much when their productivity has increased. For each country, there are increases to the high-skill wage (solid line) and temporary (1-2 quarters) decreases in the low-skill wage which widens the skill premium.

There are important questions around investments in robot technologies, especially from governments, as there is a perception that it will lead to high(er) and persistent levels of unemployment. The results for high- and low-skill employment and participation rates are shown in Figure 10. Since there are three types of labour market status: employed, unemployed and inactive, showing unemployed responses can be unclear whether it is due to changes in activity levels or changes in unemployment rates. High- and low-skill employment are shown in the first two subplots, with increases to high-skill employment across age groups and migrant status. Low-skill employment is varied across age-groups but not especially by migrant status – the older workers experience decreases, with more persistent decreases noted for Poland. The responses for low-skill working age are insignificant except for Italy where there is a relative increase.

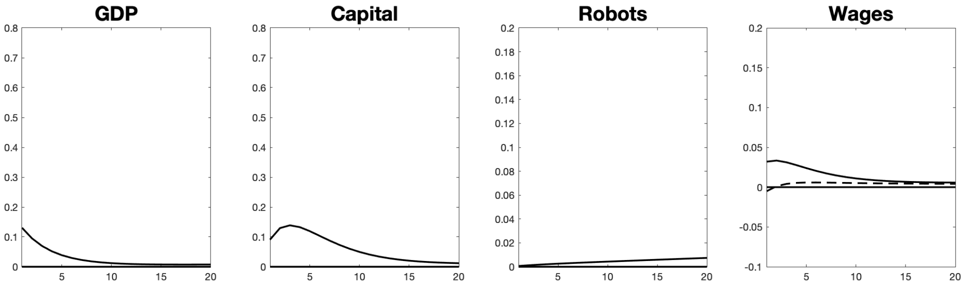
These responses are replicated in participation rates, which increase for the high-skill segment of the labour market. Low-skill working-age participation rates can increase but in Poland older workers become inactive where working-age participation increases slightly. Some of the reduction in low-skill labour supply is reflected in hours supplied to the firms. Fewer working hours is a trend that has been seen in the empirical data, particularly since the COVID-19 pandemic[18]. Workers gain utility from fewer working hours, although total labour income might decrease.

A large part of the public discourse is concerned with robots 'taking our jobs', however, for the most part, these fears are at least inaccurate. Increases in automation productivity and robots helps firms to increase output, so robots taking workers' jobs would only occur in industries where demand for goods is inelastic. Increases in production tend to make goods cheaper, so consumption would increase.

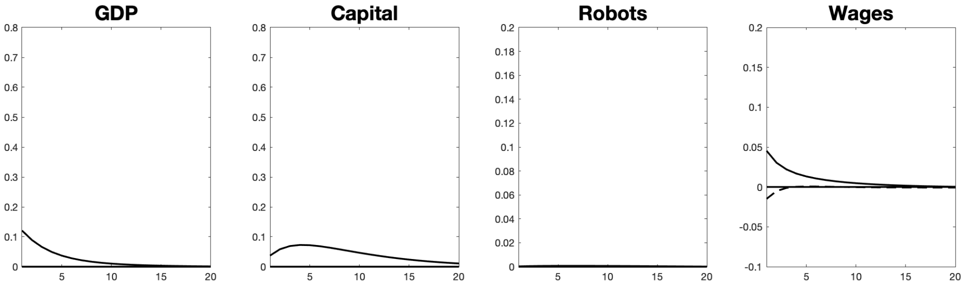
### 3.3.3 Low-skill labour productivity

This part of the analysis aims to compare the shocks to low-skill labour productivity with the robot productivity, and then contrast these with the changes to high-skill productivity. The relevant policy options can include increasing education levels or perhaps implementing new working technologies, methods and practices that enable workers to

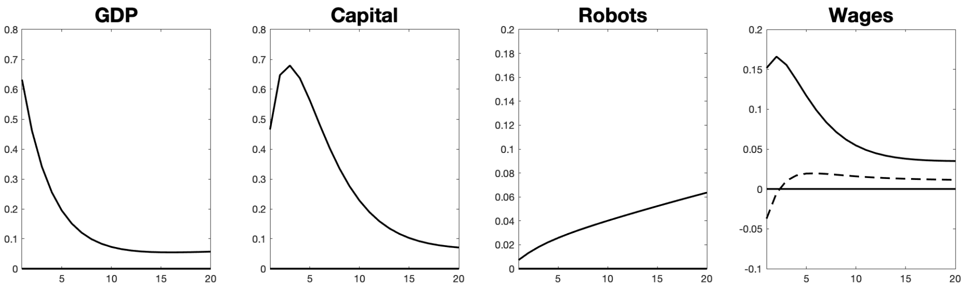
[18]See ECB Blog 'More jobs but fewer working hours'.



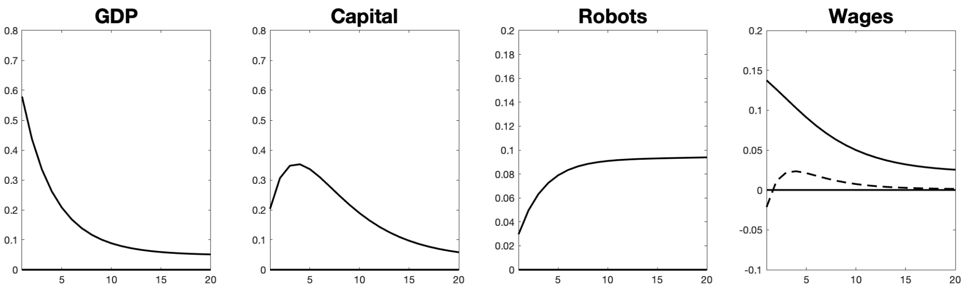

(a) Germany




(b) Sweden



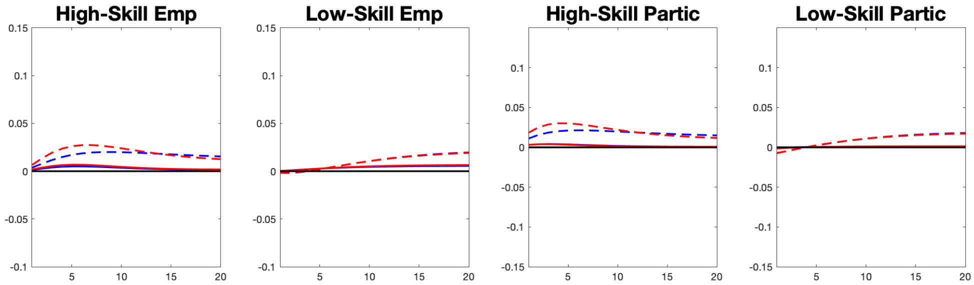

(c) Italy



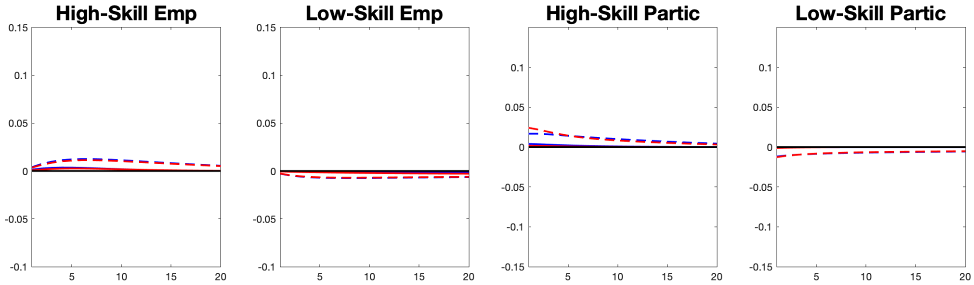

(d) Poland

Figure 9: Temporary Increases to Automation Productivity (1)

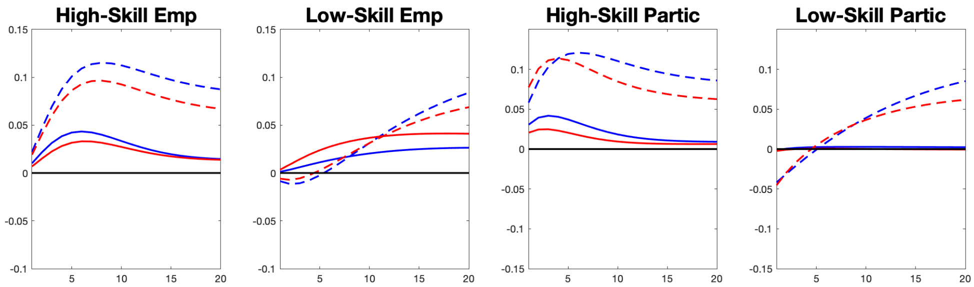
The figure shows the impulse response functions to output, capital, robots and wages following an exogenous increase in robot productivity. The axes are normalised across response variable. Wage plots show the native-born working-age wages: solid line for high-skill and dotted line for low-skill workers. The horizontal axis identifies the time (quarters).



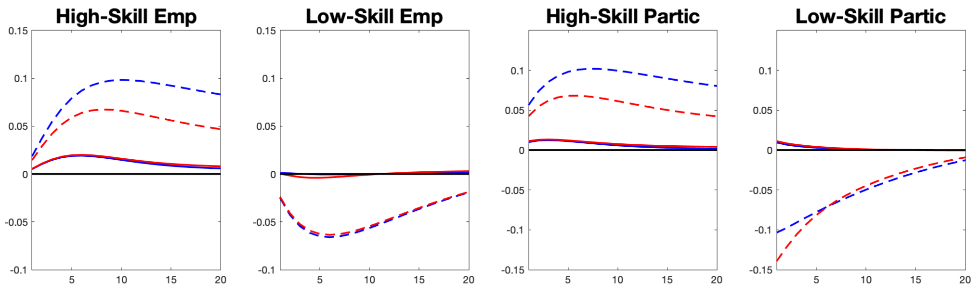

(a) Germany




(b) Sweden




(c) Italy




(d) Poland

Figure 10: Temporary Increases to Automation Productivity (2)

The figure shows the impulse response functions to aggregate high-skill and low-skill employment, and participation rates for each household following an exogenous increase in robot productivity. The axes are normalised for each response variable. Blue lines are for native-born, red lines for foreign-born, solid lines are for working-age and dashed lines are for early retirement age populations. The horizontal axis identifies the time (quarters).

achieve more per unit of labour. Short-term shifts to productivity using education as a proxy are unrealistic, however, preparing for the future requires training those currently in education to a standard that will better match the technologies of the future.

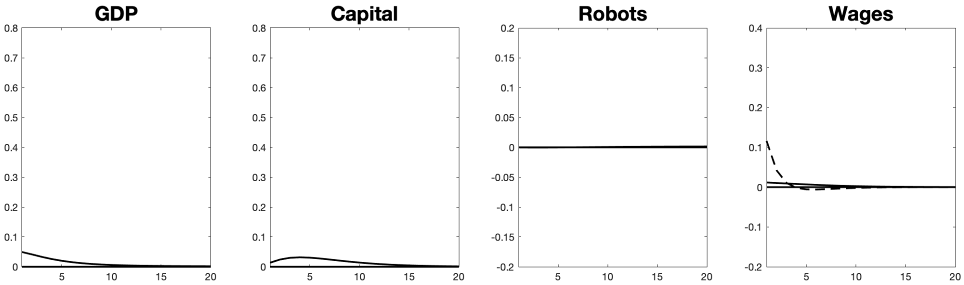
The gains to low-skill productivity produce similar increases to the overall output as automation productivity increases. Figure 11 shows the increase in output, physical capital, robots and high-skill wages (solid line), as well as low-skill wages (dashed line). Following an increase in productivity, the low-skill wage consequently increases. However, there is an insignificant change in the level of automation (number of robots), and a more pronounced increase in the physical capital. This is unsurprising since robots and low-skill workers in the model are complementary, doing the same tasks, therefore if workers are more productive then employing or purchasing a robot has a higher viability threshold.

The response on labour markets show differing responses between working-age and older workers (early retirement age). There is a lower participation rate for older workers, so any type of economic reactivation can generate a larger response, but this increase in productivity and wages is both reactivating the low-skill age groups and increasing employment. The increases for the high-skill sectors are not as pronounced.

