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September 2025

M-RCBG Associate Working Paper Series | No. 264

Mossavar-Rahmani Center for Business & Government
Weil Hall | Harvard Kennedy School | www.hks.harvard.edu/mrcbg

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July 11, 2025

Abstract

While rapid advances in generative AI (GenAI) present significant opportunities for productivity and growth, they also risk displacing workers and deepening income inequality, particularly by increasing the relative returns to capital compared to labor. In this paper, we review current policy proposals to address these risks, noting their potential benefits as well as fiscal and implementation challenges. We complement this review with simulations estimating the fiscal impact of GenAI across OECD countries, under various unemployment and growth scenarios.

We then propose a complementary policy approach: enhancing individual capital income through increased household savings and targeted financial tools. We argue that this approach can help workers manage economic transitions, reduce fiscal pressures, and promote a more equitable distribution of AI-driven capital gains. Using comparative data from OECD countries, we identify nations likely to benefit most from such policies—especially those with low household savings, limited social protection, and aging populations. We also highlight key target populations, including workers with limited access to welfare, such as the self-employed in certain countries.

KEYWORDS: Generative AI; Capital income; Labor market risks; Household savings; Economic policy; Fiscal implications

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1. Introduction

Over the past three years, generative AI (GenAI) has advanced rapidly, driven by breakthroughs in large language models—such as OpenAI's ChatGPT—along with additional tools capable of processing text, images, and more. With increasingly user-friendly interfaces and accessible API integrations, these technologies have quickly spread among individuals across workplaces (Blandin, Bick, and Deming, 2024). This rapid adoption holds significant potential for gains in the labor market, but it also poses substantial risks.

While there is growing consensus that advances in artificial intelligence, particularly the potential emergence of Artificial General Intelligence (AGI), could have far-reaching implications for labor markets, the pace and timeline of AI's potential disruption to the labor market are subjects of growing uncertainty and debate. Earlier surveys of AI researchers placed the median estimate for AGI around 2060 (Grace et al., 2018; Zhang et al., 2021). More recent assessments suggest an accelerated timeline. A 2023 survey by AI Impacts indicates a 50% probability of achieving AGI by 2040, with industry leaders such as OpenAI CEO Sam Altman and Anthropic CEO Dario Amodei projecting even earlier timelines (AI Impacts, 2023). These changing forecasts reflect increasing optimism about scaling current machine learning modelling, as well as ongoing growth in compute availability (Epoch AI, 2024). However, there is no single agreed-upon definition of AGI. Researchers differ in whether it should be understood as the ability to match human-level performance across all tasks, the capacity to generate economic value independently, or simply having a broader kind of cognitive adaptability. This lack of clarity makes it even harder to predict not just when AGI might emerge, but what exactly it would mean for labor markets when it does.

Moreover, while large language models demonstrate impressive capabilities in narrow domains, there is no consensus that they represent general intelligence, and benchmark efforts for evaluating the macroeconomic implications of AI developments, such as GATE, are still in early development (Epoch AI, 2024). Moreover, even if AGI becomes technically feasible in the near term, its diffusion into the broader economy will depend on complex institutional, regulatory, and organizational factors. Historically, general-purpose technologies have taken decades to be fully integrated into production systems. As a result, while some sectors may experience early disruption, widespread labor market effects are more likely to emerge gradually and unevenly over time, especially as the impact of AI depends on sector-specific adoption patterns and workers' ability to adapt through digital skills and task reallocation (Georgieff and Hyee, 2021).

Facing uncertainty about the long-term effects of AI, policymakers are required to find a balanced approach between encouraging innovation and protecting workers. We emphasize the importance and necessity of investing in areas such as skill development across all life stages, reskilling programs for workers at high risk of displacement by AI, and the digital and physical infrastructure required to support widespread AI adoption and growth. Our working paper briefly discusses additional public policy solutions suggested in the existing literature to mitigate AI-induced labor risks, such as higher taxes on capital and robotics, supporting human-complementing AI technologies ("pro-worker AI"), welfare policy, and, in extreme cases, universal basic income (UBI), while highlighting the associated challenges of some of them. We complement this review with simulations estimating fiscal impact of GenAI across OECD countries, under varying assumptions including its effects on unemployment and growth.

Building on this foundation, we propose a new policy approach—meant to complement the tools discussed above—to address the unemployment and inequality risks posed by GenAI: enhancing individual capital income. By broadening access to capital income, policymakers can empower workers with greater financial resilience, enabling them to better navigate economic transitions and invest in crucial reskilling opportunities, while simultaneously easing fiscal pressures. Moreover, this policy, particularly if directed towards individuals with limited existing capital holdings rather than those with high incomes, can significantly promote a more equitable distribution of the capital gains likely to be generated by GenAI-driven growth, thereby narrowing the gap between labor and capital income that is likely to deepen in the GenAI era.

We examine which countries are most likely to benefit from such policies, emphasizing those with low household savings, especially when coupled with less generous welfare systems or rapidly aging populations. In countries with higher household savings, we suggest enabling early withdrawals of a portion, such as a third, that should be permitted only when the administration or government announces a significant prolonged unemployment event. We also discuss the populations that stand to benefit most from this policy—particularly workers highly exposed to AI risks and those with limited access to conventional social welfare programs, such as the self-employed in some countries.

2. The Labor Market Effects of GenAI

2.1. Current Evidence on Predicted Effects

2.1.1. Aggregated Effects

The rapid adoption holds the potential to boost economic growth. Figure 1 in the 2024 OECD report (Gal and Schief, 2024) compiles a range of projections from the literature on the expected boost to annual labor productivity growth over the coming decade due to AI. These estimates vary significantly: some studies predict substantial annual productivity gains of 1.0 to 2.5 percentage points GDP (Goldman Sachs, 2023; Baily, Brynjolfsson, and Korinek, 2023; McKinsey, 2023), while Acemoglu (2024) offers a more cautious estimate of an annual additional growth of 0.1 percentage points (1% GDP over a 10-year period). Importantly, as the OECD report highlights, the magnitude of these productivity gains could differ considerably across countries.

At the same time, the rise of GenAI has sparked concerns about job displacement, mass unemployment, and broader risks to labor market stability. According to an Ipsos survey featured in the 2024 AI Index Report, 36% of respondents believe AI could replace their jobs within the next five years, while 57% expect it to change their roles within that timeframe. A 2023 Gallup poll similarly found that three in four U.S. adults believe AI will reduce the number of available jobs, with concern especially high among older individuals and those without a college degree. However, Autor (2024) cautions that these fears may be exaggerated. He points to falling birth rates and predicts that labor markets will remain tight, with AI unlikely to fundamentally shift that dynamic.

Importantly, the aggregated effect of GenAI on employment is likely to be ambiguous. While GenAI is expected to reduce demand for certain workers whose tasks can be automated, it may simultaneously stimulate labor demand by driving productivity gains and creating new roles. According to studies, most workers in developed economies are expected to be exposed to GenAI: Goldman Sachs (2023) estimates 70 percent for the U.S., while Cazzaniga et al. (2024) from the

IMF estimate 60 percent for advanced economies more broadly.[1] However, according to Goldman Sachs, only around 7% of these exposed jobs are at high risk of substitution, while 63 percent are more likely to be complemented by AI. Still, it is important to emphasize that due to the high share of exposed workers, there is a lot of uncertainty about the actual share of substituted workers, and therefore about the ultimate effect of AI on unemployment, which could vary significantly.

A few more studies tried to estimate the predicted effect of GenAI on aggregate employment. The World Economic Forum's Future of Jobs Report 2023, based on surveys of executives from 803 major firms across 45 economies, predicts a net employment reduction of approximately 2 percentage points in the next five years. The U.S. Bureau of Labor Statistics (2025) forecasts overall employment growth of about 4 percent in the U.S. over the decade from 2023 to 2033.

A recent report by the Tony Blair Institute for Global Change (2024), provides a comprehensive analysis of the potential combined effects of AI on economic growth and unemployment in the UK over the next 25 years. The analysis outlines four scenarios, which vary according to adoption rates, the extent of productivity benefits, whether firms choose to substitute workers or retain them, and labor demand creation through AI-driven productivity gains and job creation.

In the Tailwind scenario—which they view as the most likely— AI is projected to raise UK GDP by an average of 0.47 pp annually from 2028 to 2050, with unemployment effects ranging from a 0.7 percent decrease to a 1.0 percent increase, and peak effects expected between 2035 and 2045. The more optimistic Jet Stream scenario projects average annual GDP gains of 0.60 pp and larger unemployment reductions (–2.2 to 0.9 percent), with peak impacts arriving earlier (2030–2040). The disruptive Whirlwind scenario predicts the same GDP growth as Jet Stream but a much wider unemployment impact (–1.7 to 4.6 percentage points), peaking between 2030 and 2048. Finally, the Breeze scenario assumes slow adoption and yields more modest gains (0.23 pp average annual GDP growth) alongside relatively small unemployment changes (0.0 to 1.2 percentage points), with peak effects occurring later (2040–2050).

[1] The 2024 OECD report (Gal and Schief, 2024) reviews estimates from several studies on the predicted proportion of jobs exposed to AI. It highlights substantial variation in these projections, ranging from 18.5% to 68% of all jobs.

2.1.2. Distributional Effects

Another key question concerns the distributional effects of GenAI—specifically, its impact on different types of workers and, consequently, on inequality. Several studies suggest that workers across the skill spectrum are exposed to GenAI, meaning a significant portion of their tasks could likely be performed by these technologies (Eloundou et al., 2024; Goldman Sachs, 2023; Toni Blair Institute, 2024; IMF, 2024; McKinsey & Company, 2023b). However, the implications of exposure could vary: for some workers, it may lead to complementarity, boosting productivity and wages, while for others, it may act as a substitute, increasing the risk of job displacement and downward mobility.

Autor (2024) suggests that GenAI could enhance the productivity of middle-skill workers by enabling them to perform higher-stakes decision-making tasks typically reserved for high-skill professionals. This view is supported by experimental studies, showing that GenAI tends to boost productivity more for lower-skilled workers (e.g., Peng et al., 2023; Noy and Zhang, 2023; Brynjolfsson et al., 2025).

However, more recent experimental research suggests that GenAI may, in fact, complement high-skill workers more—particularly in complex tasks where domain expertise is essential for evaluating AI output (e.g., Haslberger et al., 2024; Otis et al., 2024).[2] In addition, several studies suggest that GenAI is most likely to substitute for low- and middle-skill routine jobs—such as retail and customer service—while complementing high-skill roles, especially in STEM fields (McKinsey & Company, 2023b; The Economist, 2025; Deming, Ong, and Summers, 2025; Bank of Israel, 2025).[3] The impact on occupations involving primarily physical or technical tasks is expected to be further away on the timeline, should it occur, and is contingent upon future AI developments being combined with significant progress in robotics (Bank of Israel, 2025). Beyond these differential effects across workers, Acemoglu (2024) warns that GenAI could also widen income inequality by increasing the returns to capital relative to labor.

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[2] See The Economist (2025) for a review of these studies.

[3] Cazzaniga et al. (2024) argue that while GenAI is indeed more complementary to high-wage workers, these workers also face relatively high substitution risks.

