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Artificial Intelligence and income inequality in Ireland

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Abbreviations

AI	Artificial intelligence
AIOE	AI occupational exposure
C-AIOE	Complementarity-adjusted occupational exposure
ISCO	International Standard Classification of Occupations
JRC	Joint Research Centre (of the European Commission)
LLM	Large language model
LMA	Labour market adjustment
PP	Percentage point
SILC	Survey of Income and Living Conditions
SOC	Standard Occupation Classification system

Executive summary

Artificial intelligence (AI) is advancing quickly and is beginning to reshape the kinds of work people do, how incomes are earned, and the balance between labour and capital in modern economies. For Ireland, a country with a highly educated workforce and a strong technology sector, AI adoption presents a unique challenge and opportunity. This report explores what AI adoption could mean for Irish households, for the distribution of income, and for public finances over the short- to medium-term. Using evidence from international research, we simulate a range of plausible scenarios for AI adoption and its effect on employment, wages and capital income. Linking these scenarios to the Irish tax-benefit system using SWITCH, the ESRI's microsimulation model, we investigate the potential distributional effects of AI adoption in Ireland.

Unlike previous waves of technological change, AI tends to place higher earning and highly educated workers at greater risk of disruption, because the occupations most exposed to AI are predominantly in these groups. In our central scenario – drawn from credible international estimates – around 7 per cent of current jobs could be displaced in the short–medium run. Those most likely to experience this disruption are found in higher income households, where the share of workers transitioning into unemployment is substantially larger than in lower income families.

For those who remain in work, AI is expected to increase productivity. We estimate that workers who are not displaced may see modest but broadly shared wage gains. These gains are not large enough to counterbalance the average fall in income due to job displacement. Increases in returns to capital as a result of AI adoption, while modest in percentage terms, benefit households at the very top of the income distribution, where the vast majority of Ireland's capital income is concentrated.

When these effects are combined, we find an average decline in household disposable income as a result of AI adoption. The largest average losses are experienced by middle and higher income households, for whom job displacement outweighs any wage or capital income gains. Lower income households also lose, but by much less. Ireland's tax and welfare system absorbs most of the income loss for lower income households, and roughly half of the loss for households at the top of the income distribution. Income inequality, measured by the Gini index, rises moderately in every scenario we examine due to the polarising effect of job losses and wage and capital income increases on the income distribution.

The implications for the public finances are also substantial. If employment losses are relatively small and productivity gains are realised, AI adoption could boost Exchequer revenues. But if job displacement is sizeable, tax receipts fall while welfare spending rises, resulting in potentially large pressures on the public finances.

These findings underline the importance of forward-looking policy. AI has the potential to increase productivity and living standards, but only if the workforce is equipped with the skills needed to use it effectively or to transition into roles that are less exposed. Ireland's high levels of educational attainment offer a strong foundation, but targeted educational support will be essential, particularly for older workers or those with lower formal qualifications. Investment in lifelong learning, retraining and programmes that help workers shift into AI-complementary or currently under-supplied occupations will be crucial.

Beyond the labour market, our analysis highlights the need to consider the future resilience of Ireland's tax base. If AI accelerates the shift from labour income to capital income, the current heavy reliance on labour taxation may become increasingly difficult to sustain. Broadening the tax base and strengthening taxation of wealth and capital may become necessary to ensure the long-term stability of public services and welfare supports.

Although the long-term effects of AI remain uncertain, Ireland is well placed to benefit from the opportunities it brings – but only if the risks are managed carefully. AI adoption will create winners and losers, at least in the short to medium term. Policymakers will need to steer this transition in a way that supports displaced workers, protects the living standards of vulnerable households and ensures that the gains from AI contribute to inclusive and sustainable economic growth.

Chapter 1

Introduction

This paper falls into a small but rapidly growing literature that considers the potential effects of AI technology on employment, income and income inequality. So far, the evidence is mixed, ranging from predictions of a jobless future, with almost universal replacement of human workers by AI (Susskind, 2020), to more positive outlooks of increased human creativity, productivity and economic growth as workers are freed from time-consuming and repetitive tasks (Gonzales, 2023; Fan and Liu, 2021). In this paper, we consider how AI is likely to affect income inequality through the channels of employment, wages and returns to capital.

We focus on Ireland, a country with an exceptionally high level of tertiary education among its workforce and a strong ICT sector (Conefrey et al., 2023). These factors make Ireland well placed to become a rapid adopter of AI technology in the workplace. Ireland is also a country that already has relatively high market income inequality although substantial redistribution is performed through the tax–benefit system (Roantree and Barrett, 2024).

The flexible nature of AI makes it a general purpose tool, lending itself to a wide variety of both predictive and generative applications across many industries (Goldfarb et al., 2023). Similar to previous general purpose technologies, AI can have adverse effects on employment by replacing human workers – the 'displacement effect' – while simultaneously augmenting certain workers' productivity and creating entirely new occupations – the 'reinstatement effect' (Acemoglu and Restrepo, 2018). The productivity-enhancing effects of AI could increase the wages of those who remain in the labour market and are exposed to it (Aghion and Bunel, 2024; Acemoglu, 2025). An increase in the relative share of capital income in national income as a result of AI adoption could also increase the return to capital for holders of capital. These contrasting channels will have heterogeneous effects across the income distribution, creating winners and losers with potentially significant consequences for income inequality, and corresponding challenges for policy.

AI-driven employment and wage changes are unlikely to be evenly distributed across occupations or income levels. Unlike previous technological revolutions, such as robotisation, the exposure of occupations to AI is positively correlated with the education level required for the occupation (Felten et al., 2021; Eloundou et al., 2024). Williamson et al. (2024) use the complementarity-adjusted AI occupational exposure (C-AIOE) index of Pizzinelli et al. (2023)[1] to identify occupations in Ireland most exposed to AI. They find a positive correlation between AI exposure and earnings in Ireland.

The literature on the causal effects of AI exposure and adoption on employment and wages is scarce due to the relatively recent trend towards AI adoption, the lag in publishing relevant survey data and the scarcity of available instruments or control groups for causal analysis. For this reason, we choose a scenario-based approach to estimating the effect of AI adoption on income inequality. The available empirical estimates are mixed and described in more detail in section 3. From these, we choose a central scenario based on the work of Briggs and Kodnani (2023). The authors estimate that 7 per cent of current US employment could be substituted by AI[2] and that those remaining employed could see a wage increase of 2.6 percentage points (pp).[3] We distribute this employment and wage shock across ISCO two-digit level occupations according to their relative exposure to AI, measured by the C-AOIE index. We also introduce an increase of 0.4 pp in the return to capital income, as suggested by Cazzaniga, Pizzinelli, et al. (2024), reflecting the likely shift between capital and income shares in national income discussed by Bastani and Waldenström (2024).

These job losses, wage increases and capital income increases are introduced into the Survey of Income and Living Conditions (SILC), which is linked to SWITCH, the ESRI's microsimulation model for Ireland. SWITCH models the Irish income distribution, taking full account of the tax–benefit system and its interaction with individual level characteristics such as employment and earnings.[4] We create AI-adjusted counterfactual earnings distributions for Ireland and, using SWITCH, we re-calculate household disposable income by applying the Irish tax and welfare system to the counterfactual earnings distribution.

Results from our central scenario indicate that AI adoption will decrease household disposable income as employment losses outweigh wage and capital income gains. This will result in an increase in the Gini index as the income distribution becomes more polarised. Expanding the analysis to include a range of potential scenarios, we confirm that, in all scenarios considered, higher income households are more affected by AI-induced

1 This measure was created by Pizzinelli et al. (2023) building upon the AI exposure index originally developed by Felten et al. (2021).

2 This is based on the assumption that all jobs for which at least 50 per cent of tasks are exposed to automation will be substituted by AI.

3 This is the median wage change estimate of a number of studies surveyed by the authors.

4 Like most survey datasets, SILC does not adequately capture the top 1 per cent of the income distribution (Callan et al., 2020). This may result in underestimates of capital income in particular.

labour market changes than low-income households. However, there are some scenarios in which average changes to disposable income are zero and the cost to the public finances is minimal.

The remainder of this paper is organised as follows. Section 2 reviews the existing literature on the labour market and distributional impacts of AI adoption. Section 3 outlines our methodology, including how we measure occupational exposure to AI, construct adoption scenarios and implement these shocks using microsimulation. Section 4 presents the results, documenting the estimated effects of AI adoption on employment, wages, capital income, household disposable income and inequality, as well as implications for the public finances. Section 4.5 concludes by outlining the policy implications of our findings.

Chapter 2

Literature review

Historically, the adoption of general purpose technologies has been linked to rising wage inequality as middle-income, routine jobs are replaced, pushing workers into low-income jobs, and productivity among high-income workers increases (Autor et al., 2003). The wave of automation experienced by European countries over the last two decades followed this pattern but the resulting increase in wage inequality did not translate into an increase in household income inequality. Doorley et al. (2023) found that the effect of automation on inequality in household income was muted by household risk-sharing, and tax and welfare policies that largely absorbed wage and employment shocks caused by automation.

AI is likely to affect a different occupation and income cohort to those affected by previous technological revolutions. Workers' exposure to AI, measured by the capacity of AI tools to perform an occupation's tasks, is positively correlated with education and income (Felten et al. (2023), Eloundou et al. (2024), Webb (2019), Williamson et al. (2024)). This means that, in contrast to previous periods of technological change, AI could primarily affect highly educated and high-income workers. While high-income workers are the most exposed to AI, they also have the largest potential productivity gains from AI complementarity, making the overall effect of AI on wage and income inequality ambiguous (Cazzaniga, Jaumotte, et al., 2024; Klinova and Korinek, 2021).

As AI technology continues to develop and become more widespread, the body of literature on the impact of AI is growing. However, aggregate-level empirical evidence remains limited (OECD, 2023; U.S. Bureau of Labor Statistics, 2022; Maslej et al., 2025). There is strong evidence that AI adoption has accelerated in many countries in recent years (see Rammer et al. (2022) for Germany; Cho et al. (2023) for Korea; Zolas et al. (2020) for the US; Eurostat (2024) for the EU and McKinsey (2025)). Many studies also report growing demand for AI skills at the firm level (Acemoglu et al., 2022; Alekseeva et al., 2021; Borgonovi et al., 2023). Firms that adopt AI tend to be larger, grow more, pay higher wages and see larger increases in sales (Babina et al., 2024; Alekseeva et al., 2021; Calvino and Fontanelli, 2023). Recent reviews of existing literature on AI exposure and the labour market report that, although growing AI exposure is widely acknowledged, varying methodologies and data set sizes often yield divergent and contradictory conclusions regarding its effect on the labour market (Ghosh et al., 2025;

Zhou et al., 2025). The literature has yet to build any broad consensus on the impacts of AI on employment, wage and income inequality. Furthermore, the effects of AI on employment are heterogeneous between countries, with evidence that positive employment outcomes are concentrated in countries with higher levels of innovation (Freire, 2025; Guarascio and Reljic, 2025). Brynjolfsson et al. (2021) suggest that the effects of AI adoption may also be systematically underestimated in the short to medium term, as AI requires large investments in new business strategies and human capital, which national accounts can struggle to capture.