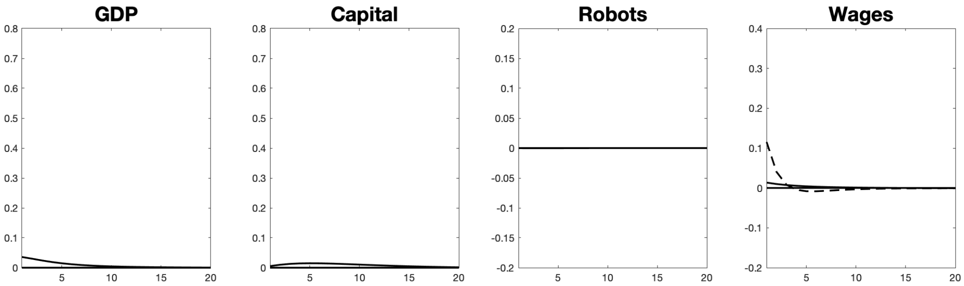
#### 3.3.4 Migration flows

Increases to migration have direct implications for the labour market because a new influx of workers creates an 'extra' workforce. Recent increases to migration flows include the influx of Ukrainian citizens to the EU. We evaluate three scenarios: a high-skill shock, a low-skill shock, and a shock that covers both skill levels. We assume that there are only increases to the working-age migrant households. The relative size of the existing migrants stock is important here. For Poland (as per Table 6), it used to be exceptionally low (the data did not include any Ukrainians who arrived since 2022 following the Russian invasion) so a 1SD is going to yield a smaller 'new workforce' than for other countries.

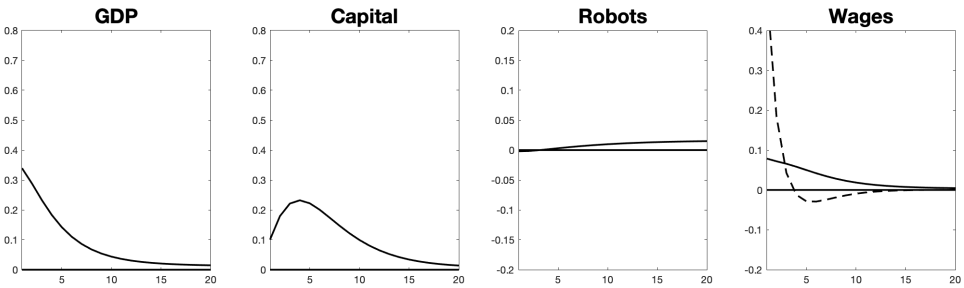
**High-skill migration** As high-skill workers have higher productivity, the effects of changes in their numbers are going to be more profound. However, for Italy and Poland, the small sizes of high-skill migrants in particular make the responses insignificant. Figure 13 illustrate the responses in terms of output, capital, robots and wages. There is a



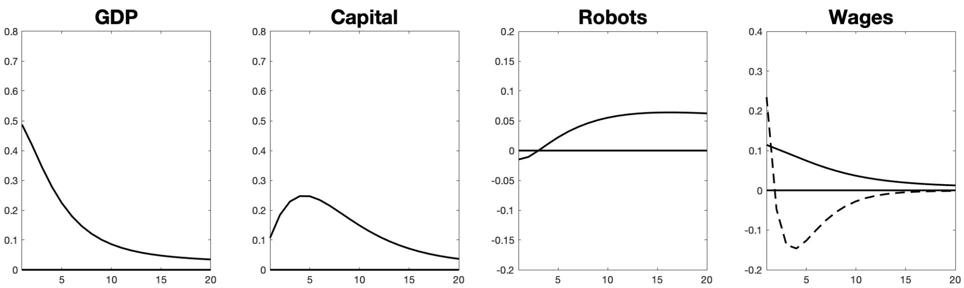

(a) Germany




(b) Sweden



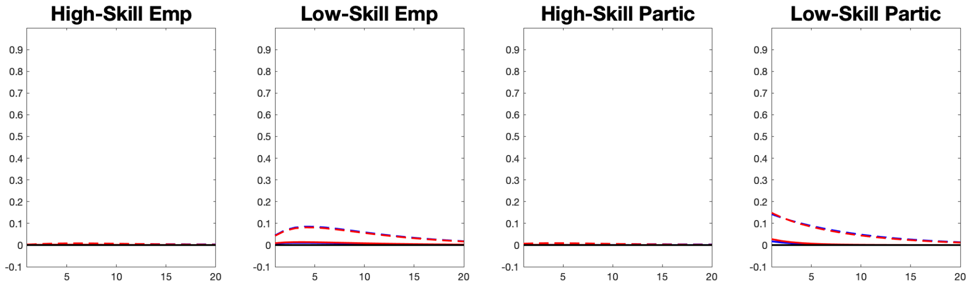

(c) Italy



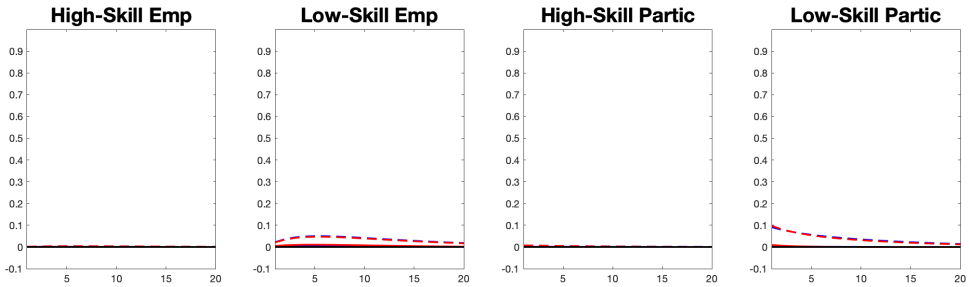

(d) Poland

Figure 11: Temporary Increases to Low-Skill Labour Productivity (1)

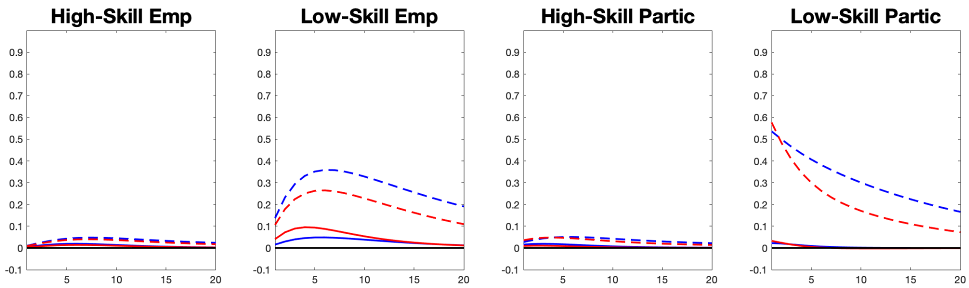
The figure shows the impulse response functions to output, capital, robots (automation capital) and wages following an exogenous increase in low-skill labour productivity. The axes are normalised for each response variable. Wage plots show the native-born working-age wages: solid line for high-skill and dotted line for low-skill workers. The horizontal axis identifies the time (quarters).



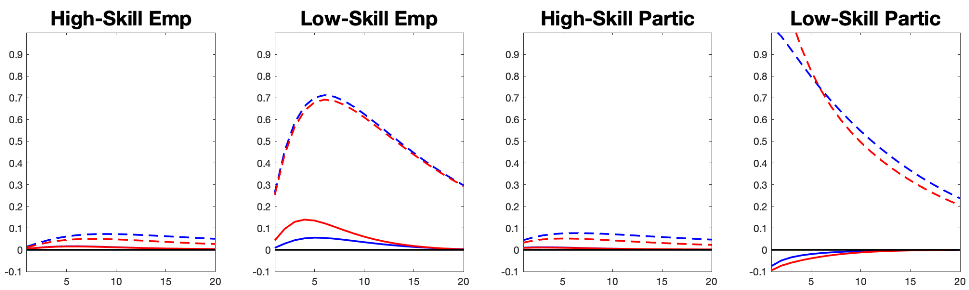

(a) Germany




(b) Sweden




(c) Italy




(d) Poland

Figure 12: Temporary Increases to Low-Skill Labour Productivity (2)

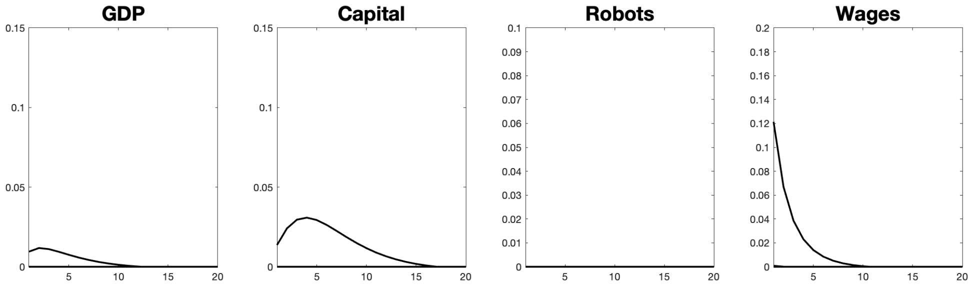
The figure shows the impulse response functions to aggregate high-skill and low-skill employment, and participation rates for each household following an exogenous increase to low-skill labour productivity. The axes are normalised for each response variable. Blue lines are for native-born, red lines for foreign-born, solid lines are for working-age and dashed lines are for early retirement age populations. The horizontal axis identifies the time (quarters).

clear expansionary effect of high-skill migration on output. The increase in high-skill productivity also increases the high-skill wage. There is a small increase to the low-skill wage but it is relatively insignificant. The increase in capital results from an increase in investment.

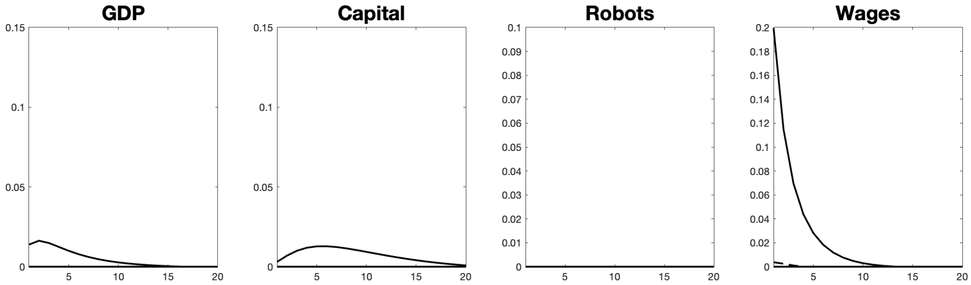
The responses in Figure 14 focus on the labour market. On the aggregate basis, the largest increase in employment is seen for the high-skilled migrant household, as the increased migrant flow enter at current business cycle conditions in the labour market. The market forces determine how the employment, unemployment and participation rates differ. In this scenario of an increase to the number of high-skill migrants, market forces increase employment across the high-skill sector, across both age groups for native-born workers, and for older high-skill migrants. High-skill participation of migrants does not change as much, because the new migrants enter at the current business cycle status. In addition, some reactivation of the high-skill older workers can be observed. The impacts on the low-skill employment are negligible.

**Low-skill migration** The responses to a low-skill migration shock are shown in Figures 15 and 16. As with the high-skill migration shock, these shocks result in an increase in output. The other results are not a mirror image though, as there are falls in physical capital, with investments switching to robots. There are differing effects to that of low-skill productivity because of the actual increase in the available workforce. In addition, the increase in productivity raises the low-skill wage. Figure 16 shows an even smaller response on high-skill labour. There are expansionary impacts on labour in the low-skill sector across ages and native/foreign-born groups. For the latter, the differences in the older workers are similar for Sweden and Germany in terms of both employment and participation, but for Italy, there is a larger effect for the native-born older workers. As for Poland, the relatively small number of existing migrant households makes any effect minimal.