2.1.3. Adoption

Importantly, the labor market effects of GenAI will depend heavily on its rate of adoption by both workers and firms. Deming, Blandin, and Bick (2024) examined adoption patterns in the U.S. and found that GenAI is spreading more quickly than previous transformative technologies like personal computers and the internet. They report that 39.4 percent of adults (ages 18–64) use GenAI, with 28 percent using it for work purposes. Adoption is higher among younger individuals, men, those with more education, and STEM majors. Usage spans diverse occupations from 49 percent in computer-related fields to 22 percent in construction. At work, GenAI is most often used for writing (38 percent), administrative tasks (27 percent), and summarizing data (23 percent). Adoption also varies across industries, with finance leading (51 percent) and leisure and hospitality lagging (15 percent). These patterns suggest that GenAI will likely continue to diffuse widely across the labor market. Recent OECD (2025) findings across G7 countries highlight that adoption within firms is also shaped by institutional and structural barriers—such as skill shortages, uncertainty about return on investment, and limited maturity of data infrastructure.

2.2. Lessons from Past Labor Market Shocks

Historical labor market shocks offer valuable insights into how GenAI might affect employment and income over time. Over the past two centuries, technological advances have driven profound structural shifts in the labor markets of developed economies (see Deming, Ong, and Summers, 2025 for a recent review). For instance, agricultural employment in the U.S. fell from around 40 percent in the late 19th century to just 3 percent by 1970. Similarly, blue-collar production and manual-labor jobs accounted for roughly 40 percent of employment in 1960 but only 20 percent today.

Yet, as Autor (2015) emphasizes, these past waves of automation have not led to lasting declines in overall employment, despite widespread fears. Automation, he argues, indeed substitutes for some tasks but also complements others, raising demand for certain roles and creating new job opportunities. Moreover, by reducing production costs and raising productivity, automation has historically boosted real incomes and consumption, fueling broader labor demand and contributing to job growth.

The primary effect of automation has thus been distributional rather than on aggregate employment levels. Autor, Levy, and Murnane (2003) show that since the 1970s, computers have increasingly substituted routine tasks primarily performed by middle-skill workers—especially in clerical, administrative, and production occupations—while complementing non-routine abstract tasks typically done by high-skill workers in professional, technical, and managerial jobs. Non-routine manual tasks, often carried out by low-skill service workers (e.g., janitors, cleaners, maintenance staff, food service workers, health aides, and security personnel), were less directly affected, though demand for these services rose as real incomes and consumption levels increased. Together, these dynamics have led to "job polarization," where employment growth has been concentrated in both high-skill and low-skill jobs, often at the expense of middle-skill employment (Autor, Katz, and Kearney, 2006; Autor, 2015).

A second instructive case is the "China shock." Autor, Dorn, and Hanson (2013) analyzed how rising import competition from China between 1990 and 2007 affected U.S. labor markets. They found that local areas specialized in import-sensitive industries experienced lasting job losses and wage declines, accounting for roughly 25% of the decline in U.S. manufacturing jobs. In follow-up work, the authors (2019) show that the adverse effects on employment and income persisted through 2019, nearly a decade after the shock had peaked. Notably, affected regions saw small reductions in labor supply (e.g., through out-migration) or compensating gains in non-manufacturing employment, meaning that the loss of manufacturing jobs translated almost directly into long-term employment declines. These findings highlight the frictions that can delay or prevent labor market adjustment to major economic shocks.

A third example comes from worldwide studies on significant unemployment events (e.g., Bertheau, 2022). For example, a series of studies by the Chief Economist's Department of Israel's Ministry of Finance (2024) examined the effects of mass layoffs between 1999 and 2009 (Aloni, Avivi, and Geva, 2024a, 2024b, 2024c). The research showed that such layoffs had a substantial and lasting impact on workers' incomes and household finances—especially during periods of economic crisis—and that the effects were particularly severe for older and higher-income workers. These findings can be relevant to GenAI-related disruptions: even in scenarios where labor markets remain tight overall, sector-specific displacement could still lead to significant short- and long-term consequences for affected individuals, underscoring the need for targeted support policies. For example, the studies highlighted the importance of active labor market policies, such as training programs, in mitigating the long-term consequences of displacement.

3. Proposed Policies to Address AI-driven Risks

As AI and automation reshape the job market, researchers highlight several approaches to help people adjust and maintain economic stability.

3.1. Education, Reskilling, and Infrastructure

One central recommendation is to significantly increase investment in education and skills throughout all life stages—starting from early childhood, continuing through schools and higher education, into vocational training, and even ongoing training at work. Many emphasize building strong foundational skills, improving digital literacy, and teaching people how to effectively interact with AI systems. This includes critical thinking, the ability to assess information sources, and understanding the strengths and weaknesses of AI models. Additionally, some argue that individuals should develop capabilities such as emotional intelligence, creativity, problem-solving, and adaptability. Empirical evidence supports this direction. Drawing on labor force data from 2012 to 2019 across 23 OECD countries, Georgieff and Hyee (2021) find no consistent link between AI exposure and overall employment growth. However, they do observe that in occupations with high levels of computer use, greater exposure to AI is associated with stronger employment growth. This suggests that digital skills can help workers adapt more effectively to AI-related changes, likely by enabling them to shift toward tasks that are less automatable and more productive. The OECD (OECD Employment Outlook, 2023) similarly highlights the rising demand for digital and data science skills, alongside cognitive and transversal skills. It calls for public investment to support skill development for workers across a wide range of occupations, ages, and backgrounds.

Furthermore, substantial investment in essential infrastructure—such as advanced computing capabilities, data availability, reliable and sustainable energy sources, engineering expertise, and human capital equipped with relevant AI-related skills—is crucial. These investments will help countries harness the economic benefits that AI industries can bring, ensuring they actively participate in, rather than merely react to, the AI-driven economic growth.

3.2. Taxation

Another policy solution focuses on taxation, with the goal of making sure the benefits of AI-driven productivity gains are shared more broadly. Some researchers suggest a robot tax or shifting the tax burden from labor to capital. Tax revenue from AI-driven businesses could incentivize retention of human workers and help fund supportive policy measures, such as expanded unemployment benefits and worker transition programs (Merola, 2022; Acemoglu, Manera, and Restrepo, 2020). Some have also suggested taxation can help slow excessive automation, allowing governments more time to design better regulations and reskilling programs (e.g., Acemoglu and Lensman, 2024).

However, these types of measures can also have downsides, for example, they might reduce the incentive for businesses to invest in innovation and productivity improvements that are important for raising living standards over time. Moreover, economies may face difficulty in implementing significant tax changes on high-income individuals and export-oriented firms, as these groups may shift profits or relocate to low-tax jurisdictions. This concern is especially relevant for small and open economies. This limits the ability of smaller countries to capture a fair share of the economic gains from AI adoption, especially compared to larger economies like the United States, which benefit from large domestic markets and greater leverage over multinational firms. At the same time, small countries typically face higher borrowing costs and more constrained fiscal space, further limiting their ability to respond to economic shocks.

While international initiatives such as the OECD's BEPS framework and the global minimum tax (Pillar II) aim to address profit shifting and tax base erosion, implementation success and enforcement remains uncertain. In addition, growing geopolitical tensions, particularly between major technology powers, make it difficult to reach lasting global tax agreements.

3.3. Supporting Human-Complementing AI Development

Another approach proposes a government-led effort to identify and promote pro-worker AI technologies. Acemoglu, Autor, and Johnson (2023) highlight concerns that the private sector's current trajectory for generative AI emphasizes automation and labor displacement, potentially worsening inequality and undermining worker well-being. To counter these trends, they advocate for active public policy to redirect AI innovation toward technologies that complement workers by enhancing their capabilities rather than replacing them. They recommend several policy tools to support this shift, including equalizing tax treatment between labor and automation-related capital investments, strengthening labor protections and worker voice in shaping technological development, and increasing public funding for research into human-complementary technologies.

Other scholars, on the other hand, highlight potential downsides of such approaches. Lerner (2020) points to underperformance of several government initiatives to promote entrepreneurship through financial incentives. He identifies three main pitfalls: political pressures that lead to geographic misallocation of funds, the tendency of public investments to exacerbate boom-bust cycles in entrepreneurial markets, and the limited capacity of governments to effectively identify and support high-potential ventures. To improve outcomes, Lerner emphasizes the importance of independent oversight and private co-investment to ensure that public funding remains disciplined and aligned with market signals.

In Israel, for example, the government has typically focused on supporting the broader tech ecosystem rather than choosing specific technologies to promote. With AI, this challenge is might be even greater because many AI tools have dual-use applications—what appears to complement human labor in one setting might end up replacing workers in another. The rapid pace of AI development makes it difficult for policymakers to predict these outcomes and attempts to steer the market could slow innovation or misallocate resources.

3.4. Universal Basic Income (UBI)

Some researchers take a broader approach, looking at Universal Basic Income (hereinafter UBI) as a way to provide financial security in a labor market that experiences severe disruptions. UBI, which would give everyone an unconditional fixed cash payment, is seen as one way to reduce economic uncertainty and address severe labor market shocks in an AI-dominated economy.

However, funding such a program at a meaningful level remains a major challenge. UBI requires a stable and substantial source of government revenue, and in many countries, this may not be fiscally realistic in the near term. While the global tax environment already poses challenges for raising revenue, these issues become even more pressing when considering the scale of funding needed for UBI. If governments are unable to effectively tax those who benefit most from AI-driven productivity gains, the burden may fall disproportionately on middle-income households or lead to cuts in other essential public services. For countries already struggling with tax collection and limited fiscal flexibility, this raises serious questions about the feasibility of implementing UBI without exacerbating existing inequalities or fiscal pressures. In Section 4.3, we explore these fiscal implications in greater depth using a simulation.

These considerations suggest that while UBI may remain part of the long-term policy discussion, it should not be seen as a one-size-fits-all solution. Policymakers will need to assess the fiscal and political context of each country carefully and consider a broader mix of tools—including targeted benefits, savings-based mechanisms, and retraining investments—to manage AI-related transitions.

4. The Fiscal Implications of AI-Driven Unemployment

There are multiple potential scenarios for how AI might shape the economy in the coming years. This paper focuses on a moderate scenario, where the labor market experiences a temporary increase in unemployment as AI displaces certain workers. Under this scenario, unemployment would initially increase, but many displaced workers would eventually reskill and transition to industries less impacted by automation or to complementary roles involving AI, with new types of jobs likely to emerge. While unemployment could settle at a level slightly higher than the current natural rate, it would not fundamentally disrupt the labor market or cause sustained instability. In a scenario where AI-driven automation increasingly threatens to displace human workers, policymakers may need to balance between potential temporary spikes in unemployment and the associated fiscal costs.

To better understand these fiscal challenges, we conducted simulations estimating the fiscal implications for OECD countries of increased unemployment payments or the introduction of UBI. We employed two complementary approaches—a "Top-Down" simulation and a "Bottom-Up" simulation—each addressing distinct but related policy questions, using simplistic assumptions. The “top-down” simulation examines the fiscal sensitivity of countries to increased unemployment, and the additional growth needed to offset the additional AI-induced unemployment. The "bottom-up" simulation assesses the fiscal implications of UBI.

4.1. Top-down simulation

This simulation assesses the potential fiscal implications of AI-induced labor market disruptions in OECD countries. Specifically, it estimates the level of additional GDP growth needed for each country to fiscally offset a hypothetical increase in unemployment resulting from AI adoption. The goal is to evaluate whether countries could absorb such a shock without breaching commonly used fiscal benchmarks.

The total revenue required to achieve an annual fiscal balance (that is, maintaining fixed level of deficit) when unemployment rises is calculated as:

$$(1)\ \Delta RevenueAI_i = \Delta U \cdot C_i^{per1\%},$$

Where:

- ΔU de notes the simulated increase in unemployment due to AI (ranging from 0% to 20%),
- $C_i^{per1\%}$ is a country-specific slope, representing the increase in government expenditures for country i associated with a 1 percentage point rise in unemployment,
- $\Delta RevenueAI_i$ represents the additional annual AI-driven GDP growth needed to fully offset the expenditure pressure from AI-induced unemployment.