Several studies point to AI adoption increasing worker and firm productivity (Briggs and Kodnani, 2023; Wu et al., 2024; Duran-Vanegas and Tuda, 2025). Eloundou et al. (2024) find that around 15 per cent of worker tasks in the US could be completed significantly faster with access to a large language model (LLM)[5]. This figure grows to 47–56 per cent of tasks with the incorporation of software built on LLMs. In particular, research has noted that the use of AI can reduce the productivity gap between high skill and low-skill workers. Studies of AI introduction in settings such as programming (Peng et al., 2023), writing tasks (Noy and Zhang, 2023), customer support (Brynjolfsson et al., 2025) and taxi driving (Kanazawa et al., 2025) observe an increase in the productivity of low-skill workers following AI adoption. These results contrast with research on previous computer technology, which was generally found to disproportionately benefit high skill workers (Akerman et al., 2015; Taniguchi and Yamada, 2022; Bresnahan et al., 2002). Such shifts in the productivity gap have the potential to reduce in-occupation wage-driven inequalities.

Research examining the effects of AI on wage and income inequality is relatively sparse due to the difficulty in isolating the causal effect of AI exposure or adoption on labour market outcomes. Most studies focus on wage inequality rather than household income inequality, although the evolution and distribution of household income has greater relevance for policymakers, who use measures of household disposable income to track household living standards, income inequality and poverty rates. Based on an empirical study of data from listed companies in China from 2014 to 2022, Wu et al. (2024) found that AI increased the wage of regular employees through productivity gains and job restructuring, and, as a result, reduced wage inequality between executives and regular employees. Rockall et al. (2025) examine the channels through which AI adoption might affect income inequality in the UK and conclude that AI could reduce wage inequality through the displacement of high-income workers. However,

5 ChatGPT and Copilot are examples of commonly used LLMs.

they warn that high-income workers could also gain from wage changes due to the complementarity of their occupations with AI. The findings of Webb (2019) for the US are similar, with the author estimating that AI adoption will reduce the 90:10 measure of wage inequality, with the caveat that the top 1 per cent would be unaffected. On the other hand, theoretical arguments posit that AI adoption has the potential to increase wage inequality through a rise in the skill premium (Grant and Ungor, 2024).

Among the studies that examine the effect of AI on income inequality, there is little consensus. A study of cities in China found that as the development of AI crossed a threshold into more general purpose technology, it progressively exacerbated income inequality, but that high education levels inverted this relationship (Mao et al., 2025). Khan et al. (2025), in a panel data study of the G7 economies, find that AI reduces income inequality while Pulkka and Simanainen (2022) simulate two scenarios for digital transformation in the EU and the UK, finding that the pessimistic scenario would increase income inequality while the optimistic scenario would slightly decrease it.

Beyond the impact of AI-induced employment and wage changes, income inequality could be further affected by the increasing capital share of income as employers replace labour with AI (Acemoglu, 2025). Liu and Liang (2025) report that increased returns to capital following AI adoption exacerbated short-term wealth disparities, although outcomes varied over the longer term. Acemoglu and Restrepo (2018) highlight how tax policies in many Western states, which tend to subsidise capital and tax employment, encourage AI adoption beyond a socially optimal level. In a study of the adoption of AI among US firms, Babina et al. (2024) raise concerns around restricted access to the large, firm-owned consumer datasets needed for training AI tools (see also Farboodi et al. (2019); Mihet and Philippon (2019)). This could result in AI technology creating an inequality inducing feedback loop of growth, increasing industry concentration and the emergence of 'superstar' firms (Autor et al., 2020). As such, tax–benefit systems could have an increasingly vital role to play in redistributing productivity gains and absorbing market shocks (Korinek and Stiglitz, 2019; Doorley et al., 2023). In particular, Bastani and Waldenström (2024) emphasise how progressive capital taxation could reduce inequality caused by AI widening the gap between workers and capital owners in a high-displacement scenario.

Chapter 3

Methodology

There are four distinct stages to our methodology, each of which is described in detail in this section. First, we measure the exposure of occupations in Ireland to AI. Second, we draw on the existing literature to develop a central scenario for how aggregate employment, wages and returns to capital might change in the short to medium term in response to AI adoption. Third, we combine the measure of occupational exposure to AI with the AI-driven shock to employment, wages and capital income in each scenario to model how the shock would be distributed at the micro level. Fourth, using microsimulation, we estimate how the distribution of household disposable income would change as a result of this AI adoption scenario in the short to medium term.[6]

3.1 Measuring AI exposure

AI is adept at performing non-routine tasks, such as image recognition and translation, which could previously only be carried out by humans. Occupations consisting of tasks that can be efficiently and reliably performed by AI technology are thus at risk of replacement. Exposure to advancements in AI is heterogeneous across occupations, with some roles, particularly those that are customer-facing or physically demanding, facing little risk of substitution.

Due to the rapid development of AI tools, together with variation of duties within occupations, estimating an exact probability for the substitution of a particular job by AI is difficult. However, various methods have been developed by decomposing occupations into a collection of human-performed tasks and linking these to AI applications (such as image generation or language modelling). These occupational tasks (such as oral expression or hand–eye coordination) are typically identified from the O*NET database developed by the US Department of Labour. Jobs that mostly consist of tasks easily performed by AI are then considered to be at elevated risk of substitution.

Felten et al. (2021) propose the AI occupational exposure (AIOE) index to directly measure this risk. The AIOE value for occupation i is constructed as:

6 Specifically, one year after the employment shock, after contributory unemployment benefits are exhausted and assuming no re-allocation took place.

$$AIOE_i = \frac{\sum_j A_j \cdot L_{ji} \cdot I_{ji}}{\sum_j L_{ji} \cdot I_{ji}} \tag{3.1}$$

where k indexes the AI application and j indexes the occupational ability. $A_j = \sum_{k=1}^{10} x_{jk}$ is the total exposure of occupational ability j to AI applications k. L_{ji} is the prevalence of ability j in occupation i, while I_{ji} is the importance of that ability. Thus, $AIOE_i$ is an average exposure to AI of the tasks performed in occupation i, weighted for their relative importance and prevalence in that occupation. In total, 52 abilities are taken from the O*NET database; these are then linked to relevant occupations. The ability of 10 AI applications to perform these occupational tasks was based by Felten et al. (2021) on the responses to a crowd-sourced survey of Amazon Mechanical Turk gig workers.

It is important to note that this index is merely a measure of exposure. It does not distinguish between AI's ability to perform a given task or augment the productivity of the worker performing the task. Additionally, the AIOE index is a relative measure. A high AIOE score does not indicate that an occupation is likely to be replaced by AI. It instead means that the occupation is relatively more likely to be replaced than one with a low score.

Another widely discussed effect of AI adoption is the potential productivity gains, which may increase demand for certain occupations, (partially) off-setting the possibility of replacement. To account for the ability of AI to exist alongside and augment human staff in the workplace, Pizzinelli et al. (2023) developed a complementarity measure θ_i. This measure considers the 'physical and social factors that influence the nature of work', as well as level and duration of training and education needed for a given occupation i. These physical and social factors are taken from O*NET's 'work contexts' section and include responsibility for the health of others, exposure to outdoor environments and face-to-face communication. Occupations in which these factors are important are more likely to make use of AI as a tool to assist, rather than replace, existing staff, due to concerns about errors, ethics, decision-making or customers' preference for human communication. The duration of education needed for a given occupation is accounted for in this measure to reflect the fact that occupations that involve lengthy training periods have more scope to implement training in AI tools. This is measured in O*NET's 'job zone' values. Like the exposure score, the complementarity score is relative in nature.[7].

7 The occupation estimated to have the least AI complementarity is Sewing machine operators (θ_{MIN}= 0.31).

Pizzinelli et al. (2023) adjust the AI exposure score $AIOE_i$ for occupation i for that occupation's potential AI complementarity, θ_i, as follows:

$$C\text{-}AIOE_i = AIOE_i * (1 - (\theta_i - \theta_{MIN})) \quad (3.2)$$

Thus, occupations that have higher AI complementarity have a reduced exposure score.

An alternative AI exposure index was developed by Tolan et al. (2021). The index, similar to that of Felten et al. (2021), uses the O*NET database to account for occupational-level cognitive abilities, but is developed for European countries. It combines general tasks from the European Working Conditions Survey, the Survey of Adult Skills and the O*NET database. Abilities are then linked to 328 AI-related benchmarks that track progress in AI technologies. We use the C-AIOE index for our main analysis but check the sensitivity of our results using the index of Tolan et al. (2021).

3.2 Creating AI adoption scenarios

We create a central scenario for how the adoption of AI could affect labour market and market income aggregates in the short term. This is based on research by Briggs and Kodnani (2023) who estimate that 7 per cent of current US employment could be substituted by AI under the assumption that all jobs for which at least 50 per cent of tasks are exposed to automation will be substituted by AI. We also use the 2.6 pp growth in annual worker productivity suggested by the authors, which is the median wage change estimate for a number of studies that they survey. This scenario could be considered an upper bound as the employment effects are larger than those estimated by Acemoglu (2025) (0.9-1.1%) and the wage increase is higher than that estimated by McKinsey (2025) (0.35%).[8] We test the robustness of our findings to a range of scenarios around this central one.

3.3 Implementing the AI adoption shock at the micro level

Williamson et al. (2024) maps C-AIOE indices for 323 'SOC 2010' occupations at the four-digit level. [9] To link this to the SILC data, we translate to ISCO using a cross-walk from the UK's Office for National Statistics (ONS).[10] This

8 Acemoglu (2025) does not estimate a corresponding wage change and McKinsey (2025) does not estimate a corresponding employment change.

9 SOC stands for the Standard Occupational Classification system, which was devised to classify roles into occupational categories for data collection and analysis.

10 See the ONS website.

results in 334 occupations at the four-digit ISCO-08 level[11]. Each individual occupation code falls into one of nine broader one-digit categories, listed in Table A.1.