**Total Migration** Figures 17 and 18 show the effects of increases to total migration expressed in per capita terms. This combines the two previous scenarios, related to the high-skill and low-skill migration. Generally, we see that migration shocks are expan-




(a) Germany




(b) Sweden

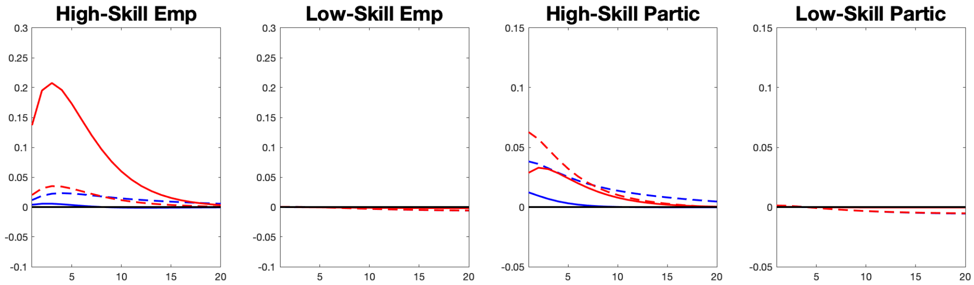
Figure 13: Temporary Increases to High-Skill Migration Flows (1)

The figure shows the impulse response functions to output, capital, robots and wages following an exogenous increase in high-skill migration. The axes are normalised across response variable. Wage plots show the native-born working-age wages: solid line for high-skill and dotted line for low-skill workers. The horizontal axis identifies the time (quarters).

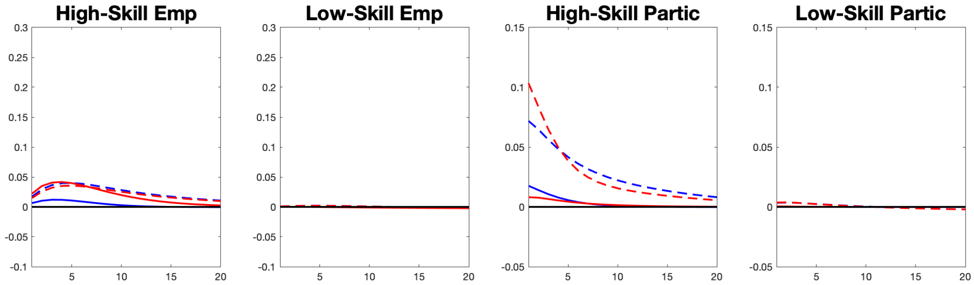
sionary to the economy, both types of capital, and several aspects of the labour market. The increase in productivity raise the wage level which helps (re)activate some of the economically-inactive labour force. The impact of the larger and more productive labour force can propagate across different sectors of the economy.

### 3.3.5 Automation investment

There are many unanswered questions around the investment in robot technologies, especially from the side of governments, given the popular perception that job automation will lead to increasing unemployment. For the most part, this view is inaccurate. Increases in automation and robots helps firms to increase output, so long-term negative impacts on employment would only occur in industries where demand for goods is inelastic. Generally, increases in production tend to make goods cheaper, so consumption would increase, boosting the economy overall. Irrespective of this, the type of shock is




(a) Germany



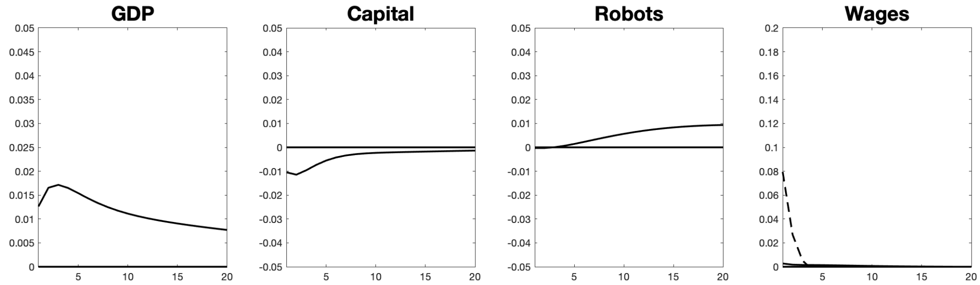

(b) Sweden

Figure 14: Temporary Increases to High-Skill Migration Flows (2)

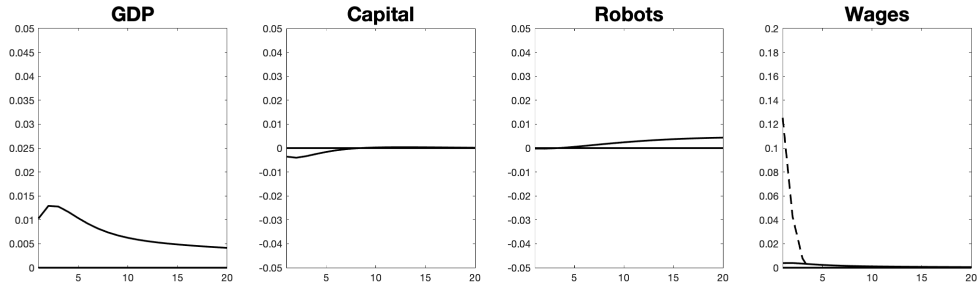
The figure shows the impulse response functions to aggregate high-skill and low-skill employment, and participation rates for each household following an exogenous increase in high-skill migration. The axes are normalised across response variable. Blue lines are for native-born, red lines for foreign-born, solid lines are for working-age and dashed lines are for early retirement age populations. The horizontal axis identifies the time (quarters).

designed to replicate a decrease in the cost of automation.

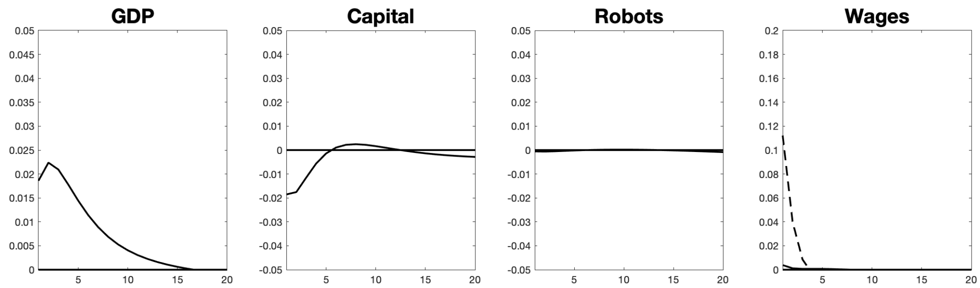
We hypothesise three situations: (i) the government provides incentives that lower the threshold value of employing new machines; (ii) the government purchases automation technology without reducing the threshold value; and (iii) the purchase of automation technology is a one-period event rather than a policy change that continues, but fades to a lesser extent. These are three alternative scenarios that can demonstrate to policy makers the potential impacts of automating. As before, the magnitude of a shock – one standard deviation – is normalised across countries. As any form of investment is more volatile than output, its relative value has been arbitrarily set to 0.035, which is the average for Germany and Sweden. We discuss these three scenarios in turn. These investments are financed by increases in government borrowing and shift of existing government investment policies.




(a) Germany




(b) Sweden

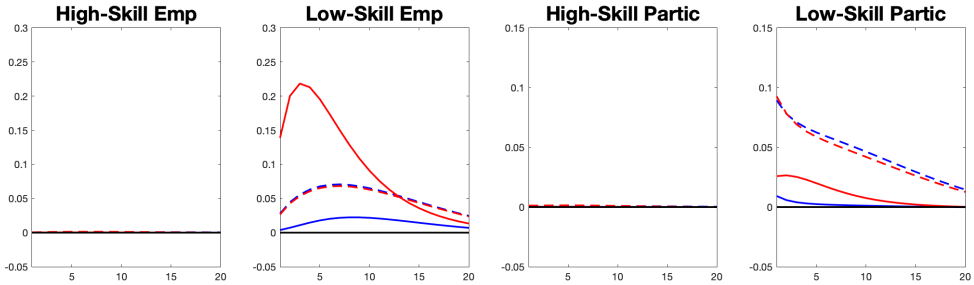



(c) Italy

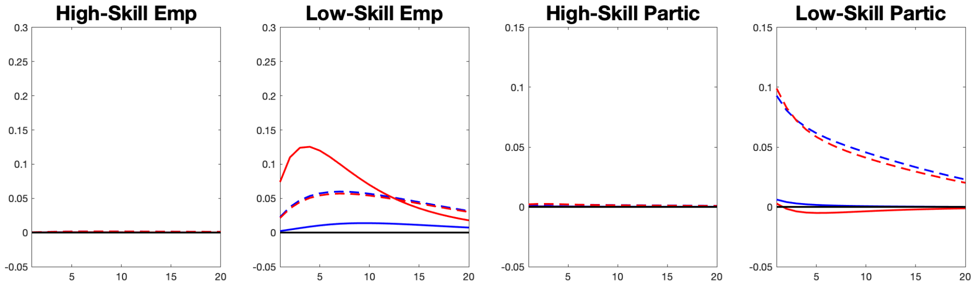
Figure 15: Temporary Increases to Low-Skill Migration Flows (1)

The figure shows the impulse response functions to output, capital, robots and wages following an exogenous increase in low-skill migration. The axes are normalised across response variable. Wage plots show the native-born working-age wages: solid line for high-skill and dotted line for low-skill workers. The horizontal axis identifies the time (quarters).

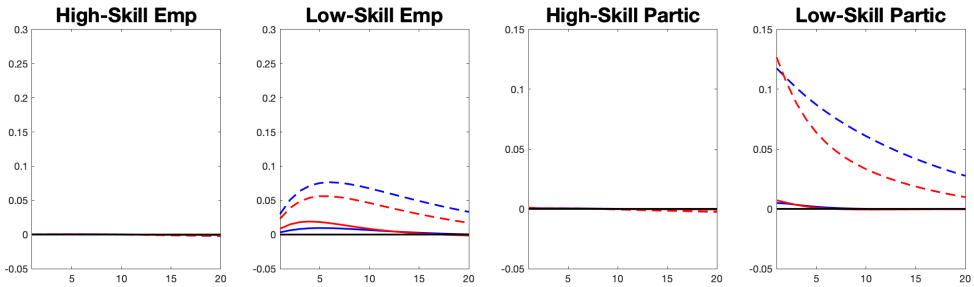
**(i) Decrease in automation threshold** The effects in this policy are mostly insignificant. In this scenario, the size of the expansions of output are less than 1%, with the effects greater for Poland (unsurprisingly) and Sweden. Each case shows a decrease in capital which is understandable as there can be a shift to the automation technologies. The number of robots increase, but not as much as would be hoped. There are negligible impacts on employment, with a small rise in low-skill employment for a short period, particularly of the older generation, which is matched in some countries with increased




(a) Germany




(b) Sweden

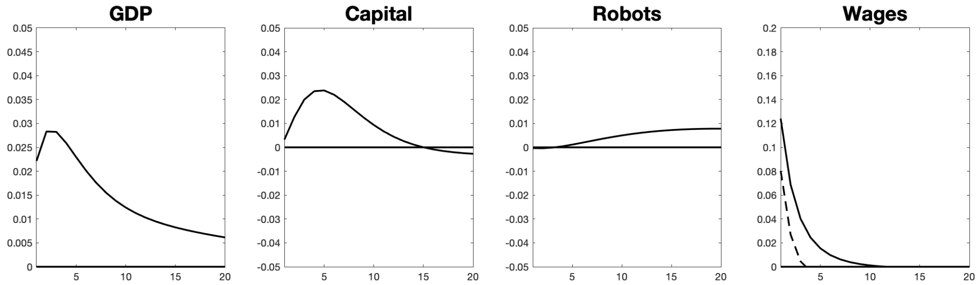



(c) Italy

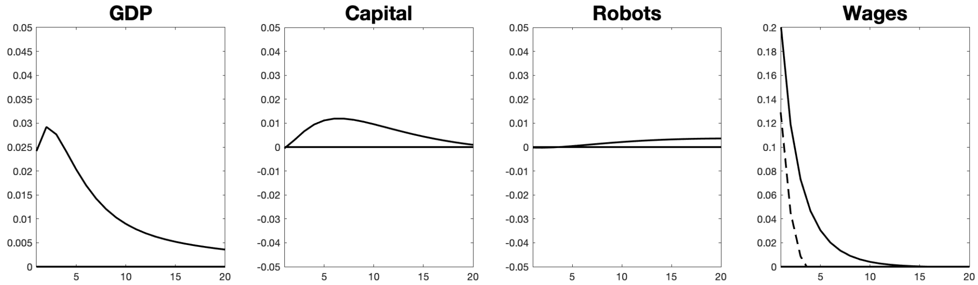
Figure 16: Temporary Increases to Low-Skill Migration Flows (2)

The figure shows the impulse response functions to aggregate high-skill and low-skill employment, and participation rates for each household following an exogenous increase in low-skill migration. The axes are normalised for each response variable. Blue lines are for native-born, red lines for foreign-born, solid lines are for working-age and dashed lines are for early retirement age populations. The horizontal axis identifies the time (quarters).