To determine the level of GDP growth needed to neutralize the fiscal impact of AI-induced unemployment, we must make an assumption about the elasticity of tax revenues with respect to GDP, denoted by:

$$(2)\ \epsilon = \frac{\Delta RevenueAI}{\Delta GrowthAI}.$$

This elasticity reflects the percentage change in government revenue resulting from a 1% increase in GDP. Following common assumptions in the fiscal literature, we apply a unitary elasticity between GDP and government revenues (ε = 1), consistent with long-run empirical estimates across euro area countries (Köster & Priesmeier, 2017). This implies a one-to-one relationship between GDP growth and revenue gains: $\Delta RevenueAI = \Delta GrowthAI$. Substituting into Equation (1), we obtain the required AI-driven GDP growth to maintain fiscal balance:

$$(3)\ \Delta GrowthAI = \Delta U \cdot C_i^{per1\%}$$

Appendix A.1 presents the results of Equation (3), generating a country-specific growth requirement curve, which plots the annual output growth needed to fully neutralize the fiscal pressure from rising unemployment, ranging from 0 to 20 percentage points (the blue line). These estimates are then compared against two benchmark scenarios: a conservative forecast based on Acemoglu's estimate of 0.1% annual productivity growth over a decade, representing the lower bound of AI-driven productivity gains in the literature, and a more optimistic estimate of 1% annual growth (see Section 2.1.1 for a review of the predictions of AI's aggregate effect on growth and unemployment in the literature). The red shaded area represents the "negative balance" zone. In each combination in this zone, the net-effect of AI (taking into account both the additional growth associated with AI adoption and the AI-induced unemployment) on the fiscal balance is negative. For instance, in the case of Australia (the first country in the alphabetical order), if AI-induced unemployment rises by 12.5 pp, maintaining fiscal balance would require AI-driven annual output growth of approximately 0.25 pp.

Countries with steeper slopes ($C_{per1\%}$) are more exposed to AI-induced labor shocks, as each additional percentage point of unemployment translates into a proportionally larger fiscal burden. This slope, derived from country-specific expenditure responsiveness, serves as a proxy for marginal vulnerability.

The simulation results are not intended to yield a single conclusion, but rather to illustrate the fiscal implications of a range of AI-induced labor market disruptions. In many of the modeled scenarios—including cases of sharp increases in unemployment—fiscal pressures appear manageable for several countries. Moreover, under the simulation's simplifying assumptions, in scenarios where AI-related growth exceeds 1% of GDP annually, the model even suggests that no country enters a negative fiscal balance within the range of unemployment rates considered in the simulation (0%–20%). However, this outcome depends heavily on simplifying assumptions such as expenditure responsiveness and growth elasticity, which may not hold universally. Moreover, each country's fiscal resilience will ultimately depend on its baseline conditions, social protection architecture, unemployment distribution scenarios (by types of workers), capacity to adapt, economic structure, and more. The simulation provides a structured lens to explore these dynamics, but its insights should be interpreted and adjusted within each country's specific policy, institutional, and macroeconomic context.

Fiscal exposure is rarely about any single indicator. Countries with high baseline deficits, large debt stocks, or narrow credit headroom may find that even modest shocks accelerate a loss of policy space. Moreover, investor confidence can erode under the weight of cumulative pressures—especially where fiscal buffers are already thin.

To contextualize this vulnerability, Table A.1 presents a stylized summary that integrates average deficits (% GDP, 2015–2019), gross debt-to-GDP (2019), current credit ratings (2024, S&P), and each country's marginal fiscal sensitivity to labor shocks, according to our simulation. The juxtaposition reveals important asymmetries: Finland and Belgium, for instance, pair high expenditure sensitivity with already elevated deficits, suggesting reduced resilience, while maintaining strong credit ratings. At the same time, countries like Korea or Japan show moderate marginal burdens despite very different debt levels—highlighting that headline debt alone is only partial predictor of fiscal stress.

This underscores the value of a multidimensional framework. Neither deficit, debt, nor sensitivity alone captures the fiscal posture of a country facing AI-induced disruption. The combined visualizations and table aim to surface these layered dynamics, offering a more actionable perspective for both policymakers and investors.

Another important consideration is the potential mismatch between where AI-related disruptions occur and where the benefits are captured. Countries facing significant risk of job losses due to automation may not be the ones capturing the associated productivity gains or revenue. Specifically, workers may be displaced by automation in one country, while profits accrue to firms headquartered elsewhere. This kind of cross-country differentiation is highlighted in recent OECD analysis (2024b), which underscores that AI-driven productivity gains are likely to vary significantly across countries based on national adoption trajectories, sectoral composition, and exposure patterns. Although our model assumes a uniform benchmark projected growth rate (0.1%

or 1%) that does not explicitly capture this asymmetry. However, the continuous structure of the simulation allows exploration of a broad range of unemployment-growth scenarios.

It is also important to note that the simulation reflects current unemployment policies and benefit structures. The slope of the required growth curve, used here as a proxy for marginal fiscal sensitivity, is driven by the generosity and expansiveness of a country's unemployment welfare system. Notably, countries such as France, Belgium, and Finland, which rank among the most fiscally sensitive, also have strong social safety nets. In theory, governments could respond to AI-induced unemployment by scaling back benefits or tightening eligibility in order to ease fiscal pressure. Yet in practice, such reforms may prove politically difficult, especially in periods of rising joblessness and public discontent. Thus, while welfare generosity contributes to vulnerability in the model, it may also constrain a country's ability to adapt. Additional complementary policy tools, such as enhanced savings mechanisms, may therefore be critical for certain countries, and are discussed more extensively in the following chapter.

4.1.1. Simulation Limitations:

While this simulation is intentionally stylized to provide directional insight and illuminate key tradeoffs, it remains a simplified representation of complex fiscal dynamics and is subject to several limitations in addition to the ones mentioned above.

1. **Fixed Unemployment Expenditure Assumption:** The simulation assumes that government expenditure per additional percentage point of unemployment remains constant. In practice, prolonged or large-scale unemployment may prompt changes to benefit duration, eligibility criteria, or generosity. Alternatively, fiscal pressures could lead to retrenchment. These potential policy responses are not incorporated, which may lead to either over—or underestimation of fiscal exposure. Moreover, the simulation does not account for variation in the composition of the unemployed. If job losses disproportionately affect high-wage workers, the fiscal cost per unemployed person could be higher than in cases where marginal layoffs may involve lower-wage or part-time jobs.

2. **Use of Pre-Pandemic Baseline Data:** The analysis relies on 2019 data to avoid the distortions introduced by the COVID-19 pandemic. However, it does not account for

structural shifts in labor markets or fiscal positions that may have occurred in the post-pandemic period due to evolving macroeconomic conditions or policy reforms.

3. **Assumption of Unity Elasticity Between Growth and Revenues:** As mentioned above, the model assumes a one-to-one elasticity between AI-induced economic growth and public revenue gains, based on the common use in long-term fiscal projections of leading international bodies, and empirical evidence from the EU (Köster & Priesmeier, 2017). In reality, the relationship between GDP growth and fiscal capacity is mediated by tax system design, collection efficiency, and the composition of growth. As such, this simplification may overstate potential fiscal offsets, particularly in countries with narrow or regressive tax bases.

4. **Static Framework Without Dynamic Feedback:** The simulation is not dynamic. It does not model the cumulative effects of deficits over time, debt accumulation, or feedback from fiscal deterioration to interest costs, policy responses (including changes in welfare policy), or economic behavior. It represents a single-period snapshot rather than a long-term trajectory.

4.2 Bottom-up simulation

The Bottom-Up simulation focuses on the fiscal feasibility of implementing a UBI or FBB (Flat Basic Benefits) scheme by calculating the direct costs of providing a fixed monthly payment of $1,000 to varying proportions of the workforce (100%, 50%, and 10%).[4] By estimating these costs as shares of GDP and total government spending, our simulation highlights the substantial fiscal challenges associated with broadly implementing UBI or even broadly use of FBB. The analysis reveals that the budgetary strain is especially severe for OECD countries with lower GDP per capita, as their relatively limited fiscal capacity makes universal income programs particularly difficult to sustain without significant fiscal adjustments or external support (see figure A.2.1-A.2.3).

[4] By Flat Basic Benefits, we refer to UBI-like instruments that provide uniform support to a subset of the population, rather than to everyone.

The results of the simulation highlight that in milder scenarios where AI-related unemployment remains relatively low and economic growth is robust, existing social safety nets and targeted measures might be sufficient to manage temporary shocks. However, even a moderate increase in unemployment can create a meaningful fiscal burden with UBI, suggesting a need to supplement the current policy toolkit. In these cases, a full-scale UBI would likely be unnecessary, but there is clear value in exploring additional, flexible tools to address temporary displacement without overstretching public budgets, as seen from the result of the top-down simulation. In contrast, if AI-related unemployment becomes more severe, implementing a broad-based UBI or FBB quickly becomes fiscally challenging. In such cases, supplementary measures can help buy time and ease the transition, allowing for the careful planning and phased introduction of a more comprehensive tools, potentially including extended unemployment benefits, or a version of UBI/FBB program, in a manner that is both fiscally sustainable and appropriately targeted.

5. Savings and capital accumulation

In light of the challenges of different policy tools and the necessity for tailored solutions for different countries due to their unique circumstances, this paper proposes a complementary approach centered on *individual savings and capital accumulation*. This approach aims to mitigate the economic impact of AI-driven labor disruptions—particularly under the scenarios of moderately rising unemployment as discussed above—by enabling individuals to build resilience through enhanced capital income, offering a proactive and holistic response to the risks posed by advanced Generative AI technologies. By broadening access to capital income, policymakers can empower workers with greater financial resilience, enabling them to better navigate economic transitions and invest in crucial reskilling opportunities (including covering program deductibles), while simultaneously easing fiscal pressures.

Furthermore, research suggests that GenAI could substantially increase returns to capital, leading to a widening gap between capital and labor incomes as the capital share of national income rises (Acemoglu and Restrepo, 2022; Acemoglu, 2025; Minniti, Prettner, and Venturini, 2025; Karabarbounis, 2024). Policies aimed at boosting individual capital income—particularly targeting low- and middle-income households with currently low capital holdings—can help achieve a more equitable distribution of the increased capital returns anticipated from GenAI-driven growth, thereby reducing income inequality between capital and labor in the emerging AI economy.

To explore the cross-country landscape and identify contexts where such savings-based approaches are most urgent, we examine household saving behavior across OECD countries. In the following sections, we first analyze saving patterns across OECD countries, categorizing these countries based on their relative saving levels. We then discuss the proposed policy tool, highlighting key considerations for its effective deployment and implementation.

6. Savings Patterns in OECD Countries

6.1. Data Sources

In this section, we utilize three primary indicators to represent the saving behavior in OECD countries: household net savings, household net wealth, and pension replacement rates. These indicators reflect the primary sources through which households accumulate savings. Household net wealth reflects accumulated financial and non-financial assets, serving as a stock measure of household resilience. Pension replacement rates act as a proxy for long-term expected reliance on public income versus personal savings in retirement, helping to contextualize the role of state-provided income support. All three indicators are sourced directly from OECD databases. Specifically, household net savings data is obtained from the OECD Economic Outlook, household net wealth from the OECD Better Life Index, and gross pension replacement rates from OECD Pensions at a Glance.[5]

The OECD also provides some information on how these saving indicators vary across income levels. Data on household net wealth distribution is available through the OECD Wealth Distribution Database, offering critical indicators such as wealth inequality, wealth shares,

[5] **Household net savings:** OECD Economic Outlook No 116, Edition 2024/2 (link). **Household net wealth:** OECD Better Life Index, Last updated: March 11, 2024 (link). **Pension replacement rates:** OECD (2023), Pensions at a Glance 2023: OECD and G20 Indicators, Table 4.1 (link).

household indebtedness, and asset poverty for recent years.[6] Data on household net savings segmented by income quintile can be found in the OECD National Accounts, though coverage is limited to a few countries.[7]

Lastly, to analyze the generosity of welfare systems across OECD countries, we use government expenditure data categorized by the Classification of Functions of Government (COFOG).[8] Specifically, we employ the "Social Protection" expenditure category, measured as a percentage of GDP, to capture variations in welfare system generosity.