We first calculate a weighted average of occupational C-AIOE scores within each occupation group. We choose to use the two-digit ISCO-08 occupational classification to balance a need for robust sample sizes with granularity.[12] We weight each occupation by its relative size, as measured by the number of employees in that occupation in the 2022 census. This ensures the sector's C-AIOE value is not distorted by relatively unimportant occupations that are particularly (un)affected by AI. It is important to note that considering C-AIOE at the two-digit sector level requires the strong assumption that all occupations within a given occupational group are equally exposed to replacement by AI. This is a simplification as there is significant within-sector variation of C-AIOE values for some sectors. However, using more a more granular ISCO classification would lead to very small sample sizes in some cases. The C-AIOE for occupation sector l is calculated as:

$$C\text{-}AIOE_l = \frac{\sum_{i \in I_l} C\text{-}AIOE_i * EMP_i}{\sum_{i \in I_l} EMP_i} \tag{3.3}$$

where $i \in I_l$ are occupations at the four-digit ISCO level in occupation sector l, which is at the two-digit ISCO level. $C\text{-}AIOE_i$ is the complementarity-adjusted AI exposure of occupation i, and EMP_i is the number of employees that work in occupation i. Sectoral C-AIOE values are then normalised and shifted such that $C\text{-}AIOE_{MIN} = 0$

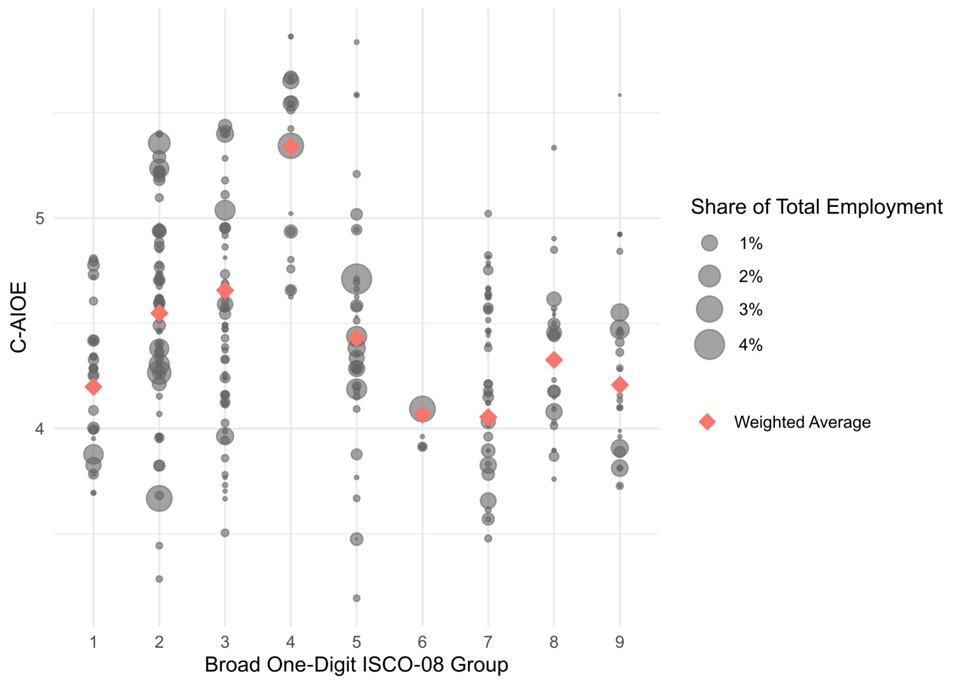
Table 3.1 shows the derived weighted C-AIOE scores for each occupation sector and the associated median salary. There is a positive correlation between AI exposure and median salary. There is significant variation in C-AIOE scores, even within ISCO groups at the one-digit level (represented in Figure 3.1 by red dots). At the four-digit level, we observe, for example a C-AIOE score of 3.5 for 'construction and building trades supervisors' and a score of 5.5 for 'financial accounts managers' although both belong to ISCO group 3: 'technicians and associate professionals'.[13]

11 There are more occupations at the ISCO-08 level as there are a number of ISCO occupations coded to the same SOC occupation. Where this happens, we assume employment is split evenly between the two ISCO occupations codes. This may introduce some non-trivial measurement error.

12 Using the three-digit classification results in many cell sizes that would violate the Statistical Disclosure Controls governing our use of the SILC data.

13 The occupations most exposed to AI at the two-digit level, after adjusting for potential complementarities, are general and keyboard clerks (41). The least exposed occupations fall within the category of health professionals (22).

Figure 3.1 Within-sector variation in C-AIOE



Source: Data from Williamson et al. (2024), adjusted from SOC2010 to ISCO-08 using a cross-walk from ONS.
Notes: Red dots show within-sector averages at the one-digit ISCO level while grey dots show within-sector averages at the four-digit ISCO level.

3.3.1 The employment shock

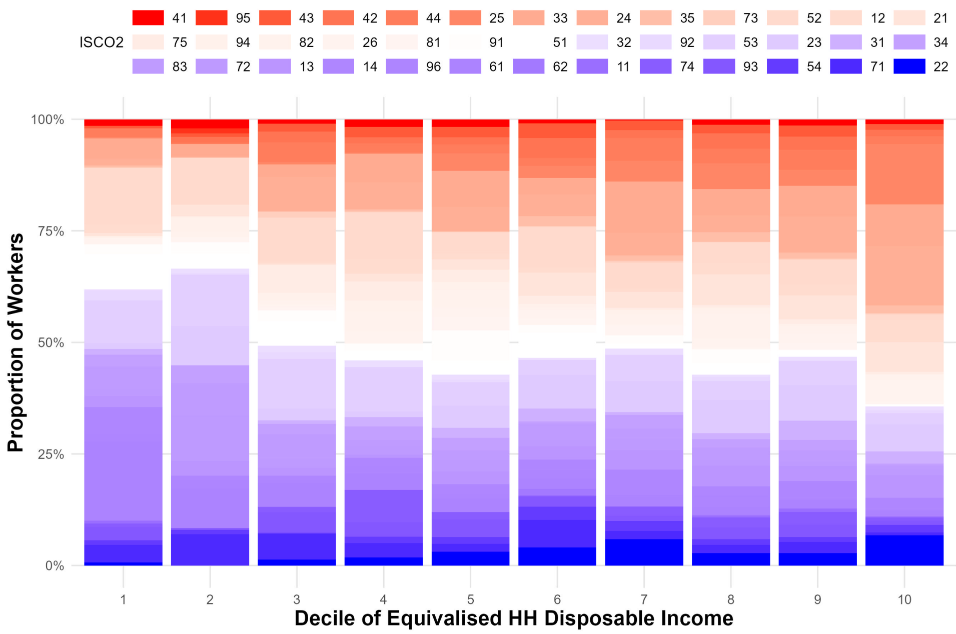
We use the C-AIOE index to distribute each scenario's employment and wage changes across the labour force using the SILC data. For example, in our central scenario, we distribute an employment loss shock of 7 per cent based on the relative share of each occupation sector in overall employment and the C-AIOE score of the occupation sector. The employment shock is therefore heterogeneous across sectors. The proportion of employees in occupation sector l who are replaced by AI is denoted as $JobLoss_l$ and is calculated as:

$$JobLoss_l = \frac{TotalJobLoss * (EMP_l * C\text{-}AIOE_l)}{(\sum_l EMP_l * C\text{-}AIOE_l)} \tag{3.4}$$

The numerator in this expression is the number of employees in two-digit ISCO-08 occupation sector l scaled by the relative exposure of that sector to AI. The denominator then rescales this relative to the overall size of the sectors, adjusted for AI exposure. The total job losses, weighted for sector size, sum to $TotalJobLoss$. The recalculated job losses are shown as a percentage of total sectoral employment in Table 3.2.

Figure 3.2 shows how occupations are distributed by decile of equivalised household disposable income in the SILC data. There are more highly exposed workers in the upper income deciles compared to the lower income deciles. This reflects both the fact that there are fewer workers per household towards the bottom of the income distribution and the positive correlation between AI exposure and education/income found in previous studies internationally (Cazzaniga, Jaumotte, et al., 2024) and in Ireland (Williamson et al., 2024).

Figure 3.2 Occupational exposure to AI by decile of equivalised household disposable income



Source: SILC 2022

Notes: The colour scale goes from dark blue (lowest C-AIOE) to white (median C-AIOE) to dark red (highest C-AIOE). Household disposable income is equivalised using the national scale, which assigns a weight of 0.66 to additional adults and 0.33 to children under 14.

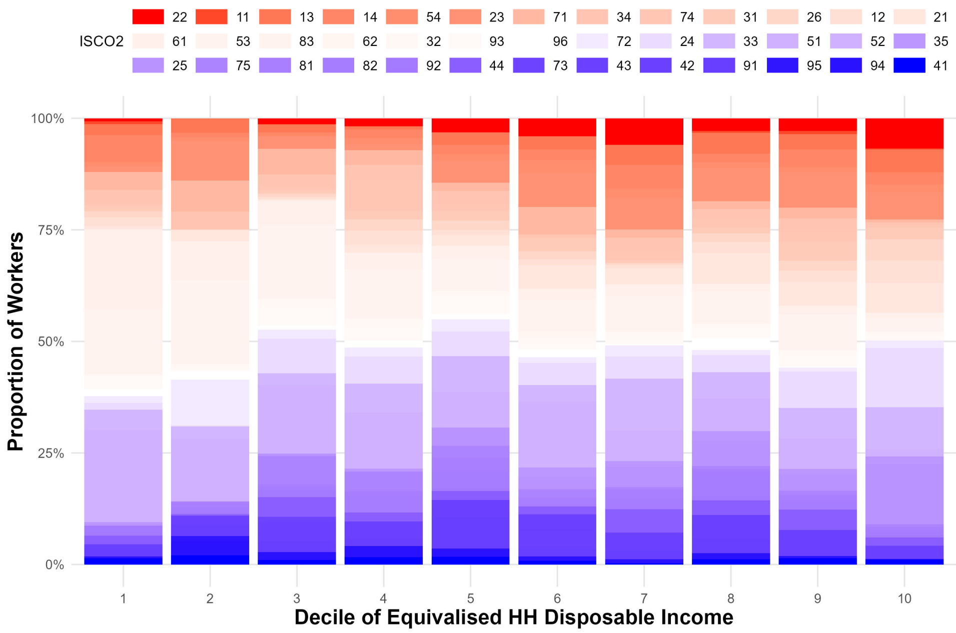
3.3.2 The wage shock

We implement the wage shock in a similar manner. In the upper bound scenario, we distribute a wage increase for those left in the labour market, which is 2.6 per cent on aggregate, but which varies by the complementarity score of each occupation sector l to AI.

$$WageChange_l = \frac{TotalWageChange * Complementarity_l}{\frac{\sum_l Complementarity_l * EMP_l}{\sum_l EMP_l}} \tag{3.5}$$

Figure 3.3 shows how occupations are distributed across the income distribution by the complementarity of the occupation to AI. Unlike exposure to AI, there is no clear pattern of how complementary occupations are distributed by income decile. We do observe more very high complementarity occupations at the very top of the income distribution and more very low complementarity occupations at the bottom of the income distribution. However, the distribution of occupations that have neither very high nor very low complementarity to AI is relatively uniform across the income distribution.

Figure 3.3 Occupational complementarity to AI by decile of equivalised household disposable income



Source: SILC 2022

Notes: The colour scale goes from dark blue (lowest complementarity) to white (median complementarity) to dark red (highest complementarity). Household disposable income is equivalised using the national scale, which assigns a weight of 0.66 to additional adults and 0.33 to children under 14.