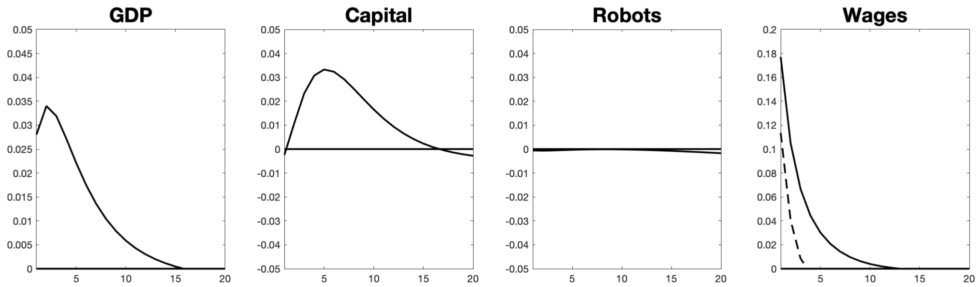
participation. However, Poland is expected only to experience these increases for a year at most, with the size of most responses being insignificant. This indicates that a small reduction in the threshold is not enough to increase automation levels alone. Consequently, only a significant decrease in the cost of automation technologies would incentivise the investment. The government, or any other investor, would need to look at the trade-offs to see the impact of the policy change and other methods. This might be politically more




(a) Germany




(b) Sweden



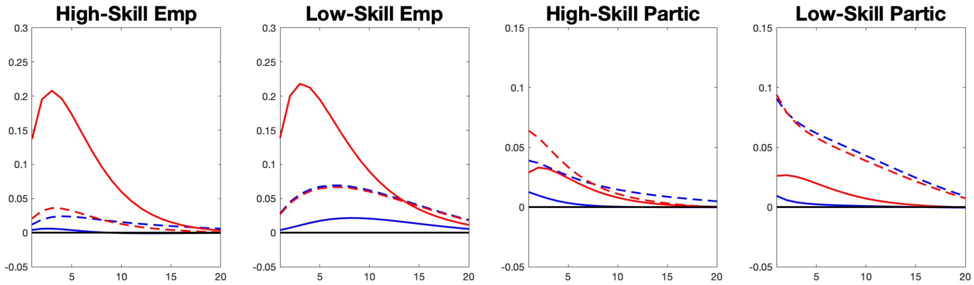

(c) Italy

Figure 17: Temporary Increases to Total Migration Flows (1)

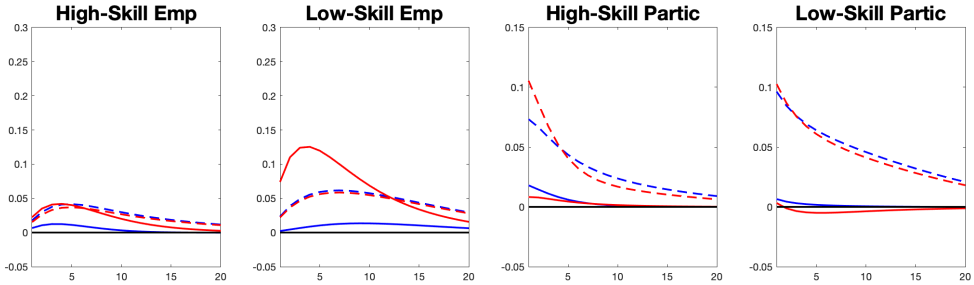
The figure shows the impulse response functions to output, capital, robots and wages following an exogenous increase in total migration. The axes are normalised across response variable. Wage plots show the native-born working-age wages: solid line for high-skill and dotted line for low-skill workers. The horizontal axis identifies the time (quarters).

tolerable but potentially less effective.

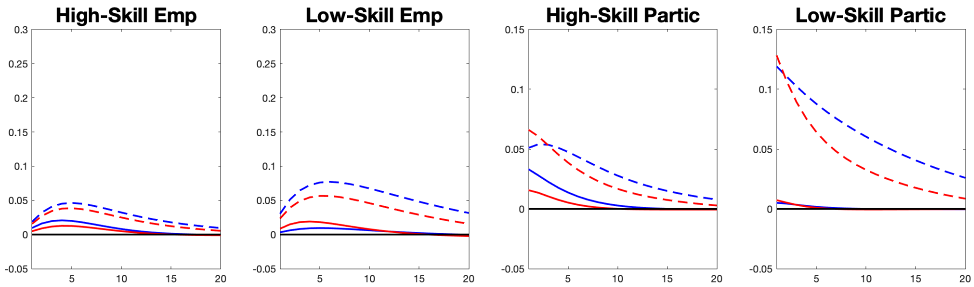
As would be expected, Italy and Poland see the most expansionary effects from the decrease in threshold due to diminishing marginal returns. Nevertheless, on the whole, the impact of decreasing the threshold would not provide the expected impact. After all, decreasing the threshold does not necessarily mean that there actually *will* be investment.




(a) Germany




(b) Sweden




(c) Italy

Figure 18: Temporary Increases to Total Migration Flows (2)

The figure shows the impulse response functions to aggregate high-skill and low-skill employment, and participation rates for each household following an exogenous increase in total migration. The axes are normalised for each response variable. Blue lines are for native-born, red lines for foreign-born, solid lines are for working-age and dashed lines are for early retirement age populations. The horizontal axis identifies the time (quarters).

**(ii) Purchases of Automation Technologies** In the second scenario, Figure 19 shows the expansionary effect of automation technologies purchased by the government for the firm. In this case, the government/investors actually provide the robots directly to the firm so there is no threshold level to decide on. The firm is given these new machines, can start using immediately, without the need for a hiring process. They are still provided with new machines over a period of time (approximately 16 quarters). This implies a huge policy shift, which enables immediate increase in output.

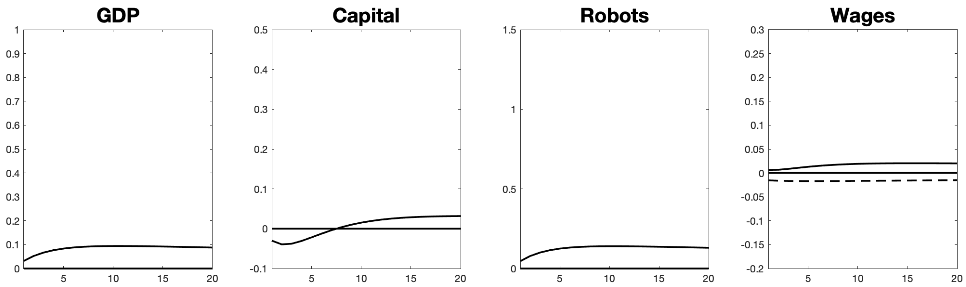
The labour market changes are different to the previous scenarios as the firm is essentially being given new (low-skill) workers. There are no large scale redundancies, as contracts under which the workers are employed. However, there is a reduction in the *number* of low-skill vacancies posted, which causes the small fall in employment in the medium term (see Figure 20).

In this scenario, there are small decreases in the low-skill wage. For these households, the labour income can be made up by hours supplied which increase. The fall in wage is driven by the reduction in marginal product of labour. The firm is still posting vacancies, to keep the labour market going, as they know that the supply of new machines will eventually stop. Eventually, the demand for workers returns to its normal levels but there is no sizeable reduction in employment that could be perceived, and participation rates actually increase. Importantly, the high-skill sector is expansionary due to the increased output from the firm. Overall, this policy proves more effective than decreasing the automation threshold.

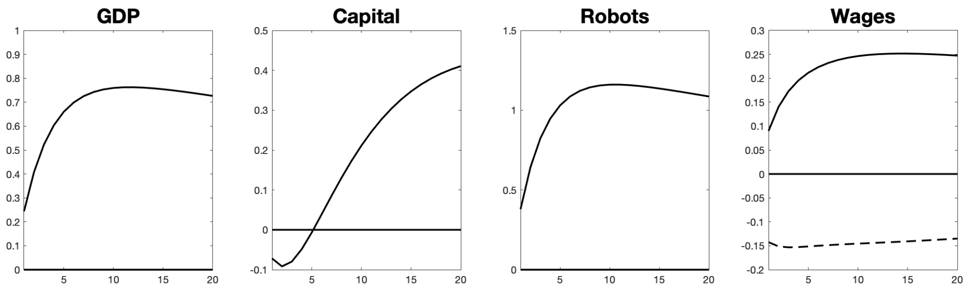
**(iii) One-period policy changes** The third scenario uses a combination of both previous policies, but assuming that the increase only happens for one quarter, with no lag. The results show similar effects to those in the second scenario, which is the dominant force here. All of the responses are small in magnitude. The effect of the policy changes continues, because the new machines enter production and only leave at the set depreciation rate, which is equivalent to an employment contract length. If the policy change of supplying the machines exogenously to the firm is a one-time action, the public perception of robots taking their jobs would be less so.

Although one period policy changes might seem that policies would only have impacts in one period, that isn't the case. If a firm is given a set of new machines in the current period, they will get these effects (ceteris paribus) until these machines are no longer useful. There can be knock-on effects to the rest of production, predominantly in the low-skill sector, but wider implications are also possible.

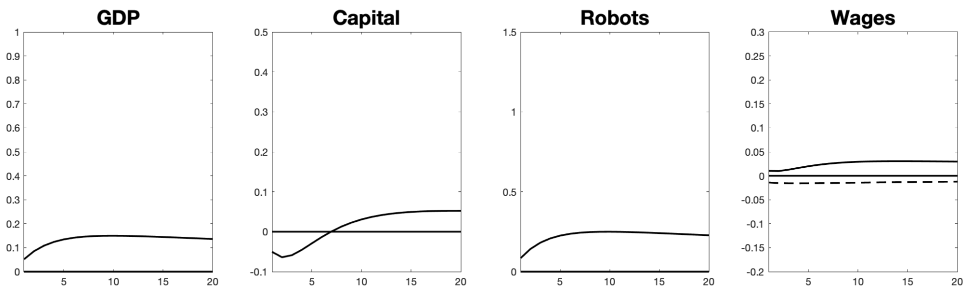
These three scenarios have provided policy options that could be of note for the governments. Especially for Poland, which lags behind in the automation race, and for



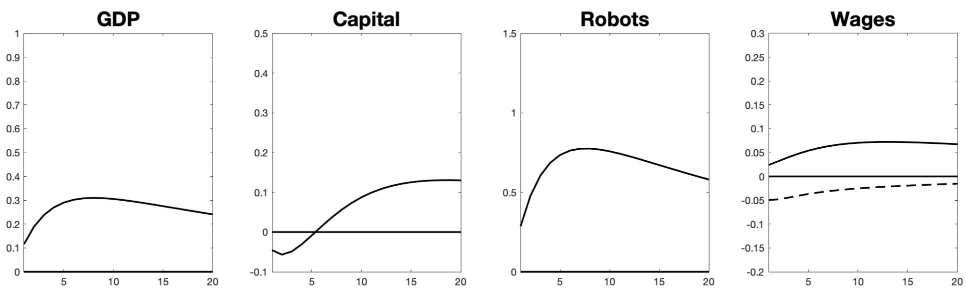

(a) Germany




(b) Sweden



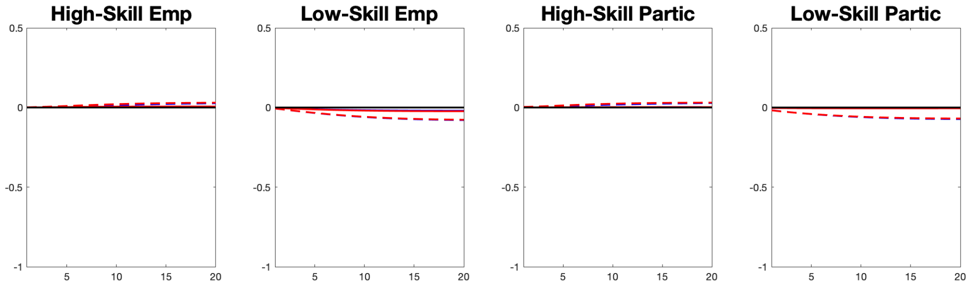

(c) Italy



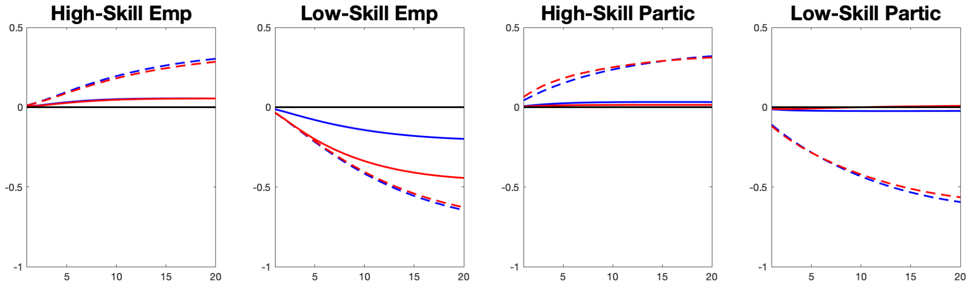

(d) Poland

Figure 19: External Purchases of Automation Technologies (1)