6.2. Analysis of Savings and Welfare Generosity

This section presents a comparative analysis of savings and welfare system generosity across OECD countries. We begin by constructing a composite indicator that integrates our three primary saving measures—household net savings, household net wealth, and pension replacement rates. To ensure comparability, we first standardize each saving indicator by converting it into deviations from its mean in terms of standard deviations.[9] We then compute the overall savings measure for each country as the average of these standardized variables, and plot this composite savings indicator against each country's social protection expenditure as a percentage of GDP (detailed results for each individual savings indicator are presented separately in Appendix A.3).

Figure 1 displays the results, categorizing countries into four quadrants based on their combined savings and social protection levels. Countries such as France, Italy, Austria, and Luxembourg appear in the upper-right quadrant, characterized by high savings and high social protection. Countries like Finland and Norway occupy the lower-right quadrant, marked by high social protection but relatively lower savings. The USA and Hungary fall into the upper-left quadrant, having higher savings but lower social protection. Lastly, the lower-left quadrant comprises

[6] See OECD Wealth Distribution Database (WDD), Key Indicators (link). For data sources, please refer to the Main characteristics of data sources guide. For metadata, including the components included in the aggregated wealth figures, please refer to the WDD Metadata.

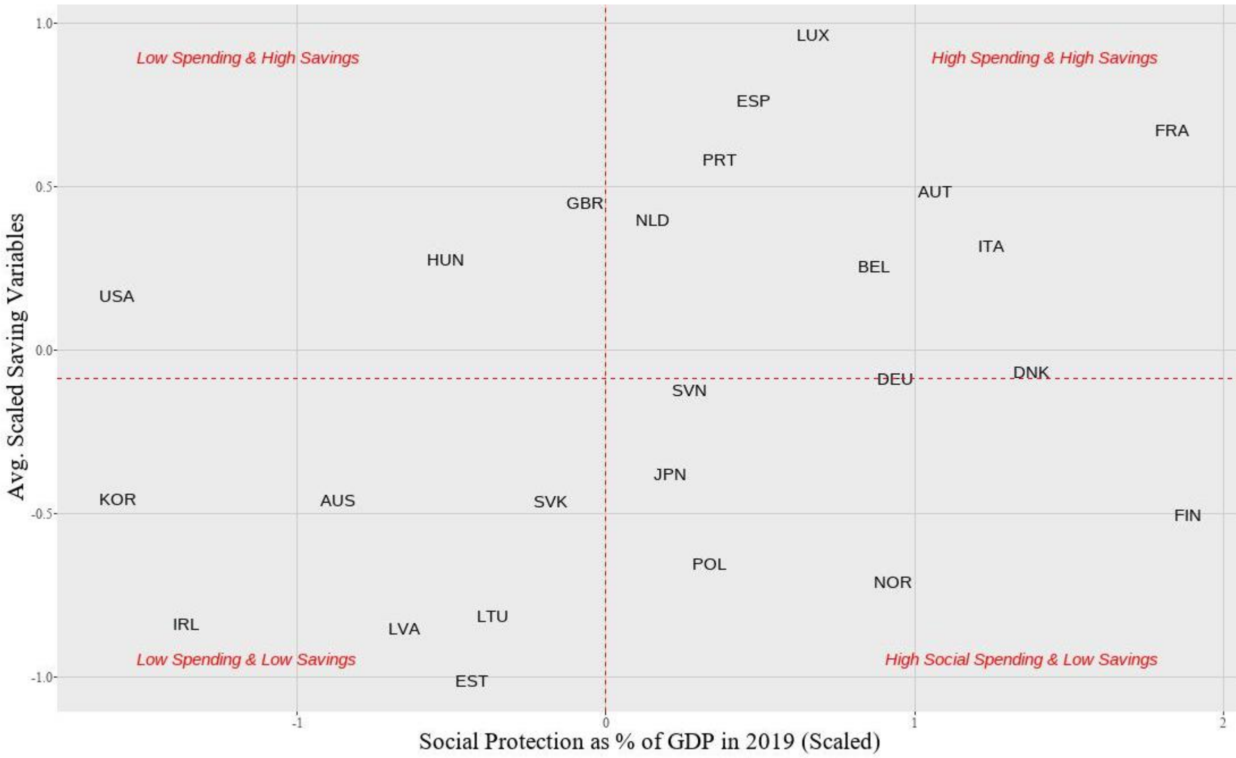
[7] OECD, Household income and saving in the National Accounts: distributions by income quintile, Last updated: March 05, 2025 (link). For the results below (Figure 4), we divide the "Saving, gross" transaction by the "Disposable income, gross" transaction.

[8] OECD Data Archive, General government spending, 2019.

[9] Formally, for each country i and variable x_i, we define the standardized variable as $\hat{x} = \frac{x_i - mean(x)}{sd(x)}$.

Eastern European countries like Latvia, Lithuania, Slovakia, Estonia, as well as South Korea and Australia, all characterized by both low social protection and low savings levels.[10]

Figure 1—Social Protection vs. Average Scaled Saving Variables (Quadrants)

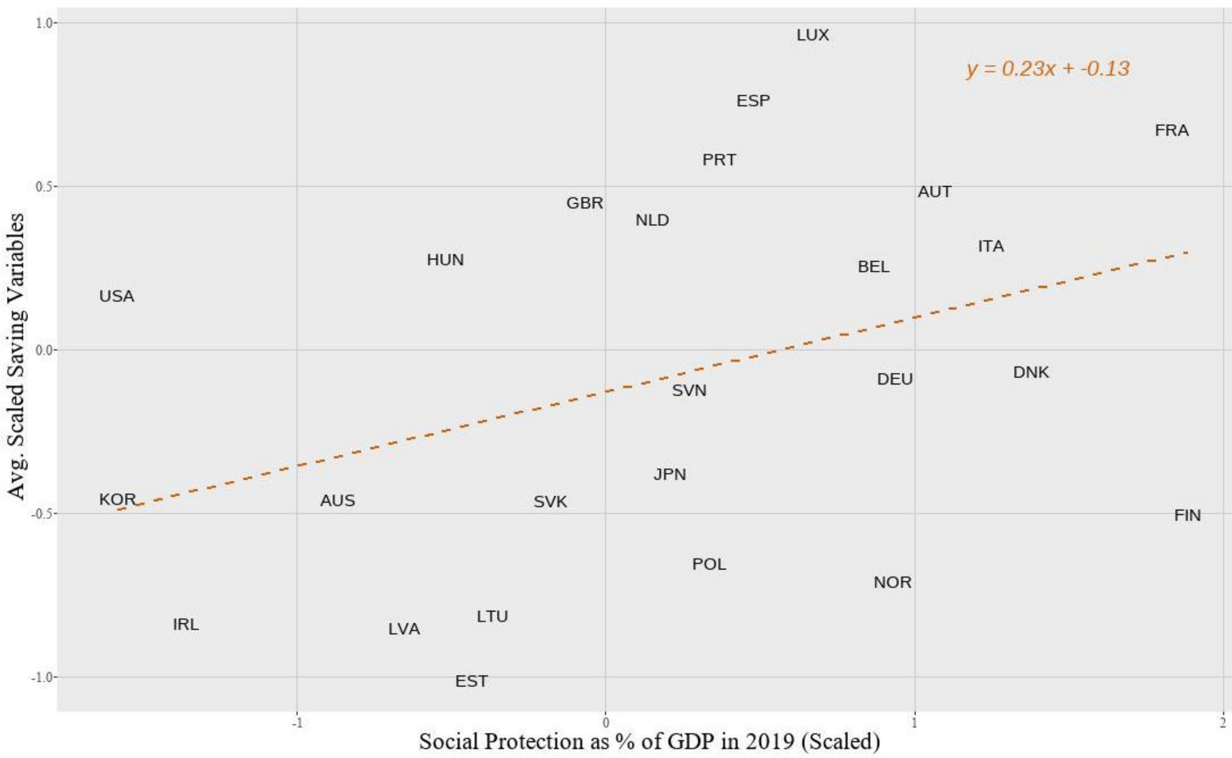


This analysis helps identify countries that are particularly vulnerable to AI-driven labor market disruptions and would benefit most from policies that promote household savings. In the event of moderate unemployment shocks, welfare systems may take time to adjust, leaving affected workers temporarily exposed. In countries with less generous social protection, workers will be most vulnerable, especially when their household savings are low. For this reason, we argue that countries in the lower-left quadrant have the greatest need—and stand to gain the most—from policies that enhance household savings. However, such policies may also be valuable for other countries, particularly those trending toward lower levels of social protection or savings.

[10] Ireland is generally excluded from the analysis due to its GDP figures being significantly inflated by multinational corporations using it as a tax haven.

Next, we explore the relationship between savings and social protection levels more closely. Figure 2 replicates Figure 1 but replaces quadrant classification with a regression line. It reveals a positive correlation: countries with one standard deviation higher social protection levels exhibit, on average, approximately 0.23 standard deviations higher savings levels.

Figure 2— Social Protection vs. Average Scaled Saving Variables (Regression Line)



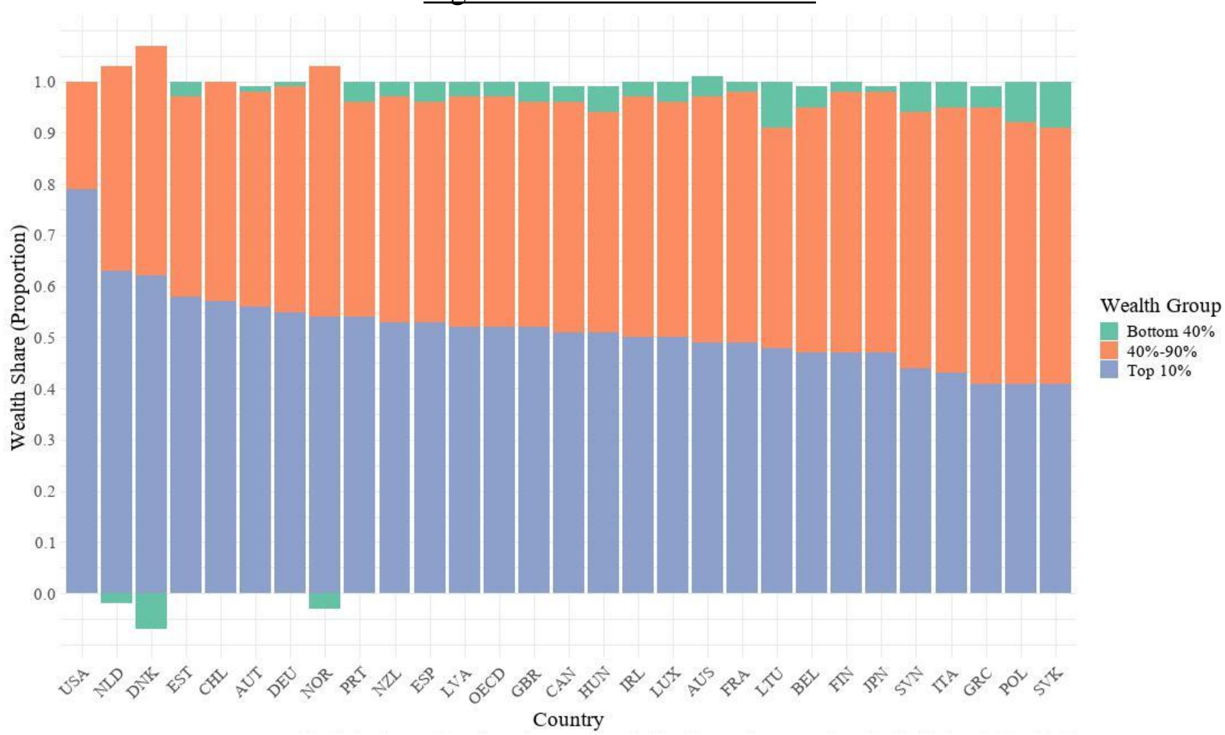
This correlation may initially appear counterintuitive, as more generous welfare systems could be expected to reduce the need for precautionary savings. To unpack this further, Appendix A.4 reports additional regression analyses controlling for GDP and overall government spending (as a share of GDP). The correlation remains largely unchanged when controlling for GDP but becomes significantly weaker when controlling for total government spending. This suggests that the observed relationship is largely driven by the fact that countries with higher levels of social protection also tend to have higher overall public spending, which itself is positively associated with household savings. A potential explanation for this relationship is that countries with larger public sectors often implement policies for wide-ranging services—both in public services and savings policies—to support their citizens throughout their lives and maintain an adequate level of household savings.