3.3.3 The capital income shock

Finally, we implement an increase in capital income, which is uniform for all households in receipt of capital income. To do so, we first need to derive the capital base. SILC collects information on two types of capital income: rent from property ownership and other capital income (interest, dividends and profits from capital investments in unincorporated business). We focus on the second of these as it is not obvious that rental income could be directly affected by AI adoption. We assume the average return on investment to be 1.005 per cent.[14] In all scenarios, the return to capital is assumed to

14 This is the average interest rate for 2022 for bank deposits with an agreed maturity of over two years and is the rate used by the Joint Research Centre of the European Commission to back out the capital base for its microsimulation model, EUROMOD. In reality, the return is likely to be more variable than this for risky assets.

increase by 0.4 pp, giving a rate of 1.405 per cent. Capital income increases are applied to all households with reported capital income of this type. This is an oversimplification as investors in technology-based companies and industries could see a much higher increase in their return compared to, for example, passive savers. As we have no information about the type of investment each household has, we are unable to simulate this dimension of the capital income effect and we rely on a uniform shock.

3.4 Using microsimulation to model income distribution

We use the SWITCH microsimulation model to estimate the effects of the AI-induced employment, wage and capital income shocks on the distribution of income. The SWITCH model is linked to the 2022 SILC data, containing information on the employment, income and demographic features of a representative sample of households in Ireland. SWITCH models the tax and welfare system for Ireland for 2025, and the underlying SILC data are reweighted to reflect the income distribution in 2022 and inflated to 2025 price levels to account for income growth between the policy and data year.[15] SWITCH allows us to simulate the distribution of disposable income before and after the AI adoption shock, accounting for the interaction between employment changes, wage changes, capital income changes, and the tax and welfare system.

We implement the employment shock using the European Commission's Labour Market Adjustment (LMA) Add-On (Bornukova et al., 2024). This add-on allows for counterfactual labour market characteristics to be imputed for groups of individuals undergoing labour market transitions. Imputed variables, such as months in unemployment and work history, are based off averages among the target population. This ensures that employees undergoing labour market transition closely resemble existing individuals in the 'target' population.

Using the sector-level probabilities of AI job replacement from equation 3.4, a corresponding proportion of employees, adjusted for weighting, is selected from each sector to be part of the 'transition' population. Assignment to the transition population is random within each sector so we average our results over 50 of these random draws. While it is clear that some demographic groups (such as younger, inexperienced workers) might be more likely to transition to unemployment than others, our method does not explicitly account for this. Rather, we rely on the fact that such workers are disproportionately in non-managerial and entry-level occupations, which have different exposure scores to the occupations in which older,

15 See Keane et al. (2023) for a detailed description and validation of the SWITCH model.

experienced workers are concentrated. The transition individuals are treated as unemployed for more than nine months by the SWITCH model, at which point they have exhausted their entitlement to contributory benefits, and their income, tax and welfare entitlement is adjusted accordingly, assuming no employment re-allocation takes place.

Figures B.1 to B.5 show how different income sources and tax liabilities are distributed by decile of the household disposable income distribution in 2025. Breaking disposable income into its constituent components across the income distribution illustrates where the AI adoption shock is most likely to be felt. Most notable from this breakdown is the distribution of capital income, which is mainly concentrated in decile 10.

Table 3.1 CAIOE at two-digit ISCO-08 level

ISCO2	WA CAIOE	WA CAIOE Normalised	WA Median Salary	Total Employment ('000s)	Share of Total Employment
11	4.00	0.53	78,658	11	0.5%
12	4.68	1.88	67,761	33	1.6%
13	4.13	0.79	56,873	71	3.3%
14	4.08	0.69	29,928	74	3.5%
21	4.63	1.78	46,681	96	4.5%
22	3.73	0.00	53,195	103	4.9%
23	4.29	1.11	46,633	113	5.3%
24	4.96	2.43	48,550	155	7.3%
25	5.20	2.90	58,940	65	3.1%
26	4.54	1.60	39,035	54	2.5%
31	4.21	0.95	45,740	45	2.1%
32	4.36	1.24	30,943	24	1.1%
33	4.99	2.49	38,739	145	6.8%
34	4.16	0.85	24,056	49	2.3%
35	4.87	2.25	36,720	18	0.9%
41	5.67	3.83	36,644	15	0.7%
42	5.30	3.10	27,219	56	2.7%
43	5.43	3.36	30,046	36	1.7%
44	5.25	3.00	28,285	71	3.4%
51	4.46	1.44	15,544	73	3.4%
52	4.69	1.90	19,196	118	5.6%
53	4.31	1.15	23,970	119	5.6%
54	3.84	0.22	45,769	32	1.5%
61	4.07	0.67	19,605	71	3.4%
62	4.03	0.59	24,871	3	0.1%
71	3.80	0.14	22,601	74	3.5%
72	4.14	0.81	31,050	49	2.3%
73	4.77	2.05	28,832	8	0.4%
74	3.94	0.41	37,135	31	1.4%
75	4.58	1.68	25,846	23	1.1%
81	4.53	1.58	29,591	52	2.4%
82	4.55	1.62	28,903	11	0.5%
83	4.14	0.81	25,457	70	3.3%
91	4.47	1.46	13,634	37	1.7%
92	4.34	1.20	19,890	8	0.4%
93	3.93	0.39	26,365	64	3%
94	4.55	1.62	15,915	26	1.2%
95	5.58	3.65	33,023	0	0%
96	4.07	0.67	22,692	17	0.8%

Source: Data from Williamson et al. (2024), adjusted from SOC2010 to ISCO-08 using a cross-walk from ONS.
Notes: Red dots show within-sector averages at the one-digit ISCO level while grey dots show within-sector averages at the four-digit ISCO level.

Table 3.2 Percentage job loss per ISCO-08 two-digit group (grouped by first digit)

ISCO	ISCO-08 title	Loss (%)
11	Chief Executives, Senior Officials and Legislators	2.5 %
12	Administrative and Commercial Managers	8.9 %
13	Production and Specialized Services Managers	3.7 %
14	Hospitality, Retail and Other Services Managers	3.3 %
21	Science and Engineering Professionals	8.4 %
22	Health Professionals	0.0 %
23	Teaching Professionals	5.3 %
24	Business and Administration Professionals	11.4 %
25	Information and Communications Technology Professionals	13.7 %
26	Legal, Social and Cultural Professionals	7.5 %
31	Science and Engineering Associate Professionals	4.5 %
32	Health Associate Professionals	5.8 %
33	Business and Administration Associate Professionals	11.7 %
34	Legal, Social, Cultural and Related Associate Professionals	4.0 %
35	Information and Communications Technicians	10.6 %
41	General and Keyboard Clerks	18.0 %
42	Customer Services Clerks	14.6 %
43	Numerical and Material Recording Clerks	15.8 %
44	Other Clerical Support Workers	14.2 %
51	Personal Services Workers	6.8 %
52	Sales Workers	9.0 %
53	Personal Care Workers	5.4 %
54	Protective Services Workers	1.1 %
61	Market-oriented Skilled Agricultural Workers	3.2 %
62	Market-oriented Skilled Forestry, Fishery and Hunting Workers	2.8 %
71	Building and Related Trades Workers (excluding Electricians)	0.6 %
72	Metal, Machinery and Related Trades Workers	3.8 %
73	Handicraft and Printing Workers	9.6 %
74	Electrical and Electronic Trades Workers	2.0 %
75	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	7.9 %
81	Stationary Plant and Machine Operators	7.4 %
82	Assemblers	7.6 %
83	Drivers and Mobile Plant Operators	3.9 %
91	Cleaners and Helpers	6.9 %
92	Agricultural, Forestry and Fishery Labourers	5.7 %
93	Labourers in Mining, Construction, Manufacturing and Transport	1.9 %
94	Food Preparation Assistants	7.6 %
95	Street and Related Sales and Services Workers	17.3 %
96	Refuse Workers and Other Elementary Workers	3.2 %

Source: Own calculations using SILC 2022 and occupational C-AOIE scores from Williamson et al. (2024)
Notes: SILC 2022

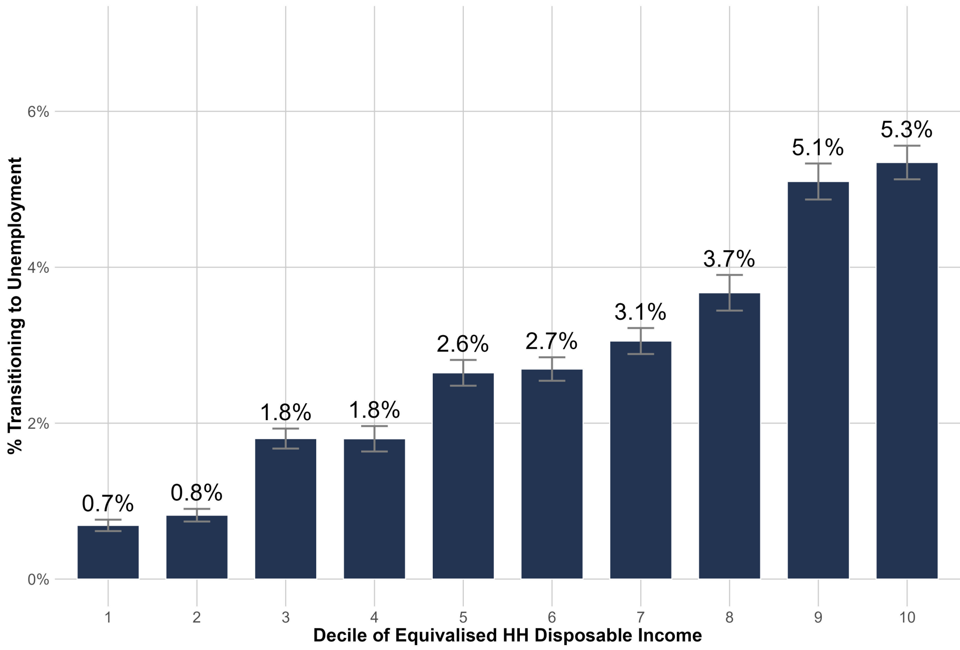
Chapter 4

Results

4.1 Employment, wage and capital income changes

We first document the effect of our central AI adoption scenario on unemployment, wages and capital income. This scenario, based on research by Briggs and Kodnani (2023) and Cazzaniga, Pizzinelli, et al. (2024) assumes a 7 per cent decrease in total employment, a 2.6 per cent increase in wages for those who remain in the labour market and a 0.4 pp increase in the return on capital.