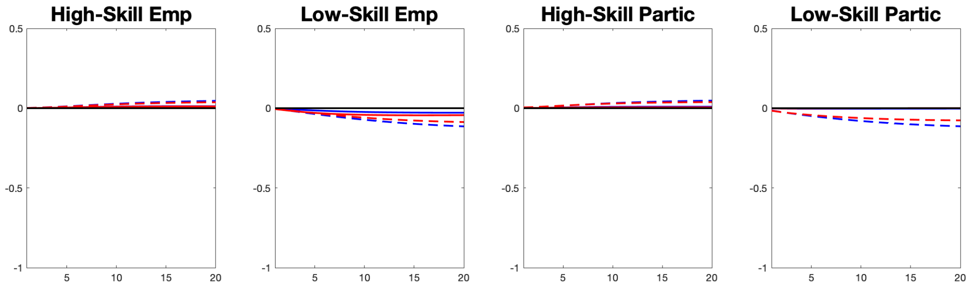
The figure shows the impulse response functions to output, capital, robots and wages following an increase of purchases of automative technologies external to the firm, by the government. The axes are normalised across response variable. Wage plots show the native-born working-age wages: solid line for high-skill and dotted line for low-skill workers. The horizontal axis identifies the time (quarters).



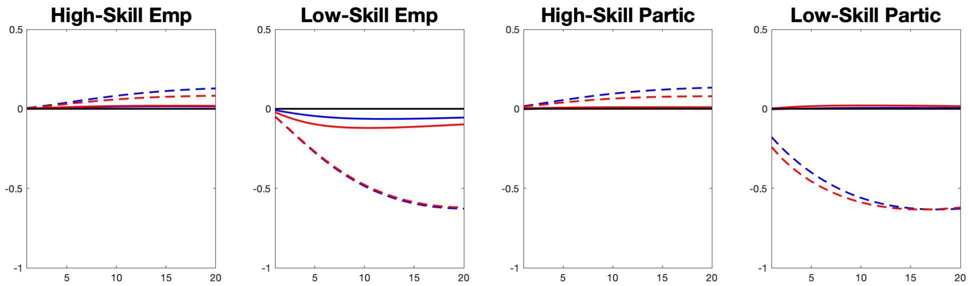

(a) Germany




(b) Sweden




(c) Italy




(d) Poland

Figure 20: External Purchases of Automation Technologies (2)

The figure shows the impulse response functions to aggregate high-skill and low-skill employment, and participation rates for each household following an increase in external purchases of robot technologies. The axes are normalised for each response variable. Blue lines are for native-born, red lines for foreign-born, solid lines are for working-age and dashed lines are for early retirement age populations. The horizontal axis identifies the time (quarters).

Italy, the responses are not as high as would be expected in terms of their magnitudes. There are some negative effects on the labour market, but the ones related to low-skill participation are predominantly limited to the the older-age group, who have a low participation and employment level to start with, so that any equivalent absolute change to their working-age counterparts looks larger. In all three scenarios, robots are not seen to be "stealing people's jobs", nor replacing them on the labour market. The reduction in employment comes from the scenario when robots are purchased exogenously, as it takes a while for the firm to balance out their production, and during the adjustment period, they post fewer vacancies. The high-skill sector expands too, allowing for production increase.

These three scenarios indicate that **both robots and workers** are required to help alleviate at least some of the challenges (ageing and general labour force shortages) of the future. Yes, some level of robotics can help solve the gap in labour supply but not all robots and workers are perfect substitutes. There are some jobs that cannot yet be fully automated. Countries with low levels of automation and current and future labour market shortages need to acknowledge this fact. Italy and Poland are the two most vulnerable to the challenges of population ageing, yet our results suggest that automation alone is not sufficient to address them.

#### 3.3.6 Demographic changes

In a final piece of the impulse-response analysis, we examine the scenarios where the relative sizes of the age groups change.[19] The first scenario is a population **increase** in the 65–74 age group, which *ceteris paribus* increases the tax burden on the remaining workforce while maintaining the same level of pension provision. The second scenario is a population **decrease** in the 65–74 group, for example due to a succession of smaller population cohorts reaching that age group, echoing the 'baby busts' from the past[20].

[19]The size of all the households is normalised to 1, where each size of the household is denoted by $\varphi_t^j$ where $j$ denotes one of the eight households. Therefore, an increase in the relative size of the household decreases another household(s). In this scenario, an increase/decrease in the corresponding age household. For example, in the case of increasing the size of the old-age household, there is a corresponding decrease in the **number** of working-age household. This number then effects the relative population sizes.

[20]Note that the relative changes in the sizes of the age groups need not result from excess mortality, and that the population renewal mechanism is a much more likely driver of such change. Still, elevated mortality cannot unfortunately be excluded, as the recent experience with the effects of the COVID-19

This would have decreased the number of older workers and people, or increased the relative size of the working-age population. By analysing these hypothetical scenarios, it can aid policy makers in where resources might need to be directed if required or adjust their expectations as to the possible future impacts of demographic change.

**Increased old-age group** We model the population increase so that 10% of the working-age population in each type of household retires, e.g. 10% of the working-age German high-skill natives join the German high-skill retirees household.

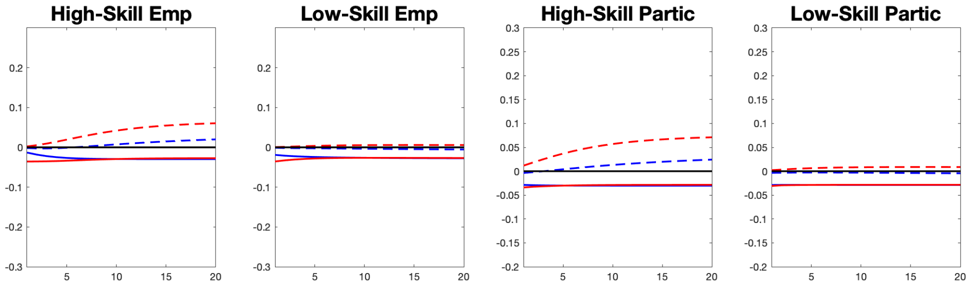
$$10\%\varphi_t^{GH} \rightarrow \varphi_t^{GHO} = \varphi_{t-1}^{GHO} + 10\%\varphi_t^{GH} \qquad \varphi_t^{GH} = 90\%\varphi_{t-1}^{GH}$$

In effect, the relative size of the working-age population decreases. For simplicity, these people maintain their current employment status but slowly adjust to their new household preferences. This is more realistic in that employment would not drastically change overnight, instead there is a slow increase. There are small effects on the wage as a decrease in workforce increases productivity. As expected, the results are that there is an increase in the early retiree employment, as the 55-64 have somewhat different preferences. This is more pronounced for the high-skill than the low-skill segments. The impulse responses for output, capital, robots, and wages are small therefore we only present the labour market effects in Figure 21.

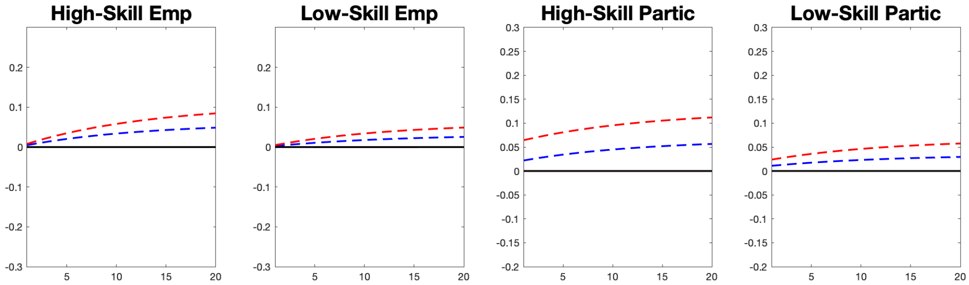
**Decreased older-age group** In contrast to the previous analysis, this scenario assumes population decline. If we were to analyse a reverse shock, with the increase in the older-age age group, for example through increasing the retirement age, the results would mainly be the inverse of those presented here. The increase in working-age employment is insignificant because of the relatively large workforce that is already in place. These individuals would only be picking up from the jobs that the older workers have left. The employment rates of older workers are around 20%, so a 10% loss of those is small, the output and wider effects are limited for the most part.

These results, however, generate tensions with other areas of the economy (and real life): a decreased dependency ratio is typically considered 'good' for the economy, but

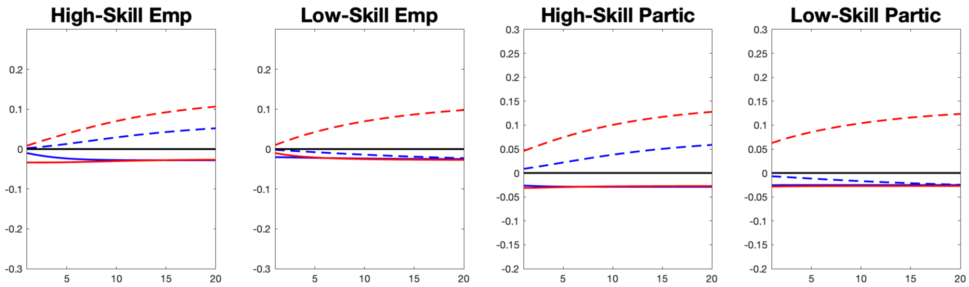
pandemic has shown, with COVID-related mortality exhibiting a clear age gradient.



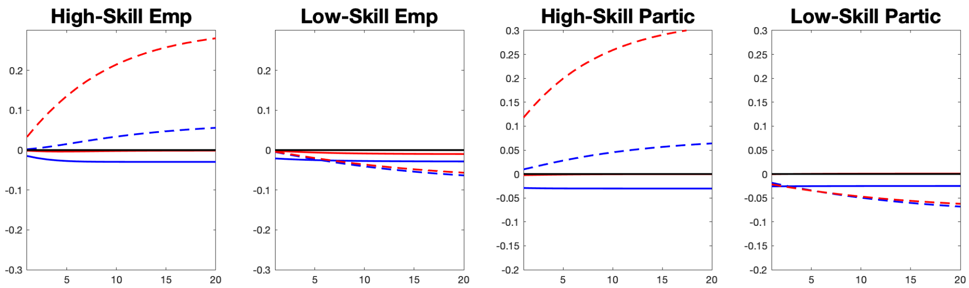

(a) Germany




(b) Sweden




(c) Italy




(d) Poland

Figure 21: Decrease in the retirement age

The figure shows the impulse response functions to aggregate high-skill and low-skill employment, and participation rates for each household following a decrease in the retirement age. The axes are normalised for each response variable. Blue lines are for native-born, red lines for foreign-born, solid lines are for working-age and dashed lines are for early retirement age populations. The horizontal axis identifies the time (quarters).

the price to pay for that may be too high. In any case, any effect on the economy, especially in terms of production, would be small, given the low participation rates of older workers. Aside from the human factor, in the larger picture if a reduction in the old-age dependency ratios is found, then this can decreases the pressure on services, such as health and social care. Still, as our model does not include young people, nor those aged 75 and above, it is not a full reflection of the whole economy and society.