6.3. Distribution of Savings Across the Income Distribution

In the previous section, we compared average household savings across countries. However, when discussing policy interventions aimed at increasing household savings, it is critical to understand how savings are distributed among different household groups within each country.

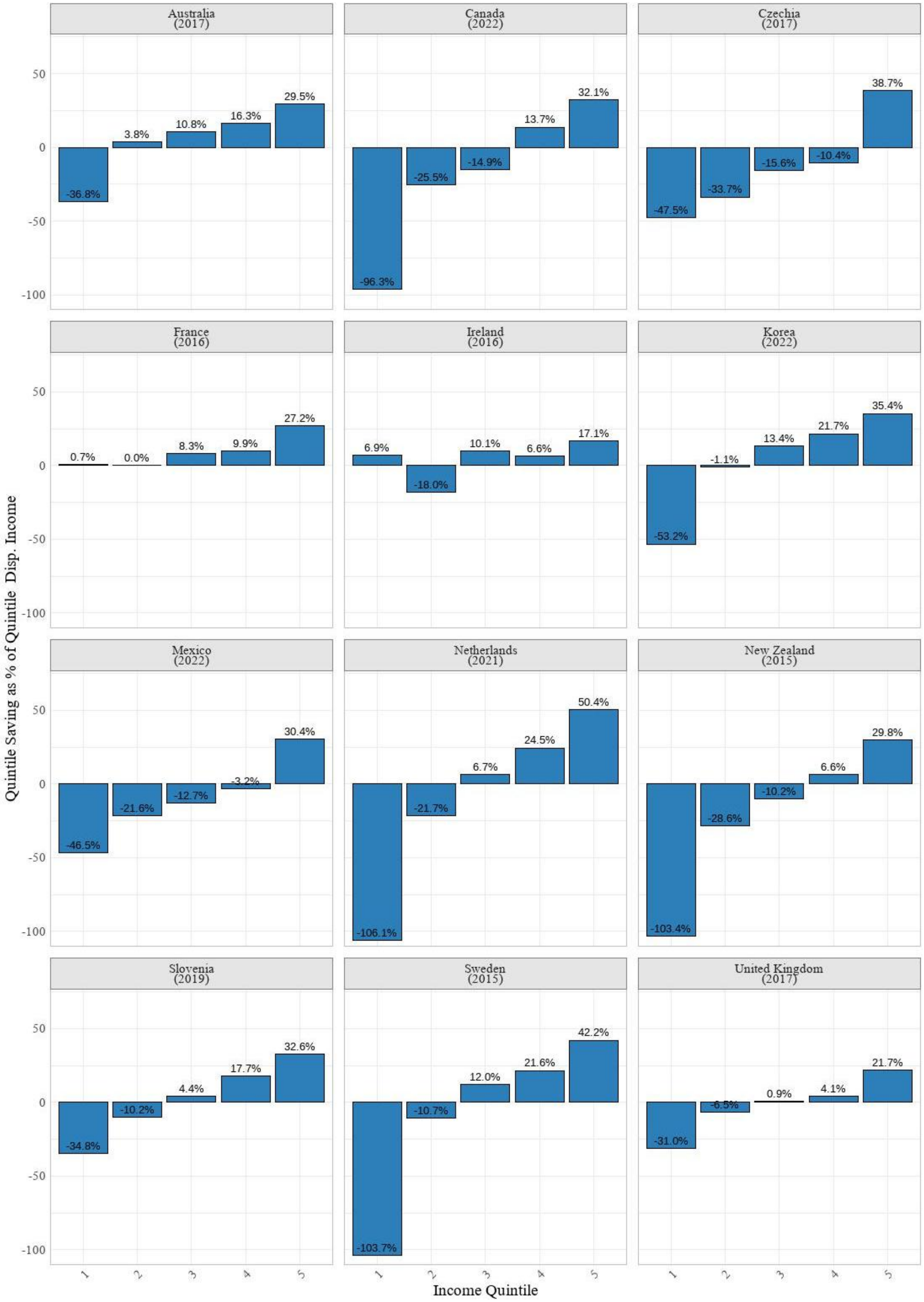
Figure 3 presents the distribution of household wealth across populations in OECD countries. It shows that while substantial variation exists between countries, significant wealth inequality is a prominent and consistent feature across all of them. On average, the wealthiest 10 percent of the population holds 52 percent of total household wealth, and this figure rises to nearly 80 percent in the United States. Conversely, the bottom 40 percent holds only 3 percent of household wealth on average, and in some countries, their net wealth is negative.

Figure 3—Wealth Distribution



Next, Figure 4 presents average household savings (as a percentage of gross disposable income) by income quintile across 12 OECD countries for which data is available. Similar to wealth distribution, household savings exhibit significant inequality. The top quintile experiences substantial positive savings, typically ranging from 30 to 50 percent of their disposable income. In contrast, the lowest quintile often faces substantial deficits, spending more than their disposable income in most countries.

Figure 4—Quintile Savings as Percentage of Quintile Disposable Income



7. Discussion

There is still significant uncertainty regarding the pace, scale, and nature of AI's development and its potential impact on labor markets. In this paper, we focus on a scenario where AI leads to a rise in unemployment, but the labor market gradually adjusts as workers reskill, new roles emerge, and productivity gains support economic growth. We propose addressing the risk of increased unemployment and inequality associated with this scenario through increased savings and capital accumulation for individuals. Under our proposal, individuals would maintain personal savings accounts to serve as "rainy-day funds," helping to bridge temporary yet prolonged periods of unemployment resulting from technological change. When invested effectively, these savings could also generate capital income for workers, thereby narrowing the gap between labor and capital owners, which could increase due to AI-driven growth.

This approach equips policymakers to manage moderate increases in unemployment effectively. Furthermore, since AI's impact on the labor market is likely to unfold gradually, this approach can serve as a transitional tool, providing time to develop more comprehensive policies (such as UBI or other measures) should more severe scenarios emerge (Amaglobeli et al., 2019).

While public unemployment insurance plays a critical role in many labor markets and remains appropriate in a wide range of circumstances, our focus is on scenarios where the economic change is gradual or temporal, and public welfare systems may not adapt quickly or sufficiently. In these cases, fiscal pressures could limit governments' ability to respond and enhancing private capital income can serve as a complementary tool, helping individuals weather periods of unemployment without placing additional strain on public resources, thereby helping build resilience and allow for more flexible, tailored responses to evolving labor market challenges.

The remainder of this section outlines key considerations for implementing the proposed policy.

7.1 Which Countries Would Benefit Most from This Policy?

In section 6.2, we analyzed countries by household saving levels and generosity of the welfare system. Thus, this analysis helps identify countries that are particularly vulnerable to AI-driven labor market disruptions and would benefit most from policies that promote household savings. If

AI leads to unemployment shocks, workers in countries with less generous welfare systems will be disproportionately affected—at least until policy adjustments are made, which can take time. If these workers also have low savings, their vulnerability increases further. Therefore, we argue that countries in the bottom-left quadrant, such as Slovakia, Lithuania, Estonia, Korea and Australia, stand to gain the most from policies aimed at boosting household savings. However, such measures could also benefit other countries, especially as they move closer to this quadrant.

Conversely, countries with higher existing savings rates could consider relaxing restrictions on early partially withdrawals, depending on the structure and type of the existing savings schemes—to swiftly address increased unemployment. In these cases, decisions could be made at a later stage, once more data and a clearer understanding of AI's labor market impact become available.

Another important consideration is demographic aging. Even if generative AI does not ultimately lead to widespread unemployment, increasing household saving rates could still be valuable as a way to prepare for the financial implications of aging populations in scenarios in which AI productivity boosts will not be sufficient—whether for retirement or other medium-term needs.[11] This is especially relevant for countries with both rapidly aging populations and low levels of retirement savings. Figure 5 shows countries positioned according to their household saving rates and the extent of population aging, measured by the old-age to working-age ratio. The figure highlights that countries such as Japan, Finland, Lithuania, and Estonia have both older populations and relatively low average household savings. For these countries, encouraging higher saving rates could be beneficial regardless of whether AI significantly disrupts labor markets.

[11] An IMF report (Amaglobeli, 2019) highlights that aging populations are expected to significantly increase pension costs and reduce national savings, particularly in advanced economies, emphasizing the importance of proactive policies to encourage household savings.

Figure 5—Old-Age to Working-age Ratio vs. Average Scaled Saving Variables

7.2. Distributional Considerations and Specific Population Groups

7.2.1. AI-Vulnerable and Low-Income Household

A key consideration in implementing this tool is identifying which segments of the population to target. Naturally, the workers who stand to benefit most are those at greatest risk of being substituted by GenAI. However, accurately identifying these workers poses a major challenge. As discussed in Section 2.1.2, some studies suggest that much like previous waves of technological change, GenAI is likely to substitute routine tasks typically performed in low- and middle-skill jobs—such as administrative and customer service roles—while complementing high-skill occupations, particularly in STEM fields. Other research, however, points to the potential of GenAI to automate even high-skilled tasks, especially in data-intensive sectors such as finance and law.

These distributional concerns are central to our proposed policy of promoting increased private savings as a means to mitigate labor market risks associated with GenAI. As shown in Section 6.3, savings and wealth are highly unequally distributed, with lower-income households often holding little or even negative net savings. Therefore, increasing the savings and capital income of lower-income workers—particularly those more exposed to automation—could be especially beneficial.

However, such efforts must be carefully designed to avoid placing additional financial pressure on already vulnerable households and suppressing consumption among groups with a high marginal propensity to consume. In fact, many low-income households already benefit from relatively high replacement rates through public welfare systems, suggesting that requiring them to save more may be unnecessary and even harmful. A more effective strategy may be to support their ability to save through targeted subsidies or fiscal incentives. For example, the Israel government introduced mandatory pension contributions for the self-employed, which was complemented by tax reductions for lower-income self-employed workers. A similar approach could help enhance savings among vulnerable groups without exacerbating financial hardship.

7.2.2. Self-Employed Workers

Another essential group warranting attention is self-employed workers, who frequently lack coverage from conventional social welfare programs. The share of self-employment varies significantly across countries—from 23.5 percent in South Korea to 6.3 percent in the US.[12] In some developed countries, these workers have limited access to unemployment insurance and similar protections available to regular employees during economic shocks, although the level of coverage varies across countries (Immervoll et al., 2022).