Figure 4.1 Share of population transitioning to unemployment by income deciles

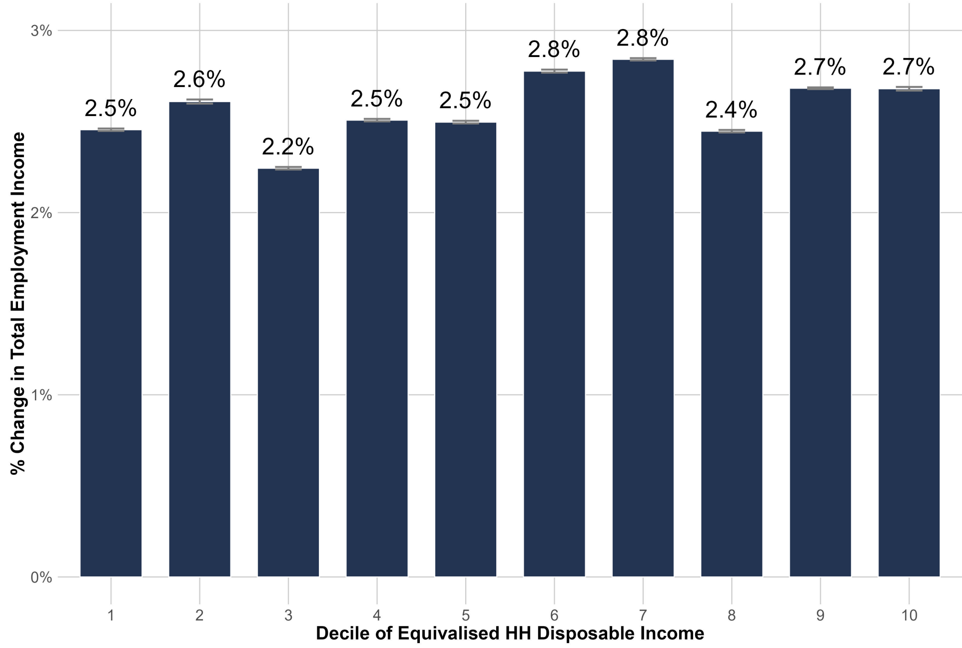


Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices

Notes: A -7 per cent employment shock is calibrated using the weighted C-AIOE index at the ISCO two-digit level. Confidence intervals for each point estimate are calculated by taking the mean value across 50 simulations, calculating the standard error and constructing a 95 per cent confidence interval using a critical value of 1.96.

Figure 4.1 shows that, of those who transition into unemployment in this scenario, 0.7 and 0.8 per cent of population are in income deciles 1 and 2, respectively. The share of those transitioning into unemployment progressively increases with the level of household disposable income, with the highest shares transitioning to unemployment found in the top income deciles: 5.1 and 5.3 per cent. This pattern confirms that the effect of AI adoption on employment is different to the effect of previous periods of technological advancement, which were more detrimental to low-educated workers than highly educated workers.

Figure 4.2 Percentage change in aggregate employment income by income deciles for non-transitioning population

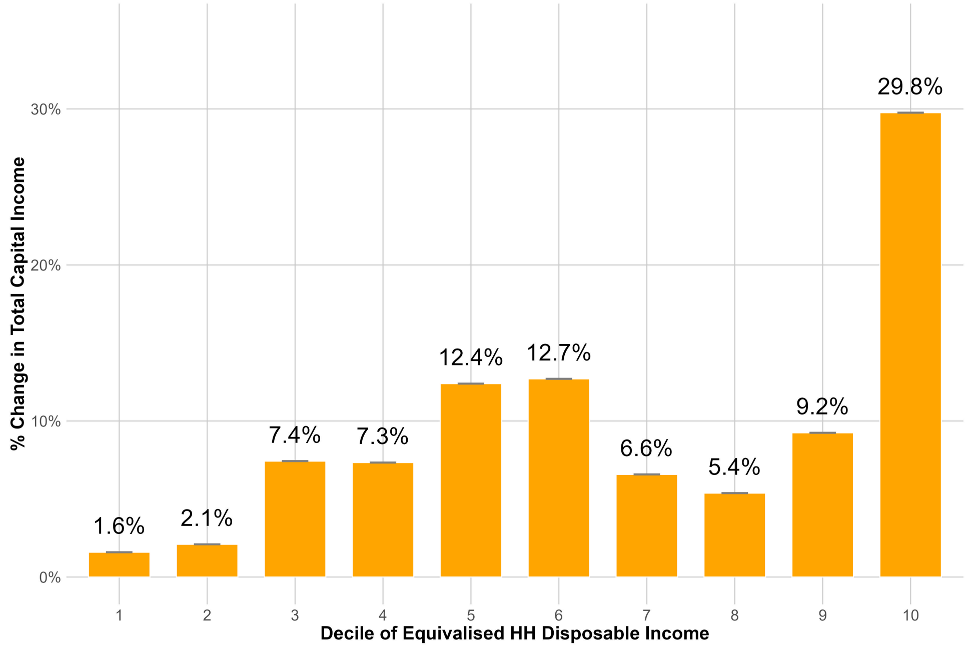


Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.
Notes: A 2.6 pp wage shock is calibrated using the weighted complementarity component of the C-AIOE index at the ISCO two-digit level

Figure 4.2 shows the estimated effect of AI adoption in our central scenario on wages for those who remain in employment. Unlike the pattern of unemployment, we find a fairly uniform increase in employment income across the income distribution. At the bottom of the distribution, we simulate a 2.2 – 2.6 per cent increase in employment income, compared to 2.7 per cent at the top of the income distribution. The highest increase is found in decile 7 – at 2.8 per cent.

While employment losses are calibrated based on the complementarity-adjusted AIOE score, wage increases are calibrated based solely on the complementarity of particular occupations with AI. The differing patterns of employment losses and wage gains across the distribution indicate, therefore, that workers in high-income households are more at risk of replacement by AI than workers in low-income households, while there is no apparent income gradient to complementarity. Workers in low-income households are just as likely to have complementarities with AI as workers in high-income households.

Figure 4.3 Percentage change in aggregate capital income by income deciles



Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.
Notes: An increase of 0.4 pp in the return to capital is simulated for all capital income recipients.

Figure 4.3 shows the percentage change in capital income if the return to capital income increases by 0.4 pp, by decile of equivalised household disposable income. Although capital income increases in all deciles, the lowest increases are found at the bottom of the income distribution (around 2 per cent). The middle of the distribution experiences slightly higher increases, around 13 per cent, while the highest capital gains are found in decile 10, of almost 30 per cent. Since the 0.4 pp increase in the return to capital income is implemented uniformly, and not according to the occupational structure, this pattern of gains occurs because most capital income is held by households at the very top of the income distribution (Figure B.2).

4.2 Income distribution

In this section, we estimate the combined effect of this AI-driven employment, wage and capital income shock on the distribution of disposable income, accounting for the full interaction between market income and the tax and welfare system. We focus on our central scenario but, given the uncertainty inherent in deriving this scenario, we also provide high-level estimates for a wide range of possible scenarios.

Figure 4.4 shows the effect of our central AI adoption scenario on the distribution of income in Ireland. We separately show the effect of AI on the distribution of market income;[16] welfare entitlement; tax liability and disposable income. These effects are expressed as a percentage of household disposable income and are additive in that the disposable income effect is equal to the sum of the other three effects.

The effect of AI adoption on market income is negative as the effect of employment losses outweighs wage and capital income gains. The effect appears strongly progressive in nature, with lower income households losing less than higher income households. However, considering that the average income losses are composed of employment losses, somewhat countered by wage and capital income gains, the overall effect may not be inequality reducing. We return to this question in Section 4.4.

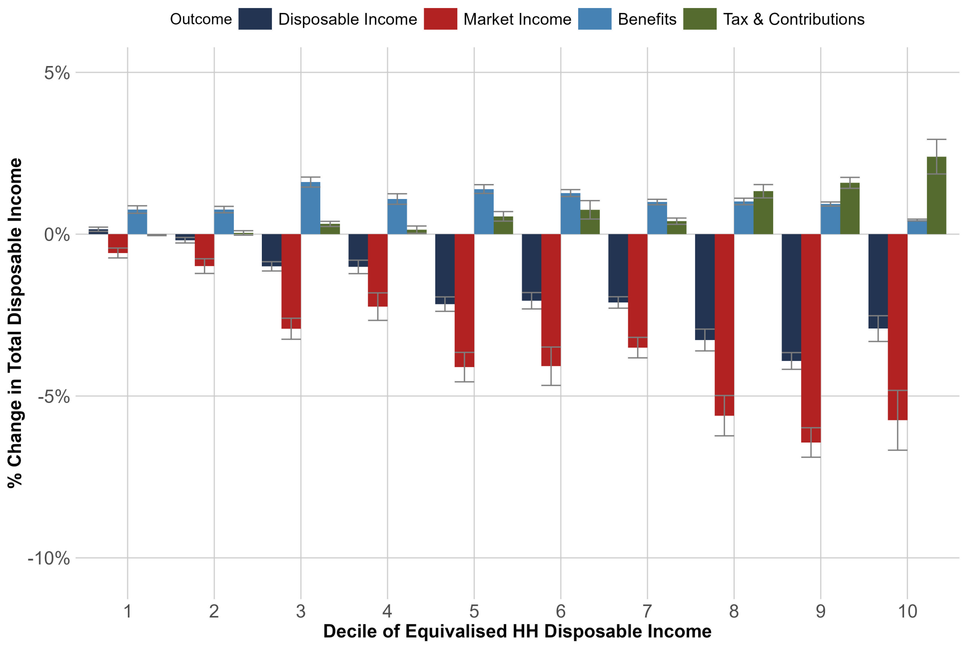
The lowest average losses are experienced in decile 1 where households lose an average of 1 per cent of market income while the highest income losses are experienced in decile 9, where households lose an average of 6 per cent of disposable income. In Figure B.6 in the appendix, we split the market income effect into the relative contributions of capital income and other market income. This separation shows that the gain in capital income experienced by households at the very top of the income distribution (decile 10) slightly insulates them from the AI shock, so that their market income losses are lower, on average, than those experienced by households in decile 9.

Figure 4.4 also shows how tax liabilities, welfare entitlement and disposable income change across the income distribution as a result of AI adoption in this scenario. Entitlement to welfare increases across the income distribution and, since many instruments in the Irish welfare system are means-tested, this is particularly true in the lower half of the income distribution. Tax liabilities and social security contributions also decrease on average. Thanks to the very progressive structure of the Irish taxation system, most of this effect is apparent at the top of the income distribution where (i) households pay more tax, on average and (ii) the decrease in market income is highest.

The tax–benefit system acts as an automatic stabiliser, cushioning the effect of the market income shock. The drop in market income is almost completely cushioned by the tax–benefit system in deciles 1 and 2 while, at the top of the income distribution, the tax–benefit system reduces the income losses from AI adoption by around one-half.

16 Market income is employment income, private pensions and capital income

Figure 4.4 The effect of AI adoption on the distribution of income



Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Notes: A -7 per cent employment shock and a +2.6 pp wage shock are calibrated using the weighted C-AIOE index at the ISCO two-digit level. An increase of 0.4 pp in the return to capital is also simulated for all capital income recipients.