## 3.4 Steady-state policy change analysis

In this section, we use the steady-state trajectories of the baseline model as a foundation to find the implications of potential policy changes, by modifying different calibrated values. The three proposed policy changes include: (i) modifying the participation rates of working-age population by increasing female participation rates to match their male counterparts; (ii) increase the participation rates of the would-be retirees aged 65-74 to match those for the 55–64 age group; and (iii) increase the number of robots by 10, 25 or 50%; while keeping the parameters the same. The reality of equating male and female participation is not as simple as introducing free childcare or some alternative policies, which would easily increase an overall working-age participation, as there are more reasons that people are inactive in the labour market (e.g. sickness, financial means to retire early, education), but the aim of this exercise is to provide foundations, on which the discussion of specific instruments and interventions can be based.

### 3.4.1 Increasing the working-age labour force participation

Table 6 provided details on the population size for each household type, alongside participation and unemployment rates. One key labour market policy open to governments would be to reactivate some of the inactive working-age population. The scenario proposed here is to envisage equating male and female participation rates. It is stereotypical that women have lower labour market participation rates than their male counterparts, which is mainly related to raising children and other caring obligations. In some countries, childcare can be so expensive that it is cheaper for a household to lose a salary than pay for childcare, irrespective of any other perceived (non-financial) benefits.

Table 8 breaks down the labour force participation rates by gender. There are some groups, such as high-skill working-age native-born workers in Sweden, known for its generous family leave policies, for whom there is not much difference between men and women. Still, these are the low-skill households, where the greatest differences can be found: as these are the dominant household groups, this offers a greater opportunity for potential policy interventions. The only instances that participation rates for women exceed those for men are for low-skill migrants in Sweden and high-skill migrants in Italy, in both case for the 65–74 age groups.

We break the analysis down into three parts so that we can establish the exact mechanisms in play. For each of the high-skill and low-skill segments, we equate the total working-age participation rates to that of the highest for that groups. For simplicity, we change the rates for native-born and foreign-born at the same time. Unemployment rates remain unchanged for simplicity, as the values do not differ hugely. Lastly, we combine the increase of both high- and low-skill groups, to indicate a theoretical gain in output.

In Table 9, the upper panel illustrates gains from increasing the high-skill participation rates to the maximum value for men and women. The second panel repeats the exercise but for low-skill participation rates, and the final panel modifies the high-skill and low-skill rates simultaneously. The motivation for the first two panels is to give an idea of where the largest gains lie. The results demonstrate that the largest gains can be found by activating the low-skill labour market, *especially* for Italy and Poland. For these countries, there is more than a 10% gain in the low-skill labour force which can result in substantial additional economic growth. This issue will become even more pronounced, as population ageing progresses.

### 3.4.2 Early retiree labour force participation

Increasing the participation rate of people aged 65–74 to match that of even the lowest rate of 15–64 is unachievable and unrealistic. What is plausible is that the rate of 65–74 is close to that of the age group for 55–74. This would be a mixture of those postponing retirement, as well as the reactivation of some retirees. The state pension age for the case study countries is 63 in Sweden, 65 years and 10 months in Germany, though will rise to 67 by 2031, 67 in Italy, and 65 for men and 60 for women in Poland. Even though all these pension ages all have variations such as minimum years of contributions, the

Table 8: Participation rates by gender, education level, age and country of birth

| Country | Skill level | | Natives | | Migrants | |
|---|---|---|---|---|---|---|
| | | | *WA* | *65–74* | *WA* | *65–74* |
| *Germany* | | | | | | |
| | High-skill | | | | | |
| | | Total | 92.7 | 19.9 | 82.5 | 22.1 |
| | | Male | 94.2 | 23.7 | 90.2 | 25.7 |
| | | Female | 90.7 | 15.0 | 75.4 | 18.1 |
| | Low-skill | | | | | |
| | | Total | 76.5 | 12.2 | 71.0 | 11.8 |
| | | Male | 79.0 | 14.8 | 80.5 | 14.6 |
| | | Female | 74.0 | 10.4 | 60.9 | 9.3 |
| *Sweden* | | | | | | |
| | High-skill | | | | | |
| | | Total | 93.2 | 26.0 | 90.4 | 21.9 |
| | | Male | 93.8 | 34.0 | 93.8 | 26.2 |
| | | Female | 93.0 | 20.4 | 87.4 | 17.3 |
| | Low-skill | | | | | |
| | | Total | 77.4 | 17.5 | 76.3 | 16.1 |
| | | Male | 80.4 | 22.0 | 83.1 | 15.6 |
| | | Female | 73.3 | 12.1 | 68.5 | 16.5 |
| *Italy* | | | | | | |
| | High-skill | | | | | |
| | | Total | 85.0 | 22.6 | 75.9 | 30.6 |
| | | Male | 87.4 | 31.6 | 89.8 | 29.0 |
| | | Female | 83.1 | 13.8 | 68.9 | 31.7 |
| | Low-skill | | | | | |
| | | Total | 60.0 | 7.1 | 69.2 | 21.7 |
| | | Male | 70.4 | 10.3 | 84.1 | 21.5 |
| | | Female | 48.6 | 4.2 | 55.5 | 21.4 |
| *Poland* | | | | | | |
| | High-skill | | | | | |
| | | Total | 91.7 | 20.6 | 85.0 | 35.3 |
| | | Male | 95.0 | 29.3 | 94.7 | 48.5 |
| | | Female | 89.4 | 13.4 | 75.7 | 18.3 |
| | Low-skill | | | | | |
| | | Total | 65.9 | 7.0 | 69.4 | 4.9 |
| | | Male | 74.8 | 10.0 | 78.5 | 8.3 |
| | | Female | 55.3 | 4.4 | 59.6 | 3.9 |

Source: Own calculation based on Eurostat data. WA denotes the main working age (15–64). High-skill is defined as ISCED 5-8, with low-skill values corresponding to ISCED 0-2 and 3-4. Participation (activity) rates are calculated using data from 2022 (authors' approximations). Rates are available for 15-64 and 15-74 age groups. Eurostat data have been used for sex, age, migration status and educational attainment level. We apply migration status to foreign born (first-generation) vs native-born. The source tables are Employment (`lfsa_egaisedm`), Employment Rates (`lfsa_erganedm`), Unemployment rate (`lfsa_urganedm`), and Population (`lfsa_pganedm`).

pension age is set to increase with increasing longevity, and for future generations there will be likely an increased dependency on private pensions.

Some jobs cannot be done by older workers, such as physical labour in construction,

Table 9: Potential Percentage Gains from Increasing Working-Age Participation

| | **DEU** | **SWE** | **ITA** | **POL** |
|---|---|---|---|---|
| *High-Skill Change* | | | | |
| GDP | 0.45 | 0.47 | 0.72 | 1.45 |
| Total Labour Gain | 0.99 | 1.08 | 1.22 | 1.75 |
| High Skill Labour | 3.02 | 2.29 | 5.02 | 4.61 |
| Low-Skill Labour | 0.00 | 0.00 | 0.00 | 0.00 |
| High-Skill Wage | -1.12 | -1.26 | -1.88 | -1.45 |
| Low-Skill Wage | 0.18 | 0.29 | 0.29 | 0.59 |
| *Low-Skill Change* | | | | |
| GDP | 0.95 | 0.66 | 4.40 | 3.39 |
| Total Labour Gain | 4.03 | 3.02 | 14.60 | 8.22 |
| High Skill Labour | 0.00 | 0.00 | 0.00 | 0.00 |
| Low-Skill Labour | 6.01 | 5.75 | 19.28 | 13.23 |
| High-Skill Wage | 0.43 | 0.47 | 1.97 | 1.60 |
| Low-Skill Wage | -0.11 | -0.12 | -0.31 | -0.64 |
| *High- and Low-Skill Change* | | | | |
| GDP | 1.40 | 1.13 | 5.13 | 4.86 |
| Total Labour Gain | 5.03 | 4.11 | 15.82 | 9.96 |
| High Skill Labour | 3.02 | 2.29 | 5.02 | 4.61 |
| Low-Skill Labour | 6.01 | 5.75 | 19.28 | 13.23 |
| High-Skill Wage | -0.70 | -0.80 | 0.05 | 0.12 |
| Low-Skill Wage | 0.07 | 0.16 | -0.02 | -0.07 |

Source: Authors' own calculation based on calibration and resulting changes.

which accounts for part of the contrast in the rates of decrease between high-skill and low-skill statistics. In some careers, however, there would be potential to transfer those workers' skills to a related job within the same field, such as supervision or education.

Table 10 shows the participation and unemployment rates of the ages 55–74 and 65–74. Our scenario involves keeping the working-age group calibration the same as in Table 6, but change the calibration for the retiree household to that for the 55–64 age group. For the 65–74 age group, the unemployment data reported to Eurostat are very close to zero. The unemployment rates for 55–74 year-olds in Poland are absent, the only values given are for total education and total or migrant status. We use the unemployment rate data from Czechia as a substitute as the total values are approximately the same (1.7% for Poland and 1.8% for Czechia, according to Eurostat data). That substitution is not perfect, but the demographic profiles of the two countries are plausibly similar.

The economic gains from increasing the labour force participation are evident from Section 3.4.1. A different set of policies would be required for increasing the participation rate of 'early retirees'. Providing free childcare, or childcare related policies would potentially have a knock on effect by way of reducing the need for grandparents in childcare. The role of this would be small, however, and if a grandparent wants to retire, then removing this childcare requirement would not necessarily lead them back to work in the absence of other incentives. Still, such policy instruments can be more positive, by incentivised work force participation for example through tax breaks, or more stringent, with more years of contributions being required to access the state pension (thus risking increasing inequality).

Table 10: Participation and unemployment rates for 55–74 and 65–74

| **Country** | **Skill level** | | **Natives** | | **Migrants** | |
|---|---|---|---|---|---|---|
| | | | *55–74* | *65–74* | *55–74* | *65–74* |
| *Germany* | | | | | | |
| | High-skill | | | | | |
| | | Participation Rate | 58.4 | 19.9 | 53.8 | 22.1 |
| | | Unemployment Rate | 1.6 | 0.0 | 3.8 | 1.3 |
| | Low-skill | | | | | |
| | | Participation Rate | 47.2 | 12.2 | 44.9 | 11.8 |
| | | Unemployment Rate | 12.4 | 2.0 | 8.5 | 3.7 |
| *Sweden* | | | | | | |
| | High-skill | | | | | |
| | | Participation Rate | 58.2 | 26.0 | 64.9 | 21.9 |
| | | Unemployment Rate | 2.6 | 4.4 | 8.9 | 13.5 |
| | Low-skill | | | | | |
| | | Participation Rate | 49.5 | 17.5 | 51.0 | 16.1 |
| | | Unemployment Rate | 3.6 | 3.5 | 17.1 | 5.1 |
| *Italy* | | | | | | |
| | High-skill | | | | | |
| | | Participation Rate | 60.3 | 22.6 | 59.2 | 30.6 |
| | | Unemployment Rate | 1.1 | 0.1 | 4.8 | 5.1 |
| | Low-skill | | | | | |
| | | Participation Rate | 31.9 | 7.1 | 53.2 | 21.7 |
| | | Unemployment Rate | 4.8 | 3.4 | 10.3 | 8.5 |
| *Poland* | | | | | | |
| | High-skill | | | | | |
| | | Participation Rate | 48.2 | 20.6 | 57.5 | 35.3 |
| | | Unemployment Rate | 0.6 | 1.3 | 0.6 | 1.3 |
| | Low-skill | | | | | |
| | | Participation Rate | 30.3 | 7.0 | 31.5 | 4.9 |
| | | Unemployment Rate | 2.4 | 3.6 | 2.0 | 3.7 |

Source: Own calculation based on Eurostat data. The ages listed are 55-74 and 65-75. The 65–74 are placed for comparison purposes only. High-skill is defined as ISCED 5-8, with low-skill values corresponding to ISCED 0-2 and 3-4. Participation (activity) rates are calculated using data from 2022 (authors' approximations), based on available rates for ages 15–64, 55–74 and 15–74. Eurostat data have been used for sex, age, migration status and educational attainment. We apply migration status to foreign born (first-generation) vs native-born. The source tables are Employment (`lfsa_egaisedm`), Employment Rates (`lfsa_erganedm`), Unemployment rate (`lfsa_urganedm`), and Population (`lfsa_pganedm`).