Becker, Schoukens, and Weber (2024) review unemployment protection systems across several European countries, highlighting this variation. Denmark provides one of the most inclusive systems, allowing self-employed individuals to voluntarily join the same unemployment insurance scheme as employees, with recent reforms enabling mixed-income workers to qualify more easily. Spain offers mandatory coverage tailored to the self-employed and economically dependent workers, though strict eligibility conditions and income thresholds limit access to some workers, particularly those with low-income. Hungary formally includes self-employed workers in its general scheme with employees. However, the self-employed often apply reduced contribution

[12] See OECD self-employment rate data for country-specific rates: https://www.oecd.org/en/data/indicators/self-employment-rate.html.

rates, which lower the level of unemployment benefits they receive or even exclude them from unemployment protection completely.

Other countries provide only partial or conditional access. In Austria, self-employed individuals can voluntarily opt for unemployment insurance, but participation is very minimal, with only around 0.43% of the self-employed participating. In addition, the self-employed are free to choose their contribution level, which affects the unemployment benefit they receive. Belgium excludes the self-employed from the general unemployment system but offers a separate "bridging right" scheme triggered only by predefined events like bankruptcy, with limited coverage for part-time or economically dependent self-employment. Estonia's fragmented classification of self-employment results in narrow coverage, and individuals combining multiple work forms often fall through the cracks. Switzerland, notably, offers no unemployment insurance for the self-employed, except in relatively rare cases where their business fails, and they have previously paid contributions as an employee.

Pension systems for the self-employed also vary widely across OECD countries.[13] In many countries such as Austria, Canada, Czechia, Finland, France, Hungary, Portugal, and the United States, most self-employed workers are covered under the same schemes as employees and are, at least in principle, eligible for similar benefits. However, in practice, in many of these countries, self-employed workers tend to receive lower pensions due to lower reported incomes, reduced contribution rates, and irregular work patterns. Countries such as Belgium, Israel, Italy, and Spain mandate self-employed participation in pension systems, though contribution rates or assessment bases are often lower than for employees, which can limit future benefits.[14] In Denmark, Japan, Sweden, Switzerland, and Norway, self-employed workers are not required to contribute to occupational pensions but are included in public systems that offer a partial safety net (the level of coverage varies between these countries). In Australia, Germany, and New Zealand, most self-employed workers are not even mandated to participate in public pension schemes. Although they may opt in, take-up rates are typically low, leading to significant coverage gaps. Overall, across

[13] For a comprehensive review of each country's pension policy, including those related to the self-employed, see the OECD Pensions at a Glance 2023 report (OECD, 2023c).
[14] It is worth noting that self-employed individuals may invest more in their businesses and thus benefit from it in the future.

all countries, the self-employed tend to have lower pension benefits than employees, although the size of this gap varies.

Moreover, general labor market policies—such as those designed to preserve job attachments—often fail to benefit the self-employed. As a result, countries often introduce targeted measures to support the self-employed during large-scale labor market shocks like the COVID-19 crisis, such as the US Pandemic Unemployment Assistance (PUA) and the UK's Self-Employment Income Support Scheme (SEISS).

However, in scenarios involving more moderate, gradual shocks—the context where our proposed policy is most relevant—governments may be slower to respond, or may not intervene at all. In such scenarios, self-employed workers and others with limited access to social protection are likely to face the greatest risks. This is particularly true in countries where the coverage of both unemployment protection and pension systems for the self-employed is relatively limited, such as Switzerland or Belgium. Implementing targeted savings-enhancement policies specifically tailored to these populations could play an important role in helping them build financial resilience and manage the transition.

7.3. Additional Points for Consideration

In this section, we highlight several additional points that governments should consider when choosing the most appropriate tools to enhance individual capital income. These tools should not follow a one-size-fits-all approach, but rather be tailored to the institutional structures, economic conditions, and public preferences of each country. The considerations below are intended to support such context-sensitive policy design:

- **The relationship between savings and growth:** Saving levels should also consider each country's specific economic growth trajectory. The link between savings and growth has been widely discussed in economic literature. Solow (1956) established the theoretical foundation for the positive relationship between savings and long-term output growth, highlighting the role of capital accumulation in the neoclassical growth model. Empirical evidence from India (Singh, 2009) supports a bidirectional long-run relationship between domestic savings and income, while Alper (2018) finds that in emerging economies, a 1% increase in savings rates is associated with a 0.5% increase in GDP. However, the relationship is not always linear or immediate. Misztal (2011) notes that in both developed and developing countries, higher savings rates can be associated with slower short-term growth, especially where they reduce household consumption. Furthermore, policy design matters: evidence from Israel's pension reform shows that mandatory savings policies may reduce consumption among lower-income households (Frish, 2025), underscoring the importance of careful calibration. These insights suggest that while increasing savings is essential, it must be pursued in a way that reflects country-specific economic conditions, income levels, and short-term fiscal realities.

- **Public Support:** People might prefer policies that empower them directly. A recent survey by The Times (Feb. 2025) shows a shift in public sentiment, with more people favoring tax cuts over expanded government spending. This preference might reflect broader public attitudes around government efficiency and a growing desire for personal financial control. As such, policymakers should carefully assess public support for specific tools when deciding which policies to pursue. In countries with higher institutional trust or a tradition of self-reliance, such tools may be more politically feasible.

- **Increased Savings vs. Private Insurance:** We argue that this savings-based strategy is more practical and effective than collective private insurance schemes for the populations we argue the policy tool should target. Although collective private insurance may appear initially appealing, it poses risks of moral hazard, potentially leading individuals to take greater risks knowing unemployment burdens are shared (such as for the self-employed population where verifying unemployment is more difficult). Furthermore, for the general population, the uncertain and potentially widespread nature of AI-driven employment disruptions makes it unlikely that private insurance markets could sufficiently evolve to cover these risks. By contrast, personal savings accounts clearly assign responsibility and incentivize individuals to mitigate their own employment risks.

- **Leveraging Existing Institutional Frameworks:** Each country has distinct institutional arrangements and policy traditions. Utilizing existing mechanisms such as pension plans or medium-term savings schemes can minimize bureaucratic complexity and allow for quicker policy implementation. Each government should consider the different saving framework in its country and decide on the exact solution according to its goal.

- **Timing and Monitoring:** For countries with low savings levels or with low saving rates among specific groups and high exposure to AI-related employment disruptions, implementation should occur at an early stage to allow sufficient capital accumulation. In contrast, countries with higher savings rates, or with higher saving among groups with high exposure to AI replacement, should closely monitor labor market conditions and consider allowing early withdrawals promptly if employment conditions deteriorate. Governments could also define early warning indicators, such as rising displacement in specific occupations or sectors, that would trigger the activation or acceleration of savings-based policy tools or flexible withdrawal.

- **Voluntary vs. Mandatory Mechanisms:** The additional savings could be facilitated through voluntary or mandatory tools, determined based on each country's institutional context, demographic characteristics, and fiscal capacity. When designing mandatory savings programs, setting the level of savings should take into account the potential crowding-out effect of voluntary savings should be taken into account. However, the literature indicates that crowding out effect is usually relatively small. Friedberg et al., (2024) found that only 30% of the voluntary contributions are offset by mandatory contributions. Recent PEW research found that auto-IRA program complement, rather than crowd out, private retirement plans for small business in California, Oregon, Illinois, and now Connecticut continues (Guzoto et al., 2024).

  In voluntary mechanisms, governments could explore providing tax incentives or subsidies to encourage saving behaviors. Additionally, enhancing financial literacy and clearly communicating the benefits and mechanisms of these savings schemes to the public can improve participation rates and overall effectiveness. For instance, governments may prefer drawing from more liquid, medium-term savings before touching retirement funds. For example, emergency savings schemes may be used first. These choices should be tailored to the structure of household wealth and the government’s approach to managing social risk.

- **Balanced Risk-Sharing:** Countries should carefully calibrate incentives and clearly define how financial responsibilities are distributed among employees, employers, and the state, ensuring fair and equitable risk-sharing tailored to national economic realities. For example, some governments may require employers to match a portion of worker savings, while others may subsidize contributions for low-income earners.

- **Replenishment of Savings Post-Recovery:** In cases where the labor market successfully adjusts, and individuals return after reskilling or as new suitable jobs emerge, governments might consider temporarily requiring increased savings contributions to replenish any capital used during periods of unemployment. This could take the form of temporary higher contribution rates to pension or emergency savings accounts once re-employment is achieved. This is particularly relevant if individuals subsequently benefit from higher wages due to productivity gains associated with technological advancements.

Importantly, the proposed savings-based approach is not a substitute for broader strategies such as investment in education, training, and infrastructure, or for more comprehensive welfare support, such as unemployment benefits or an income support version of UBI/FBB, in the case of more extreme disruptions. However, it can offer practical and flexible support in moderate scenarios, or serve as a complementary tool during a transitional phase if the impact of AI unfolds gradually. It can provide individuals with greater economic security, reduce public spending pressures, and buy time for governments to assess and respond to evolving labor market challenges. We believe that incorporating this tool into the broader policy mix can enhance overall resilience and public confidence in the face of AI-driven change.

Acknowledgments

I am grateful to Dan Levy and the leadership team of the Senior Fellows Program at the Mossavar-Rahmani Center for Business and Government (MRCBG) at the Harvard Kennedy School—Professor Richard Zeckhauser, Professor John Haigh, Dan Murphy, and Susan Gill—for their valuable advice, thoughtful feedback, and ongoing support. I am also thankful for the insightful comments and suggestions received from the Senior Fellows at the Mossavar-Rahmani Center for Business and Government, which were invaluable throughout various stages of this work.

My sincere appreciation goes to the experts I interviewed or consulted, whose insights greatly enriched this paper. Among them, in alphabetical order: Aharon Aharon, Ami Apelbaum, Asaf Geva, Avi Hasson, Avi Lavon, Haim Shani, Isaac Ben-Israel, Kfir Batz, Orna Berry, Sagi Dagan, Shlomo Dovrat, Zvi Eckstein, and Yishay Yafeh, as well as numerous Israeli tech founders and CEOs.

Above all, I would like to express special thanks to Merav Kaplan and Guy Lichtinger for their extraordinary contributions as co-authors and for their exceptional research assistance.