4.2.1 Comparing to a uniform shock

To understand how much of the pattern of gains and losses we estimate as a result of this AI scenario is due to exposure and complementarity of different occupations to AI, and how much is due to the baseline income distribution and nature of the tax and welfare system, we simulate a further scenario. We keep the scenario parameters identical: a 7 per cent employment loss, a 2.6 pp wage increase and a 0.4 pp increase in capital income. However, we distribute all of these shocks uniformly across occupations rather than based on their C-AIOE index.

Results, shown in Figure B.7 in the appendix, indicate that the AI-induced shock results in steeper losses in disposable income for high-income households compared to a uniform shock.

4.2.2 An alternative AI exposure index

We next compare our central results to estimates using an alternative index of AI exposure. Rather than using the C-AIOE index, we re-run our analysis using the index developed by Tolan et al. (2021) at the European Commission. The authors develop this index by mapping 59 tasks drawn from worker surveys and an occupational database to 14 cognitive abilities, extracted from the cognitive science literature. These are then mapped to a list of 328 AI benchmarks.

We use the index of Tolan et al. (2021) to calibrate job losses due to AI adoption. As there is no complementarity component to this index, we continue to use the complementarity component of the C-AIOE index to calibrate wage changes. Our results, in Figure B.8, are very similar to the results (in Figure 4.4) derived using the C-AIOE index. In particular, the progressive pattern of losses in disposable income is apparent using either index.

4.2.3 Further scenarios for AI adoption

Given the scarcity of estimates for how AI will affect employment, wages and capital income, we have so far focused on one scenario. In this section, we show how our main result – the average change in household disposable income – would change for a range of scenarios around this central scenario. We simulate employment and wage changes in a stepwise fashion, beginning with a scenario in which there is no employment or wage effect, moving to scenarios with an employment loss between 1 and 10 per cent and a wage increase of between 1 and 5 per cent. This results in 50 scenarios.

Figure 4.5 The average effect of AI adoption scenarios on household disposable income

Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.
Notes: A range of employment and wage shocks are calibrated using the weighted C-AIOE index at the ISCO two-digit level. An increase of 0.4 pp in the return to capital is also simulated for all capital income recipients.

Figure 4.5 shows the pattern of changes in average household disposable income as a result of each of these scenarios. Results for household income deciles are displayed in Figure B.9 and those for household income terciles are displayed in Figure B.10 in the appendix.

There are three main takeaways from this analysis. First, regardless of the scenario, higher income households are more affected by AI-induced labour market changes than low-income households. Second, in the range of scenarios we have considered, the potential income losses (reaching -6 per cent in the top income tercile in the extreme scenario of 10 per cent employment loss and no wage gain) are larger than the potential gains (reaching 4 per cent in the top income tercile in the most favourable scenario of 5 per cent wage increase and no employment loss). Third, there are some scenarios in which average changes to disposable income are zero. These scenarios can be broadly characterised as having similar and moderate proportional increases in wages and decreases in employment. Figure B.11 in the appendix replicates this analysis without the capital income shock. In the absence of an increased return to capital, we simulate smaller potential household income gains and larger potential losses from AI adoption.

4.3 Exchequer cost

We next estimate the implications of each scenario described in Section 4.2.3 for net government revenue. This exercise accounts for household level changes in income tax, social security and welfare expenditure due to employment losses, wage increases and capital income increases. These changes are aggregated up to population level and expressed as a proportion of net government revenue from income tax, social security and welfare, as simulated by SWITCH for 2025.

Figure 4.6 The effect of AI adoption scenarios on net Exchequer revenue

Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.
Notes: A range of employment and wage shocks are calibrated using the weighted C-AIOE index at the ISCO two-digit level. An increase of 0.4 pp in the return to capital is also simulated for all capital income recipients.

Figure 4.6 shows that the Exchequer effect of AI adoption will be highly dependent on the balance between employment loss and wage increases. In scenarios in which employment losses are low, net government revenue may increase as a result of AI adoption. Conversely, in scenarios in which employment losses are high, there may be a negative impact on government finances. In our most negative scenario, this results in a reduction in net revenue of nearly one-quarter. The most optimistic scenario, by contrast, registers a net revenue increase of 14 per cent. This exercise illustrates the case for devoting government resources to upskilling workers to use AI productively or carry out tasks that AI cannot do, thereby smoothing the transition for workers and firms to AI adoption. It also suggests that, if a negative employment shock cannot be avoided, some revenue-raising measures may need to be considered in order to finance the resulting increased welfare bill and decreased income tax revenue.

4.4 Headline income inequality

Figure 4.7 shows the effect of the range of AI adoption scenarios considered on the Gini index, a commonly used measure of disposable income inequality. Despite the apparent progressive nature of the AI adoption shock (in Figure 4.4), each scenario results in an increase in the Gini index. This is because the average changes in disposable income by income decile displayed in Figure 4.4 mask two opposing effects, both of which are inequality increasing. Our simulations of AI adoption move a number of households into a low-income band due to employment loss, while increasing the labour income of those remaining. When these effects are aggregated by the original income decile of the household, we observe a fall in disposable income across the board, which is higher for high-income families, as the employment loss outweighs the wage increase. However, assessing inequality of disposable income given the new placement of the household in the disposable income distribution, as the Gini index does, we note an increase in overall inequality as employment losses coupled with wage increases increase polarisation in the income distribution. The increase in the Gini index is moderate, ranging from a low of 0.3 pp when only the capital income shock is implemented to a high of 1.2 pp in a high unemployment and high wage shock scenario.

4.5 Discussion

While AI will pose a significant challenge for labour markets globally, similar technological shifts in the past have not led to long-term unemployment. Instead, the labour market has adapted and the supply of and demand

Figure 4.7 The effect of AI adoption scenarios on the Gini Index

Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Notes: A range of employment and wage shocks are calibrated using the weighted C-AIOE index at the ISCO two-digit level. An increase of 0.4 pp in the return to capital is also simulated for all capital income recipients.

for goods and services has evolved. However, the pace at which AI is developing poses a risk to this type of adjustment and, in the short to medium term, there may be signs of upheaval in the labour market with implications for household income, employment and public finances. It is crucial that policymakers consider solutions to mitigate the potential risks associated with AI adoption, while at the same time ensuring that AI's productivity-enhancing benefits and opportunities are capitalised on.

We find that, in a short–medium term AI adoption scenario, the negative effects of employment loss on household incomes broadly outweigh the positive effects of wage growth and increases in capital income. Redistribution by the tax and welfare system cushions these income losses for low-income households and roughly halves them for high-income households.[17] Income losses for the highest income households are also somewhat cushioned by projected increases in capital income. Overall, we estimate that AI adoption will result in disposable income losses one year after the shock, and that these losses are larger for medium to higher income households.

Our analysis suggests that the tax and welfare system is well positioned to cushion the impact of AI adoption on low-income households, although this will come at a cost to the Exchequer. In the medium to longer term, affected workers would ideally transition to employment that is unaffected

17 The newly introduced Pay-related benefit, the effects of which were not captured in this analysis, could also further offset income losses during short-term job transitions.

by or complementary to AI. Cazzaniga, Pizzinelli, et al. (2024) find that college-educated workers in the UK and Brazil are more likely to transition to AI-complementary occupations than non-college-educated workers, indicating the job and income loss for high-income households may be transitory. However, there could be general equilibrium effects that are beyond the scope of this research, such as increased demand for low-skill jobs and decreased demand for goods and services, both of which could result in more displacement of low-educated workers. Education and re-training programmes could prove essential to smoothing these transitions.

Ireland's high level of tertiary educational attainment suggests that the widespread development of AI-complementary skills could be straightforward through their inclusion in third-level courses.[18] What is perhaps a more pressing challenge for policymakers is supporting the adaptation of older workers and those with a lower level of education. Greater investment in lifelong learning programmes to promote re-training and up-skilling would help exposed workers move into jobs for which there is growing demand. Widespread literacy in AI skills will also allow workers to better capitalise on the productivity gains offered by AI. In addition to training focused on AI-complementary roles, promoting training in non-AI-exposed occupations with existing capacity constraints, such as in the construction sector, could further diversify the labour market and increase its resilience. Although beyond the scope of our analysis, it is important to acknowledge that AI is also likely to create new occupations and employment opportunities, providing further avenues for transition.

Our analysis suggests AI adoption could also have significant implications for the public finances in the short–medium term. Reduced income tax revenue following a rise in unemployment, combined with increased expenditure on social welfare, could result in net losses in Exchequer revenue. Losses in revenue could in turn affect future welfare expenditure, limiting the system's capacity to cushion household income. In the longer term, a structural decline in the labour share of income alongside an increase in the capital share together pose a fiscal risk given the role of income tax in Ireland's tax base. In 2025, income tax revenues are estimated to have contributed 34 per cent of total tax revenues, followed by corporation taxes (32 per cent) and consumption taxes (29 per cent). Only 5 per cent of total tax revenue came from taxes on wealth and capital (Department of Finance (2025)). If labour income declines and capital income increases following AI adoption, Ireland's overall tax base will narrow significantly. This highlights

18 In 2024, 57 per cent of people aged 25 to 64 years old in Ireland held at least a third level degree, the highest attainment rate of the EU countries with available data (Eurostat, 2025)

the need to broaden and diversify taxation, in particular by expanding taxes on wealth and capital. That said, if growing investment in AI is appropriately harnessed through capital taxation, AI adoption could have a positive impact on public finances, improving fiscal sustainability. Furthermore, if the effect of AI-related productivity growth dominates its labour displacement effect in the long run, AI adoption could in fact lead to higher incomes and increased income tax revenue as a result.

There are several limitations of our study. Our analysis of changes to capital income as a result of AI adoption is constrained by the broad nature of the capital income measure contained in the SILC data, as well as the scarcity of empirical evidence surrounding how AI will affect capital income. Future work could use the Household, Finance and Consumption Survey to provide more detailed estimates of the distribution of different types of capital income and the expected changes to each as a result of AI adoption. This would provide a broader evidence base for future discussion around optimal labour and capital taxation.

Furthermore, our framework only allows for the assessment of AI exposure through task replacement and complementarity, but does not take into account the creation of new tasks and occupations related to AI. Agrawal et al. (2026) develop theoretical models in which AI enhances worker productivity without task automation. In their framework, human capital plays an important role in intermediating the effects of AI-related technological shocks on wage inequality, highlighting the important role of education and training policies in preventing wage inequality increases in such a scenario.

Overall, the long-term implications of AI adoption remain uncertain. Examining the dynamic effects of changes in labour supply, wages, capital acquisition and prices following AI adoption are all important areas for future research. It is clear, however, that the adoption of AI carries both downside and upside risks for Irish households and the economy, and that these risks are also faced internationally. Policymakers will need to carefully consider appropriate policy responses that minimise losses due to AI exposure, while maximising benefits.