Trying to cover a whole range of proposed tax adjustment policies is too extensive for this report. Still, there is a consensus in several countries that the tax base needs reforming. Some of these policies focus towards the high-skill segment, who actually do have a higher participation rate. From the point of view of population ageing, it is important to examine how people build wealth to retire. Older age groups are more likely to hold investments, and thus be in receipt of dividends or hold a second property they rent out. For example, in the UK, 31% of people aged 55-64 own a second home, which could be either for personal use or rental purposes (UK Government, 2023). However, at the other end of the spectrum, nearly two million households headed by someone aged 55+ are living in poverty, which includes home owners[21]. As more people depending on private rentals move into the 'retiree' group, many will be forced to continue working to afford rents as they can take a large portion of the pension or any savings.

For average earners, the net (gross) pensions replacement rates are: 65.3% (62.3%) in Sweden; 55.3% (43.9%) in Germany; 82.6% (76.1%) in Italy; and 40.3% (29.3%) in Poland (OECD, 2023). The differences between net and gross replacement rates are the effects of social security and tax contributions, which are taken into account in the net measures, but not in gross ones. Inter-country comparisons are not simple and can be rather subjective, given the economic and demographic contrasts between the four case study countries, as well as within them. Given that the DSGE model focuses on a horizon of 20 quarters or 5 years, not much is expected to change to the pension systems as such, although for longer horizons, more pronounced changes can be anticipated.

Table 11 shows the production and labour market gains from the proposed increase in labour market participation of the older-age groups by country. The model has not been modified in any further way apart from the participation rates. The largest potential gain can be seen for Poland, which is a result of the older-age group having an especially low participation rate in comparison to the other countries. In contrast, the gain for Sweden is small due to the relatively high participation rates. The largest gains are seen in the low-skill labour force, which has the lowest participation rates across age categories. One explanation for this, is that low-skill workers are more likely to have manual jobs which can prohibit working to an older age even if the person would want to. Here, an opportunity for technological support (exoskeletons or similar) could extend the working

[21] Source: Centre for Ageing Better The State of Ageing 2023-24.

horizon while reducing the physical burden and health costs of work.

The gains in participation do not fully account for the real life effects of activating the older workers, as they can bring experience that would help improve productivity. In this model, the older worker are assumed to be similarly productive as the working-age ones. Table 11 also presents hypothetical values on wages, however, these can easily be distorted by capital-skill complementarity factors, or elasticity of substitutions. The increase in participation

Table 11: Potential Percentage Gains from Increasing Old-Age Participation and Employment Rates

| | **DEU** | **SWE** | **ITA** | **POL** |
|---|---|---|---|---|
| GDP | 2.26 | 1.88 | 2.47 | 3.04 |
| Total Labour Gain | 7.55 | 6.39 | 7.35 | 6.20 |
| High Skill Labour | 6.75 | 4.70 | 3.54 | 2.94 |
| Low-Skill Labour | 7.94 | 7.92 | 8.57 | 8.19 |
| High-Skill Wage | -1.92 | -1.92 | -0.47 | 0.05 |
| Low-Skill Wage | 0.26 | 0.42 | 0.07 | -0.03 |

The participation and employment rates of the older-age group are changed to that of 55–74 year-olds instead of 65–74. Source: Authors' own calculation based on mode calibration and resulting changes.

In these two calibration exercises, we have not set to equalise the labour market disparities between native-born and foreign-born workers. This is yet another way in which activity gains can be made: *brain waste* is a well-documented phenomenon, where migrants experience tougher labour market conditions than their native equivalent, and as a result, do not fully utilise their human capital (Barker, 2020). The calibrated data have shown differences between native-born and foreign-born groups, so if foreign-born workers were given the same labour market recognition as native-born ones, then their participation and employment rates could increase further.

### 3.4.3 Increasing automation levels

The steady-state analysis uses calibrated values from the labour market, as presented in the previous section. In this part of the analysis, we use country-specific labour market and production functions calibrated for each country. We then increase the values of automation levels by 10%, 25% and 50% for demonstration purposes. These hypothetical scenarios result in changes of the wage premium, modifying the elasticities of substitution, with the overall effects being country-specific. Particular focus of this part of the analysis is on Italy and Poland, due to the lower levels of automation and predicted greater labour market challenges associated with population ageing. Financing could come from private or public investment, whether international or domestic. Still, the purpose of this scenario is to illuminate the areas of possible gains, rather than trying to incorporate financing of the increased automation levels explicitly in the model.

In this part of the analysis, our focus is on production. Each column on Table 12 shows the percentage gain as a result of the respective increases in automation levels. As shown, there is greater gain the more existing robots there are already – a feature related to the calibration of the model. This is in part due to the increasing marginal returns from automation. The analysis in Section 4 provides an alternative analysis of automation levels. In this case, there are no changes to the labour force to be expected. There are also diminishing marginal returns at higher levels of automation, where the elasticity of substitutions would change, making the effect on wages somewhat irrelevant. The policy take-away from this exercise is an approximation of the extent to which increases in automation levels have the potential to boost the economy.

Table 12: Potential Percentage Gains from Increasing Automation Levels

| | **DEU** | **SWE** | **ITA** | **POL** |
|---|---|---|---|---|
| *10% increase* | | | | |
| GDP | 6.90 | 6.74 | 6.26 | 4.24 |
| High-Skill Wage | 3.05 | 4.73 | 2.79 | 2.00 |
| Low-Skill Wage | -0.40 | -0.99 | -0.40 | -0.76 |
| *25% increase* | | | | |
| GDP | 17.18 | 16.71 | 15.60 | 10.54 |
| High-Skill Wage | 7.39 | 11.56 | 6.78 | 4.89 |
| Low-Skill Wage | -0.92 | -2.29 | -0.92 | -1.78 |
| *50% increase* | | | | |
| GDP | 34.19 | 33.02 | 31.06 | 20.90 |
| High-Skill Wage | 14.12 | 22.38 | 13.00 | 9.45 |
| Low-Skill Wage | -1.63 | -4.09 | -1.65 | -3.23 |

The percentage gains for output (GDP), high- and low-skill wages at increase levels of 10%, 25% and 50%. Source: Authors' own calculation based on calibration and resulting changes.

# 4 Discussion and conclusions

The results of the analysis presented throughout this report suggest that all of our four case study countries, despite their demographic, economic and technological differences, have potential to benefit from increasing labour force participation, technologies, and migration. Here in particular, lowering the retirement age would be a backwards step for the economies, as it would lead to losing valuable members of the labour market. Conversely, increasing incentives for older workers to stay active, can be highly beneficial. There are of course also other implications, which are not represented in our DSGE models, and as such which go beyond the scope of the current study. They include the health service and social care provision, or government spending for the pensions. While it can be speculated that the future generations will be more dependent on private pensions than state pensions, these areas, and their interactions with labour markets and technological change, will require further research.

In our analysis, based on DSGE models studied through the lens of impulse-response functions, we used two complementary approaches: (i) exogenous increases to selected economic and demographic features, and (ii) evaluation of potential policy changes using the model's steady-state. The exogenous increases covered changes to productivity of input factors, relative size of migrant or old-age household sizes, and the economic effects of having endogenous automated production levels. We focused the analysis on total output, the labour market and automation levels. The results show that increases in automation levels are expansionary to the economy and not contractionary to employment levels in the low-skill sector.

In particular, the results presented in this report include a series of related scenarios that policy makers can consider. We have studied four countries that have different socio-economic and technological profiles. Sweden and Germany have more developed economies, labour markets, and high rates of automation, and some of the labour market challenges can be remedied by (re)activating workers across all age groups. Italy and Poland show some concerning signs regarding demographic and automation trends, both in the data and in the results of our modelling. Italy has high rates of automation, yet these can be largely considered to be industry-focused. Both countries have high forecast dependency ratios for the immediate future, until 2050 (as well as beyond). Italy's primary challenge is the activation of the labour market, whilst Poland has the demographic challenges as well as economic and technological ones.

In addition, Italy has a been a high(er) receiver of migrants for a while now, which offers only a short-run solution for labour market shortages. What is especially policy relevant in this case is the effect on Poland, which of the four case study is the furthest behind in the automation race. The governments who find themselves in similar scenarios, which are not limited to Central and Eastern European countries, have potentially unpopular choices to make: stay in the robot race to keep the future of the country aligned with international equivalents, or reject automation in the face of public perception, which risks the future sustainability of the country through an ageing population. Prior to the arrival of Ukrainian citizens under the temporary protection scheme, who are not included in the statistics used for model calibration, Poland had less than 1% of the 15-74 population born abroad, so the loss of population through ageing would require a dramatic shift to replace the 'lost workers'. The figures about the country's emigrants that might return in old-age is not easy to report.

One further takeaway from the steady state analysis, particularly in Sections 3.4.1 and 3.4.2 is that (re)activation of the labour market is key and probably the only longer-term policy solution. There are issues that pertain as to why raising labour force participation is difficult. For instance, low-skill workers might be physically unable to continue their jobs into older ages, since especially some demanding manual jobs can limit the length of a productive period in work. However, this does provide opportunity for technology to come in, in the form of e.g. exoskeletons or robots that take the manual load away from the workers, so that they can focus on their specific task. Various technologies can help offer different opportunities here.

With respect to skill, possible policy solutions can target either high- or low-skill workers. Together, there are insignificant effects on wages, but overall gains for the economy are possible. In reality, increasing either high- or low-skill segment will have knock-on effect of increasing the other one. High-skill workers need the support of low-skill workers to maximise the use of technologies, while expansion of the low-skill market and automation incentivises high-skill workers to maximise gains from their skills. If we take a standard production company, an increase in high-skill workers and complementary technology requires the increase in low-skill workers and robots to produce the good as supported by the calibration of the model. At the same time, an increase in the numbers of robots and low-skill workers can lead to increasing the demand for high-skill workers to manage work and maximise the use of the technology available.

There are various policy lessons that can be taken from our analysis. One that has not been address in much detail is the training of workers for modern technologies – providing skill match for new technologues. The structures of education systems are to change. If we have a limited workforce then training tomorrow's workforce can be targeted so that when these younger generations enter the labour market with appropriate skills to boost the economy and maximise production. As an (almost stereotypical) example, teenagers and young adults who have grown up with computers and smartphones, are perfectly capable of been delegated tasks by older relatives to sort out their phone problems. However, this does not translate as well to meeting the challenges of the labour market in terms of digital skills, such as programming or use of specialised software. If we take the opportunities to train teenagers the skills they need from an earlier age then a gap between leaving school and being useful to the labour market can be shortened. It might seem to be a complex or overly ambitious overhauling of the education system, but small steps can be taken. This will help to solve some of the labour market issues at both the high-skill and low-skill levels. If we consider labour markets, this type of modification would improve matching of jobs and workers, and increase employment rates. This is a further step to reducing long-term dependency on migration.

The premise of this paper was to evaluate specific solutions to address the challenges of population ageing, with focus on migration and job automation problem. As stated before (Barker and Bijak, 2024*a*), migration can fill gaps in the labour market but a constant increased and *guaranteed* flow is required to do this. Eventually, the source of migrants would diminish, leading to international competition for workers and human capital. At the same time, robots, or automation capital, even when perfectly substituting human workers, would require a lot of investment in the technology to keep up with the requirements. At the same time, there do not seem to be significant threats to wages, as is constantly perceived. Of course, to promote the use of robots, governments have to be cautious in their approach, convincing voters that robots are not out there to take their jobs. Rather, a more nuanced argument for automation is needed, recognising the complexity of modern economies and societies.

With all the caveats regarding the theoretical nature of the presented models, and the limitations of the conclusions that can be drawn from them, our research confirms the proposition that robots can help boost the economy, but are not always a sufficient solution, and certainly not *the only*. Specific types of robots can help boost productivity of work, they will not resolve the challenges of ageing, and certainly not in the near future. Since some of the solutions considered, such as migration, offer only temporary (transient) effects, (re)activating the workforce is an essential element of any reasonable policy mix. This is especially important for the countries that will have significantly smaller workforce over the next two decades. Fully utilising the potential of the existing population, including older workers, which provides the source of necessary labour and human capital, coupled with making the most of the technological change, offers the easiest way of providing necessary economic conditions for the future societies to flourish.

# References

Adjemian, S., Juillard, M., Karamé, F., Mutschler, W., Pfeifer, J., Ratto, M., Rion, N. and Villemot, S. (2024), Dynare: Reference Manual, Version 6, Dynare Working Papers 80, CEPREMAP.