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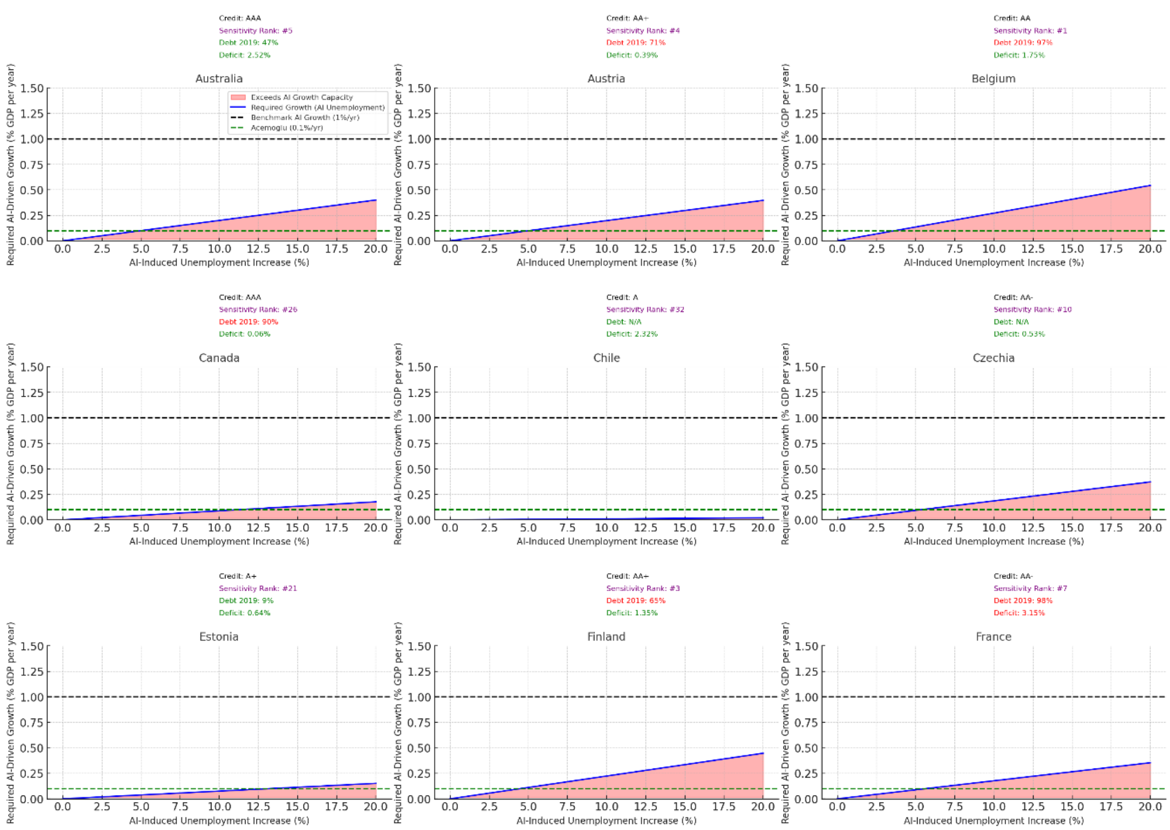
Appendix

A.1 Top-Down Country by Country Simulation

Each panel in the appendix visualizes a country's projected fiscal pressure resulting from AI-induced unemployment shocks. The horizontal axis shows a range of hypothetical increases in unemployment (from 0% to 20%) due to AI adoption. The vertical axis shows the corresponding level of GDP growth each country would need annually over a 10-year horizon to fiscally offset the resulting increase in social expenditure. The blue line reflects this required growth. For comparison, two horizontal reference lines are included: a dashed black line representing a 1% benchmark scenario for AI-driven growth, and a green line representing Acemoglu's more conservative 0.1% productivity estimate.

The red-shaded area highlights the portion of the curve where the required growth is lower the fiscal cost of unemployment would outpace plausible economic benefits from AI. Annotations provide key fiscal context, including each country's gross debt level, average deficit, S&P credit rating, and a sensitivity ranking derived from their expenditure responsiveness to unemployment. Together, the graphs are intended to help policymakers and analysts identify which economies may be most fiscally vulnerable to labor displacement from AI, and under what conditions that vulnerability becomes acute. As noted, this is a stylized simulation with simplifying assumptions—as discussed in Section 4.1.

<u>Figure A.1—Required AI-Driven Growth to Maintain</u>




Credit: AAA
Sensitivity Rank: #2
Debt 2019: 59%
Deficit: 1.32%
Germany
Exceeds AI Growth Capacity
Required Growth (AI Unemployment)
Benchmark AI Growth (1%/yr)
Acemoglu (0.1%/yr)
Required AI-Driven Growth (% GDP per year)
AI-Induced Unemployment Increase (%)
Credit: BBB-
Sensitivity Rank: #30
Debt 2019: 184%
Deficit: 0.20%
Greece
Credit: BBB-
Sensitivity Rank: #17
Debt: N/A
Deficit: 2.06%
Hungary
Credit: A+
Sensitivity Rank: #9
Debt 2019: 67%
Deficit: 2.50%
Iceland
Credit: AA
Sensitivity Rank: #12
Debt 2019: 56%
Deficit: 0.51%
Ireland
Credit: A
Sensitivity Rank: #22
Debt 2019: 59%
Deficit: 2.29%
Israel
Credit: BBB
Sensitivity Rank: #15
Debt 2019: 134%
Deficit: 2.20%
Italy
Credit: A+
Sensitivity Rank: #31
Debt 2019: 236%
Deficit: 3.18%
Japan
Credit: AA
Sensitivity Rank: #13
Debt 2019: 40%
Deficit: 1.38%
Korea
Credit: A
Sensitivity Rank: #20
Debt 2019: 38%
Deficit: 0.82%
Latvia
Exceeds AI Growth Capacity
Required Growth (AI Unemployment)
Benchmark AI Growth (1%/yr)
Acemoglu (0.1%/yr)
Credit: A
Sensitivity Rank: #23
Debt 2019: 36%
Deficit: 0.27%
Lithuania
Credit: AAA
Sensitivity Rank: #6
Debt 2019: 22%
Deficit: 2.08%
Luxembourg
Credit: AAA
Sensitivity Rank: #11
Debt 2019: 48%
Deficit: 0.60%
Netherlands
Credit: AA+
Sensitivity Rank: #14
Debt 2019: 32%
Deficit: 0.29%
New Zealand
Credit: AAA
Sensitivity Rank: #33
Debt 2019: 41%
Deficit: 5.86%
Norway
Credit: A-
Sensitivity Rank: #19
Debt: N/A
Deficit: 1.49%
Poland
Credit: A-
Sensitivity Rank: #16
Debt 2019: 116%
Deficit: 1.90%
Portugal
Credit: A+
Sensitivity Rank: #N/A
Debt 2019: 48%
Deficit: 1.68%
Slovak Republic

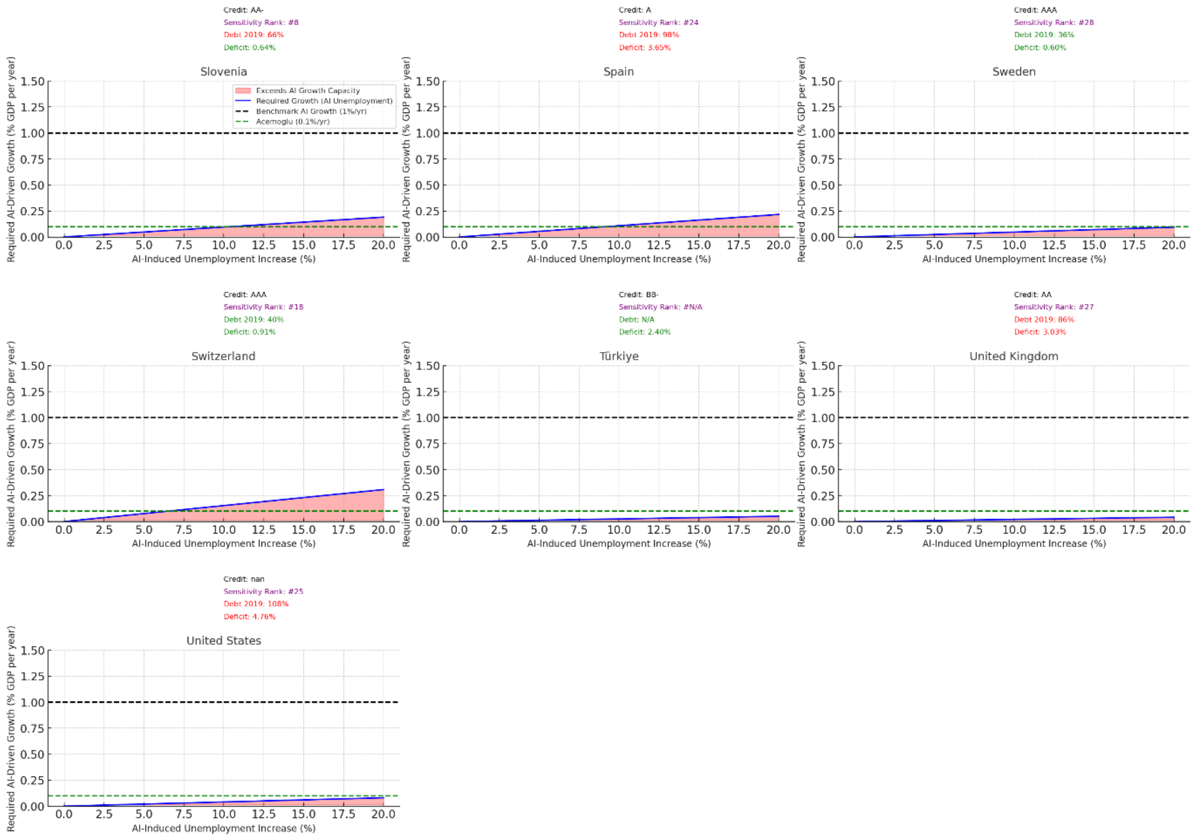

Credit: AA-
Sensitivity Rank: #8
Debt 2019: 66%
Deficit: 0.64%
Slovenia
Exceeds AI Growth Capacity
Required Growth (AI Unemployment)
Benchmark AI Growth (1%/yr)
Acemoglu (0.1%/yr)
Credit: A
Sensitivity Rank: #24
Debt 2019: 98%
Deficit: 3.65%
Spain
Credit: AAA
Sensitivity Rank: #28
Debt 2019: 36%
Deficit: 0.60%
Sweden
Credit: AAA
Sensitivity Rank: #18
Debt 2019: 40%
Deficit: 0.91%
Switzerland
Credit: BB-
Sensitivity Rank: #N/A
Debt: N/A
Deficit: 2.40%
Türkiye
Credit: AA
Sensitivity Rank: #27
Debt 2019: 86%
Deficit: 3.03%
United Kingdom
Credit: nan
Sensitivity Rank: #25
Debt 2019: 108%
Deficit: 4.76%
United States
Required AI-Driven Growth (% GDP per year)
AI-Induced Unemployment Increase (%)
0.00
0.25
0.50
0.75
1.00
1.25
1.50
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

Table A.1

Country	Unemployment[1]	Slope ($C_{per1\%}$)[2]	Debt to GDP[3]	Deficit[4]	Rating[5]
Australia	5.16	0.2	46.72	-2.52	AAA
Austria	4.84	0.2	71.006	-0.39	AA+
Belgium	5.37	0.27	97.461	-1.75	AA
Canada	5.69	0.09	90.21	-0.06	AAA
Chile	7.22	0.01	28.33	-2.32	A
Czechia	2.02	0.19	29.552	0.53	AA-
Estonia	4.48	0.08	9.047	-0.64	A+
Finland	6.74	0.22	65.241	-1.35	AA+
France	8.43	0.18	98.104	-3.15	AA-
Germany	2.98	0.27	58.701	1.32	AAA
Greece	17.88	0.03	183.691	-0.2	BBB-
Hungary	3.26	0.09	65	-2.06	BBB-
Iceland	3.93	0.2	66.528	2.5	A+
Ireland	5.01	0.12	55.924	-0.51	AA
Israel	3.8	0.08	59.092	-2.29	A
Italy	9.93	0.09	133.823	-2.2	BBB
Japan	2.35	0.07	236.381	-3.18	A+
Korea	3.78	0.12	39.73	1.38	AA
Latvia	6.32	0.09	37.911	-0.82	A
Lithuania	6.28	0.07	35.586	0.27	A
Luxembourg	5.59	0.21	22.339	2.08	AAA
Netherlands	4.43	0.18	47.597	0.6	AAA
New Zealand	4.1	0.11	31.814	0.29	AA+
Norway	3.88	0.07	40.558	5.86	AAA
Poland	3.23	0.04	45.2	-1.49	A-
Portugal	6.65	0.08	116.11	-1.9	A-
Slovak Republic	5.72	0.06	47.918	-1.68	A+
Slovenia	4.44	0.1	66.02	-0.64	AA-
Spain	14.11	0.11	97.579	-3.65	A
Sweden	6.91	0.05	35.694	0.6	AAA
Switzerland	4.39	0.15	39.637	0.91	AAA
Türkiye	13.74	0.03	34.1	-2.4	BB-
United Kingdom	3.8	0.02	85.657	-3.03	AA
United States	3.67	0.04	108.197	-4.76	AA+