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Appendix

A Additional tables

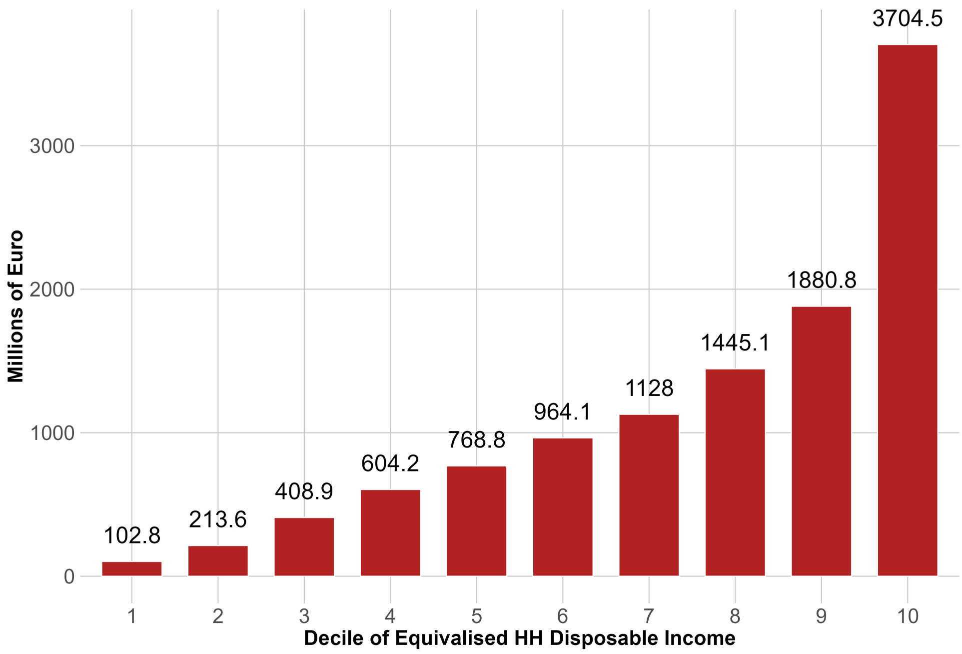
Table A.1 Broad single-digit ISCO-08 major groups

Code	Single-Digit Group Name
1	Managers
2	Professionals
3	Technicians and associate professionals
4	Clerical support workers
5	Service and sales workers
6	Skilled agricultural, forestry and fishery workers
7	Craft and related trades workers
8	Plant and machine operators, and assemblers
9	Elementary occupations

Source: International Labour Organisation (ILO)

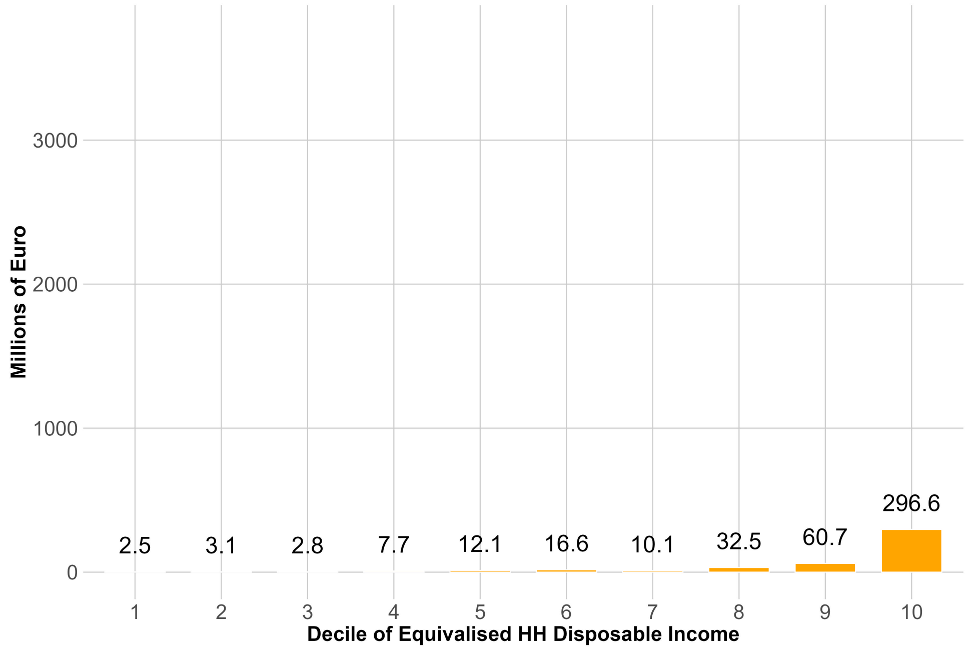
B Additional graphs

Figure B.1 The distribution of aggregate market income (less capital income)



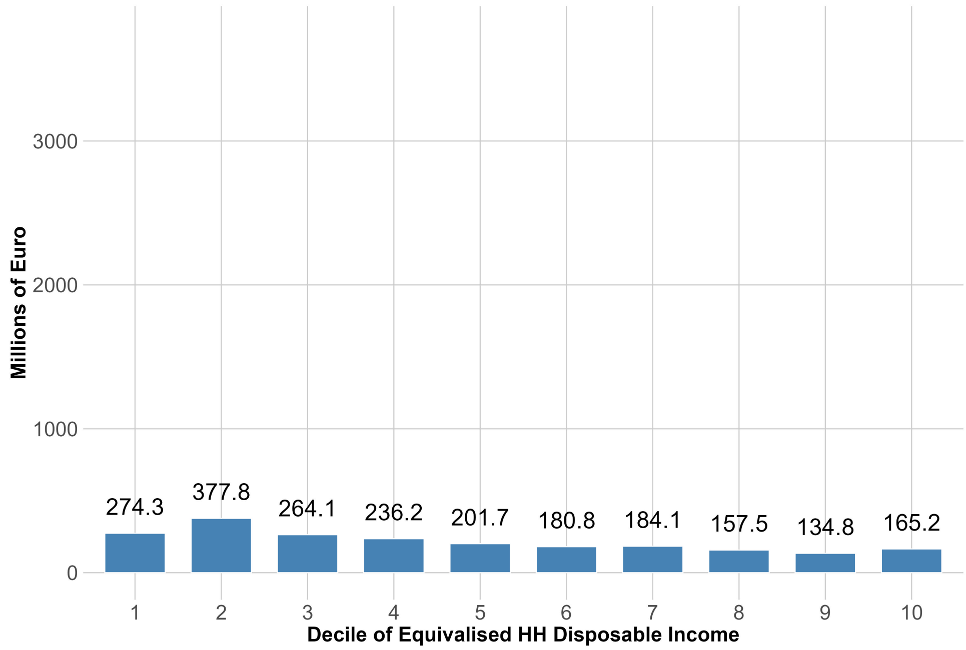
Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Figure B.2 The distribution of aggregate capital income



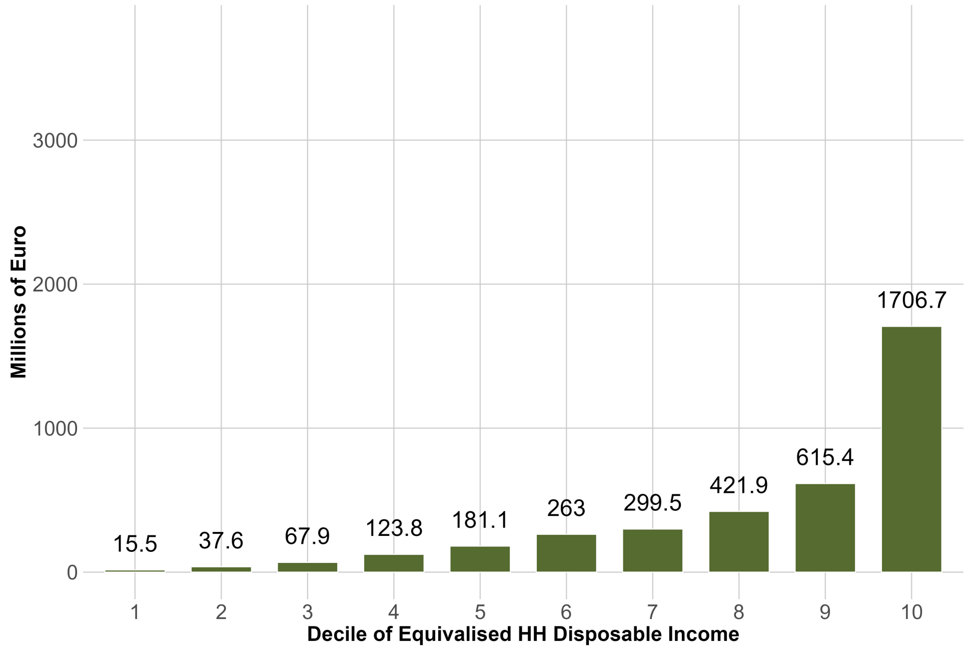
Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Figure B.3 The distribution of aggregate benefits



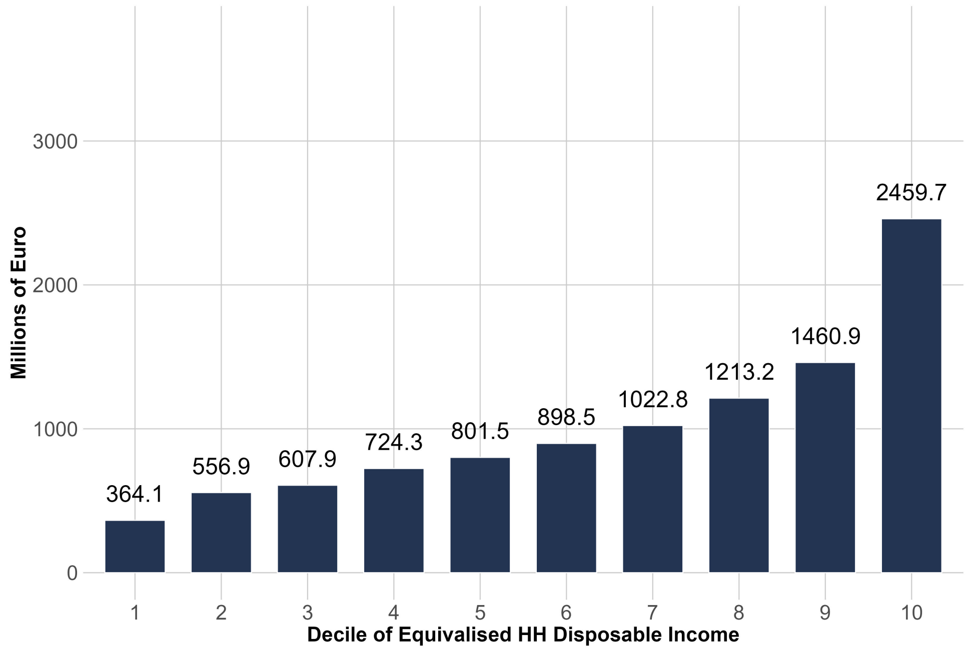
Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Figure B.4 The distribution of aggregate tax and social security contributions