Ali-Yrkkö, J., Seppšlä, T., Nikulainen, T. and Pajarinen, M. (2010), *Nokia and Finland in a Sea of Change*, Taloustieto Oy, Helsinki.

Australian Productivity Commission (2006), Economic Impacts of Migration and Population Growth, Technical Report 20.

Barker, E. R. (2020), The Migrants' Plight: A Skill-Job Mismatch. Brain Waste in Canada, Technical report, The University of Sheffield.

Barker, E. R. and Bijak, J. (2024*a*), Can robots and migration help address the challenges of ageing? Specification and initial analysis of dynamic model for examining policy resilience, FutuRes Project Deliverable D4.1, University of Southampton, Southampton.

Barker, E. R. and Bijak, J. (2024*b*), 'Mixed-frequency VAR: A new approach to predicting and analysing future migration in Europe using macroeconomic data', *Data & Policy* **Forthcoming**.

Batalova, J., Fix, M. and Bachmeier, J. D. (2016), 'Untapped Talent: The Costs of Brain Waste among Highly Skilled Immigrants in the United States', *World Education Services* .

Dolado, J. J., Motyovszki, G. and Pappa, E. (2021), 'Monetary Policy and Inequality under Labor Market Frictions and Capital-Skill Complementarity', *American Economic Journal: Macroeconomics* **13**(2), 292–332.

Dustmann, C., Glitz, A. and Vogel, T. (2010), 'Employment, wages, and the economic cycle: Differences between immigrants and natives', *European Economic Review* **54**(1), 1–17.

Hasell, J. (2023), 'Measuring inequality: What is the gini coefficient?', *Our World in Data* . https://ourworldindata.org/what-is-the-gini-coefficient.

Hierlaender, R., Huber, P., Iara, A., Landesmann, M., Nowotny, K., O'Mahony, M., Peng, F., Robinson, C. and Stehrer, R. (2010), Migration, Skills and Productivity, wiiw Research Reports 365, The Vienna Institute for International Economic Studies, wiiw.

Huber, P., Landesmann, M., Robinson, C. and Stehrer, R. (2010), 'Migrants' skills and productivity: A european perspective', *National Institute Economic Review* **213**, R20–R34.

Kangasniemi, M., Mas, M., Robinson, C. and Serrano, L. (2012), 'The economic impact of migration: productivity analysis for Spain and the UK', *Journal of Productivity Analysis* **38**(3), 333–343.

Leduc, S. and Liu, Z. (2019), Robots or Workers? A Macro Analysis of Automation and Labor Markets, Working Paper Series 2019-17, Federal Reserve Bank of San Francisco.

Leduc, S. and Liu, Z. (2020), Can pandemic-induced job uncertainty stimulate automation?, Working paper series 2020-10, Federal Reserve Bank of San Francisco.

Merz, M. (1995), 'Search in the labor market and the real business cycle', *Journal of Monetary Economics* **36**(2), 269–300.

Nam, H. and Portes, J. (2023), Migration and Productivity in the UK: An Analysis of Employee Payroll Data, IZA Discussion Papers 16472, Institute of Labor Economics (IZA).

OECD (2023), *Pensions at a Glance 2023*.

Resolution Foundation & Centre for Economic Performance, LSE (2023), Ending stagnation: A New Economic Strategy for Britain, Technical report, Resolution Foundation.

Thuemmel, U. (2018), Optimal taxation of robots, Working Papers 7317, CESifo.

UK Government (2023), English Housing Survey 2021 to 2022: second homes - fact sheet, Technical report, Department for Levelling Up, Housing & Communities.
**URL:** *https://www.gov.uk/government/statistics/english-housing-survey-2021-to-2022-second-homes-fact-sheet/english-housing-survey-2021-to-2022-second-homes-fact-sheet*

# Appendix

## International labour market and automation comparison

In Section 3.4, we examined at a set of steady-state changes and hypothetical gains or losses to the economy. In an additional steady-state exercise, we use the baseline calibration of Germany, while changing labour market demographics and specific automation levels. Across different countries, the elasticities of substitution and parameters of the production function (to target the skill wage premium) vary, but for the purpose of this thought experiment, we use the German calibration results to benchmark all of the model parameters[22].

Table A.1 shows the aggregate employment rates, aggregate participation rates, robots per 10,000 workers, and percentage reduction in robots levels compared to Germany. These indicators lay the foundations for explanations relative to results of the calculations in Table A.2. Aggregate participation and employment rates refer to the total population, whereas earlier figures have been for specific households. These figures include foreign- and native-born populations together, for all age groups under observation (15–74). In this scenario, Sweden has the highest participation and participation rates, followed by Germany, with Poland significantly lower, and Italy lower still. A near 17% change from Sweden to Italy for employment rates, and similarly to Germany. This includes all type of employment hours – full and part time.

The *employment* rate is one indicator that helps policy makers outline some issues. In the household-specific analysis, it is easy to miss this 'lost' workforce. If we look at Italy, nearly *half* of this population are not employed: half of the 15–74 population is trying to support the economy for the young-population (0–14) *and* old-age population (75+). This is clearly unsustainable, especially given the indicators in Table 2. There are legitimate reasons for some people in this age group would be inactive, such as education, which is especially important for the future of high-skill workers, or long-term illness, but structural changes are required to fix this gap. Increasing employment rates is not a simple

[22]The authors are aware that this is a highly hypothetical situation with no adjustments being made for international comparison and as such is only be used for demonstration purposes.

fix in the short run, as investment in education (both for younger and older workers) is required to create additional jobs. Further discussions on this are beyond the scope of this paper but lays the foundation for changing to country specific labour market levels (see Scenarios 1 and 2 in Table A.2).

This paper has placed a large focus on the use of robots. Table A.1 repeats the numbers of robots per 10,000 workers, which are expressed as the percentage difference to Germany. Even though the relationship between robots and workers is up for debate (substitutes or complements), this exercise illustrates the aggregate rate change. The composition of the economy means that the same levels of automation are not necessary but as the number of jobs that robots can do expands, this will increase the number of robots employed. The differences in the numbers of robots lay the foundations for Scenarios 2 and 3 presented in Table A.2.

Table A.1: Steady State Analysis - Labour Market and Robots

| **Country** | **Agg Emp Rate (%)** | **Agg Partic Rate (%)** | **Robots per 10,000 workers** | **% Change in robots** |
|---|---|---|---|---|
| Germany | 67.7 | 69.9 | 397 | |
| Sweden | 68.9 | 74.5 | 321 | -19% |
| Italy | 52.2 | 56.8 | 217 | -45% |
| Poland | 61.2 | 63.0 | 63 | -84% |

Source: Authors' own calculation based on Eurostat data. The specific tables are Employment (`lfsa_egaisedm`), Employment Rates (`lfsa_erganedm`), Unemployment rate (`lfsa_urganedm`), and Population (`lfsa_pganedm`). Robots per 10,000 workers is gathered from IFR for the 2021 values.

The first scenario in Table A.2 uses the respective country's labour market calibration with the same automation level as Germany, thus all changes have to do with the number of workers employed. The second column shows the value of output with the following one showing the percentage change in output compared to Germany as a result of the labour market changes. From this, we see that the aggregate employment rate, or rather increased employment, produces an increase in output for Sweden. Sweden's labour market has a 1.2% higher employment rate than Germany; as such, this counterfactual scenario would result is a 3.2% increase in GDP. The increase in relative share of high-skill workers, as well as higher employment rates, explains the gains.

For Italy and Poland, with lower employment rates (and higher shares of low-skill labour), there is a reduction in output. Italy has an employment rate difference of 15.5%

which would hypothetically see a 9% reduction in GDP. There is a 6.5% employment rate decrease from Germany to Poland which results in a 2% reduction in output. Unsurprisingly, higher employment levels equate to higher production, and for every 1% fall in aggregate employment rates leads to a less than 1:1 percentage change (except in Sweden, which has proportionally more high-skill workers). As a small illustration, Sweden has a high-skill migrant share population of 8.9% (as per Table 6), while Italy has a high-skill native population share of 13.8%. Italy has a low-skill population share of 83.2%, to Germany's 71.7%, Poland's 72.4% and Sweden's 60.1%. High-skill workers are more productive, so contribute more to the economy, as measured by GDP per capita.

Table A.2: Steady State Analysis - Change to Output

| **Country** | **Scenario 1** | | **Scenario 2** | | **Scenario 3** | | |
|---|---|---|---|---|---|---|---|
| | $A^j = A^G$ | **wrt DEU** | $A = A^j$ | **wrt DEU** | $A^j = A^j$ | **wrt S1** | **wrt DEU** |
| Germany | 3.1901 | | 3.1901 | | 3.1901 | | |
| Sweden | 3.2907 | 3.2% | 2.753 | -13.7% | 2.8513 | -16.3% | -10.6% |
| Italy | 2.903 | -9.0% | 2.1722 | -31.9% | 1.9182 | -25.2% | -39.9% |
| Poland | 3.1274 | -2.0% | 1.261 | -60.5% | 1.1827 | -59.7% | -62.9% |

Calibrated steady state value of production output (or GDP) for the selected countries with Germany as the baseline calibration. Scenario 1 use the calibrated model for Germany and the automation level of Germany with the labour market variables specific to country $j$. The variables include population share, participation (activity) rates and unemployment rates - the percentage change is calculated with respect to Germany. Scenario 2 uses the steady state labour market and calibration of Germany but the change of automation level to that of country $j$ - the percentage change is calculated with respect to Germany. Scenario 3 uses the labour market variables and automation level of the individual country automation level with that of country $j$. The first percentage change calculation is the change in automation levels from the steady state value calculated in scenario 1. The second percentage change is relative to the steady-state level of Germany. Source: Own calculations.

The second scenario combines the features of German labour market with country-specific automation level so the changes in output are only to do with number of robots. The calibration shows the effect of having lower automation levels, as the labour market is benchmark to Germany's. The production function is complex, and there are no changes in the elasticity of substitution, but a 19% reduction in automation gives a 13.7% reduction in output (Sweden), 45% reduction in robots gives a 32% reduction in output (Italy), and an 84% reduction in robots – a 60.5% reduction in output (Poland).

In the third scenario, we combine the effects of a change in labour market status *and* change in automation levels in the German calibrated production function. We report the two percentage changes, (i) the effect of the change of automation levels after the change in labour market as used in Scenario 1 (column 'wrt S1'), and (ii) the total change with respect to Germany (column 'wrt DEU'). This explains why the net change in Sweden is smaller in total, gain from employment but loss from robots.

We compare the given country's output for the same automation level as Germany's, with that country's own calibrated labour market (Scenario 1), to the automation level of country a given country. For Sweden, there is 16.3% loss from the small gain made from employment to the loss of robots. The combined effects mean a 10.6% output loss in this hypothetical scenario. Italy and Poland have lower employment levels and lower robots levels, so the total losses are sizeable. Italy's lower employment levels than Poland made the drop in Scenario 1 higher, but the compensation of a smaller level of robots results in an overall smaller loss with respect to Germany. Poland's massive problem in this set up is that they have 63 robots per 10,000 workers to Germany's 397. The real world economies have different structures that aren't reflected in a DSGE model, however, the countries have approximately the same low-skill population ratio to Germany but Germany have an 'extra' workforce in robots. Italy's robots per 10,000 workers is above the EU average but lags behind the leaders in Europe and the world. Changing the levels of automation has impacted Poland and Italy to an even greater extent, as shown in Table A.2.

The third scenario combines the German labour market calibration with the respective country's automation levels. The calibration shows the effect of having lower automation levels, as the labour market is benchmark to Germany's, but with a given country's automation level. The production function is complex and there are no changes in the elasticity of substitution, but a 19% reduction in automation gives a 13% reduction in output (Sweden), 45% reduction in robots gives a 32% reduction in output (Italy), and an 84% reduction in robots results in a 60% reduction in output (Poland).

These startling figures bring into sharp focus the challenges that countries across the EU (and developed world more broadly) are facing. A reduction in the labour force has a contractionary effect on the economy, and while robots are an option, they are not going to replace workers completely. There is no quick fix, and as seen from the analysis presented throughout this report, migration on its own is also not a solution to the challenges of ageing, while investment in robotics at scale may remain too expensive for some countries to be achievable.