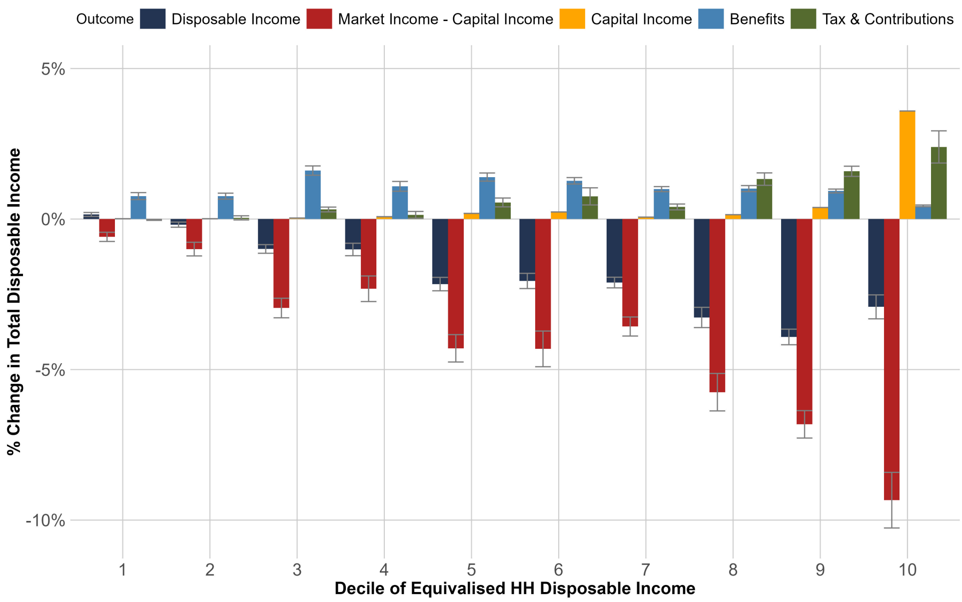
Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Figure B.5 The distribution of disposable income



Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

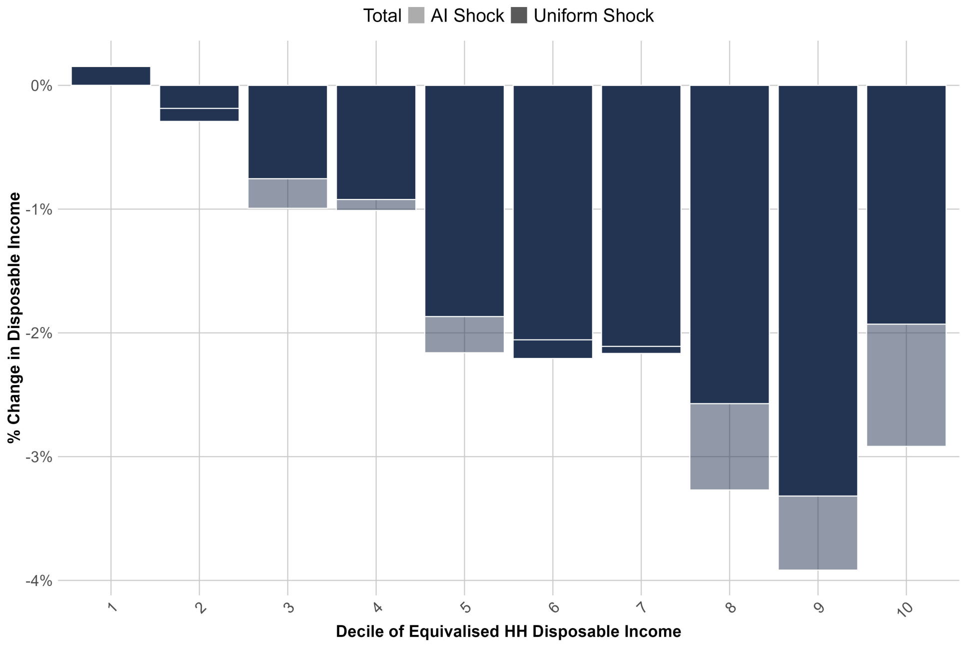
Figure B.6 The effect of AI adoption on the distribution of income



Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Notes: A -7 per cent employment shock is calibrated using the weighted C-AIOE index at the ISCO two-digit level and a 2.6 per cent wage shock is calibrated using the weighted complementarity score. A 0.4 pp increase in capital income is simulated for all who hold capital. Confidence intervals for each point estimate are calculated by taking the mean value across 50 simulations, calculating the standard error and constructing a 95 per cent confidence interval using a critical value of 1.96.

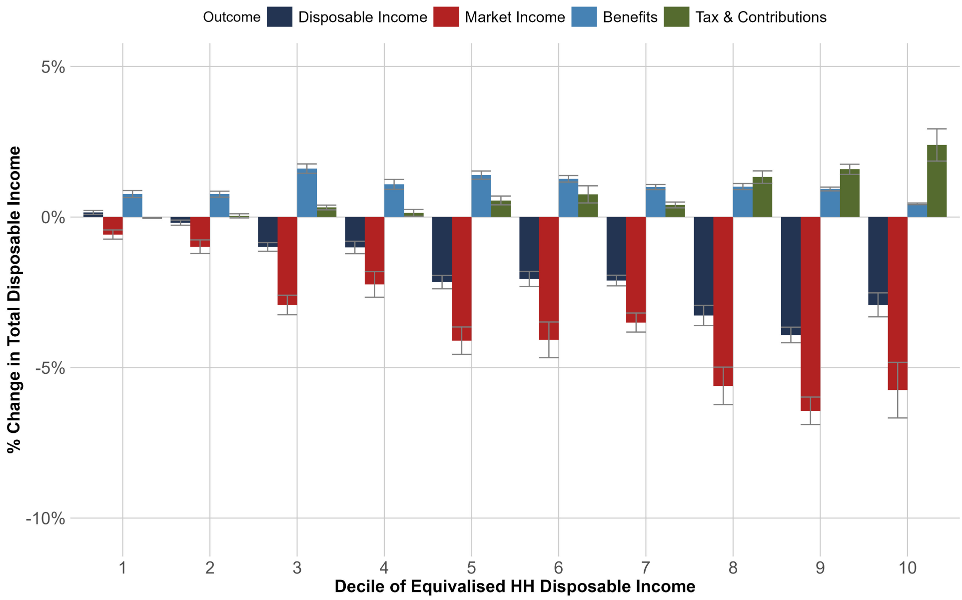
Figure B.7 The effect of an AI adoption scenario compared to a uniform employment and wage shock



Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Notes: A -7 per cent employment shock and a +2.6 per cent wage shock are distributed uniformly. Confidence intervals for each point estimate are calculated by taking the mean value across 50 simulations, calculating the standard error and constructing a 95 per cent confidence interval using a critical value of 1.96.

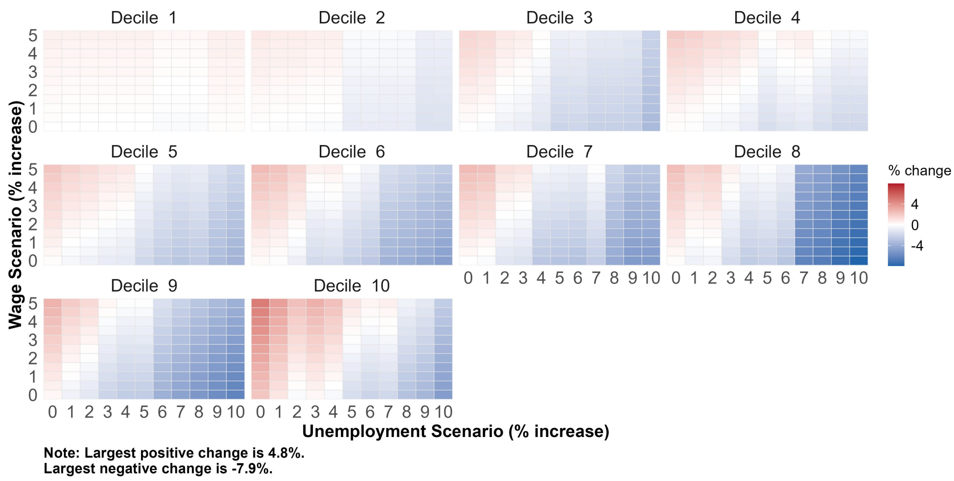
Figure B.8 The effect of an AI adoption scenario using the AI exposure index of Tolan et al. (2021)



Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Notes: A -7 per cent employment shock is calibrated using the weighted Tolanetal2021 index at the ISCO two-digit level and a 2.6 per cent wage shock is calibrated using the weighted complementarity score. A 0.4 pp increase in capital income is simulated for all who hold capital. Confidence intervals for each point estimate are calculated by taking the mean value across 50 simulations, calculating the standard error and constructing a 95 per cent confidence interval using a critical value of 1.96.

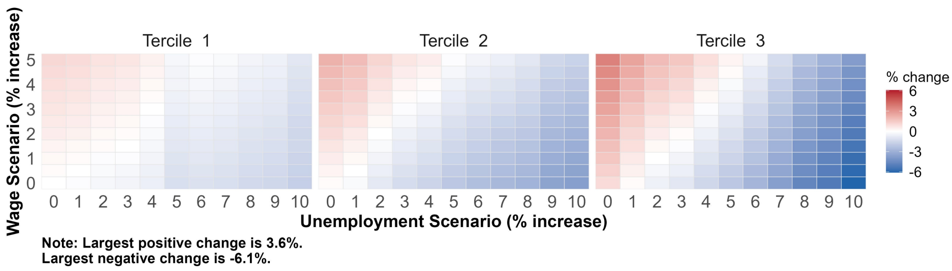
Figure B.9 The effect of AI adoption scenarios on household disposable income by decile



Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.

Notes: A range of employment and wage shocks are calibrated using the weighted C-AIOE index at the ISCO two-digit level. An increase of 0.4 pp in the return to capital is also simulated for all capital income recipients.

Figure B.10 The effect of AI adoption scenarios on household disposable income by tercile



Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.
Notes: A range of employment and wage shocks are calibrated using the weighted C-AIOE index at the ISCO two-digit level. An increase of 0.4 pp in the return to capital is also simulated for all capital income recipients.

Figure B.11 The average effect of AI adoption scenarios with no capital shock on household disposable income

Source: Own calculations using the 2025 policy system in SWITCH v8.2 linked to 2022 SILC data, uprated to 2025 using income growth indices.
Notes: A range of employment and wage shocks are calibrated using the weighted C-AIOE index at the ISCO two-digit level. There is no increase for return to capital