[1] Unemployment rate in 2019 (OECD). *Below 3% = tight labor market, frictional unemployment (Green) ; 3–6% = moderate unemployment (Orange) ; Above 6% = elevated unemployment (Red).*

[2] Estimated spending on unemployment benefits per 1% unemployment (as % of GDP, based on 2019 simulation using PPP GDP). *Lower third = low cost per % of unemployment (Green) ; Middle third = middle cost per % (Orange) ; Upper third = highest cost per % of unemployment (Red).*

[3] Gross government debt as % of GDP (IMF, 2019). *<30% = very low debt (Green) ; 30–60% = moderate debt (Orange) ; >60% = exceeds Maastricht threshold (Red).*

[4] Average fiscal deficit, 2015–2019 (% of GDP, OECD). Negative values reflect a deficit. *<1% = low deficit (Green) ; 1–3% = moderate deficit (Orange) ; >3% = Maastricht limit breached (Red).*

[5] Sovereign credit rating by S&P. (2024). *AA or above = high credit quality (Green) ; A / BBB = investment grade (Orange) ; Below BBB = speculative grade (Red).*

A.2 The Fiscal Implications of UBI and Flat Basic Benefits (FBB)

Figure A.2.1—FBB as Percent of Government Expenditures: 10% Workforce

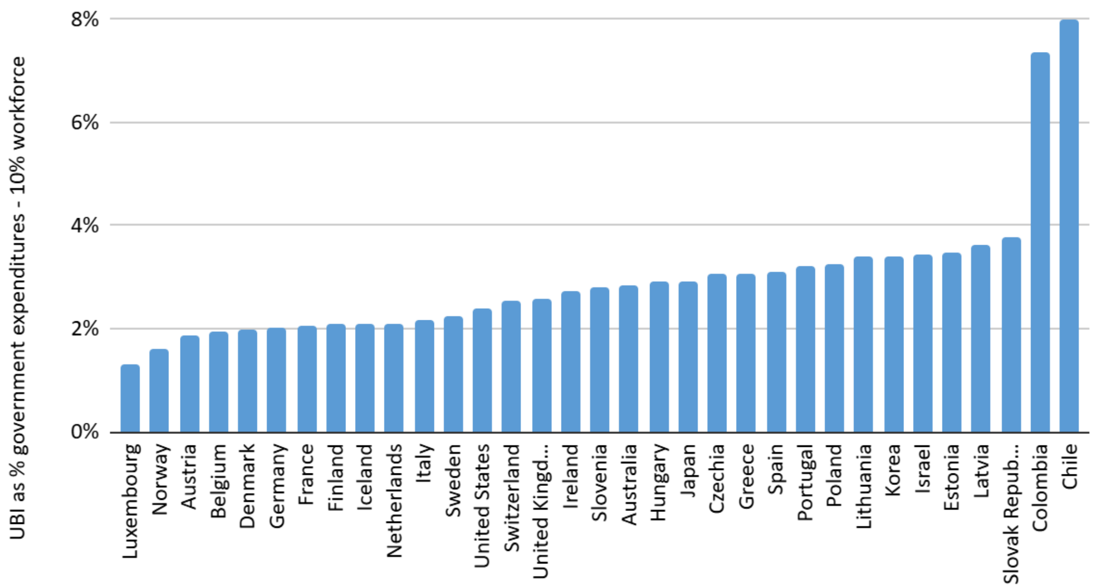


Figure A.2.2—FBB as Percent of Government Expenditures: 50% Workforce

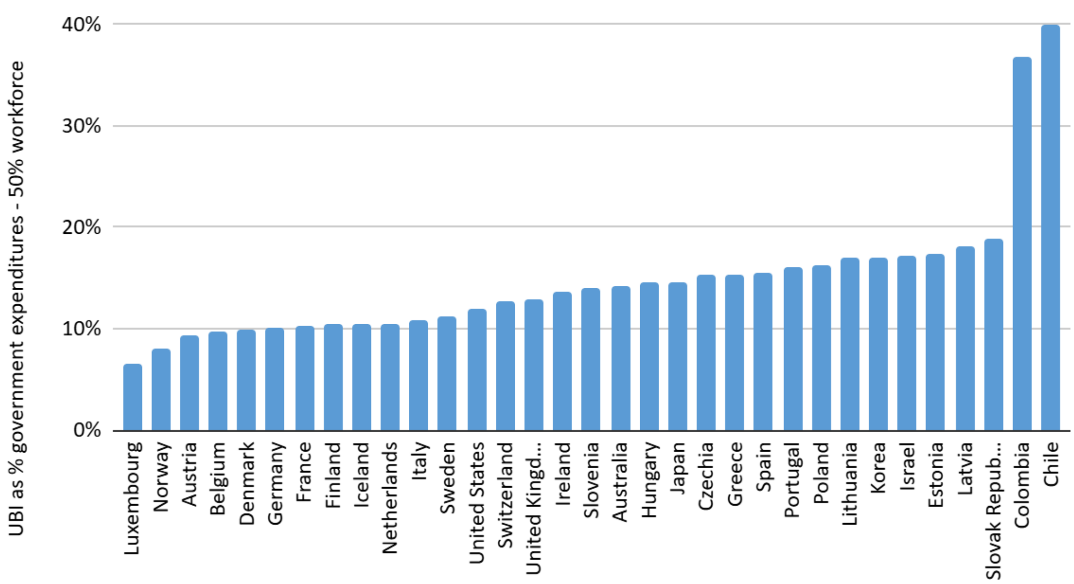
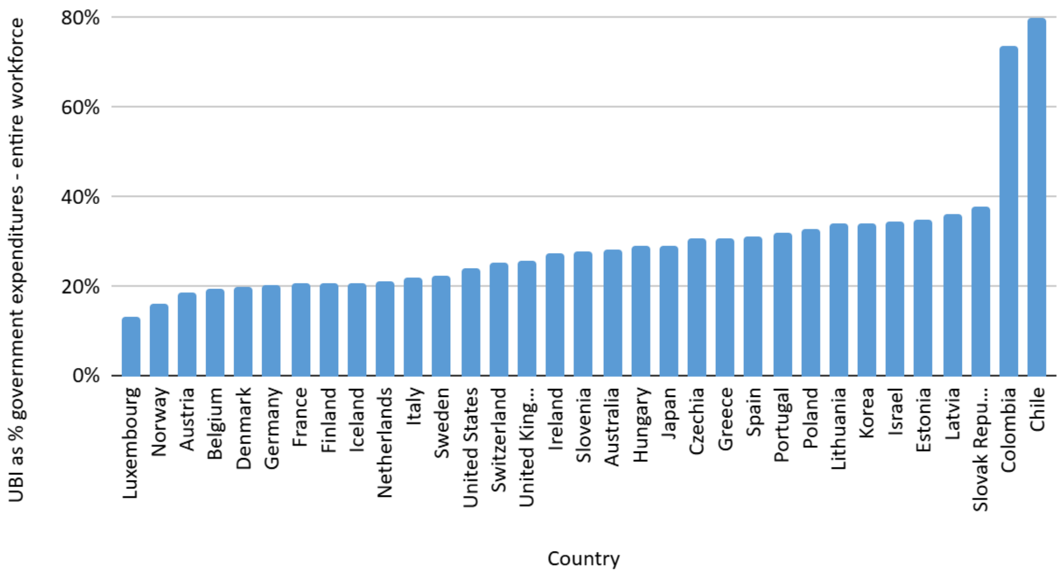


Figure A.2.3—FBB as Percent of Government Expenditures: 100% Workforce



A.3 Social Protection and Savings—Each Variable Separately

Figure A.3.1—Social Spending vs. Household Savings

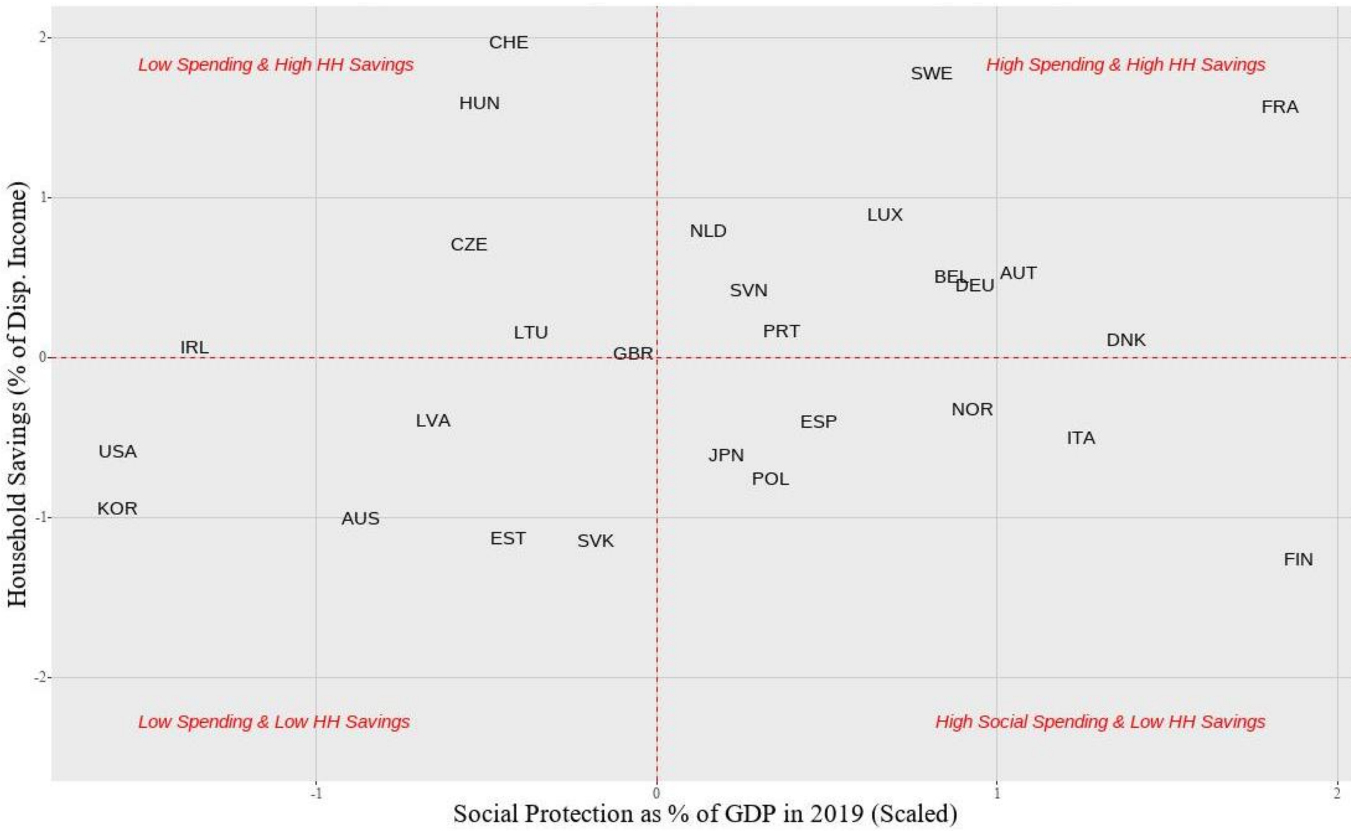


Figure A.3.2—Social Spending vs. Wealth

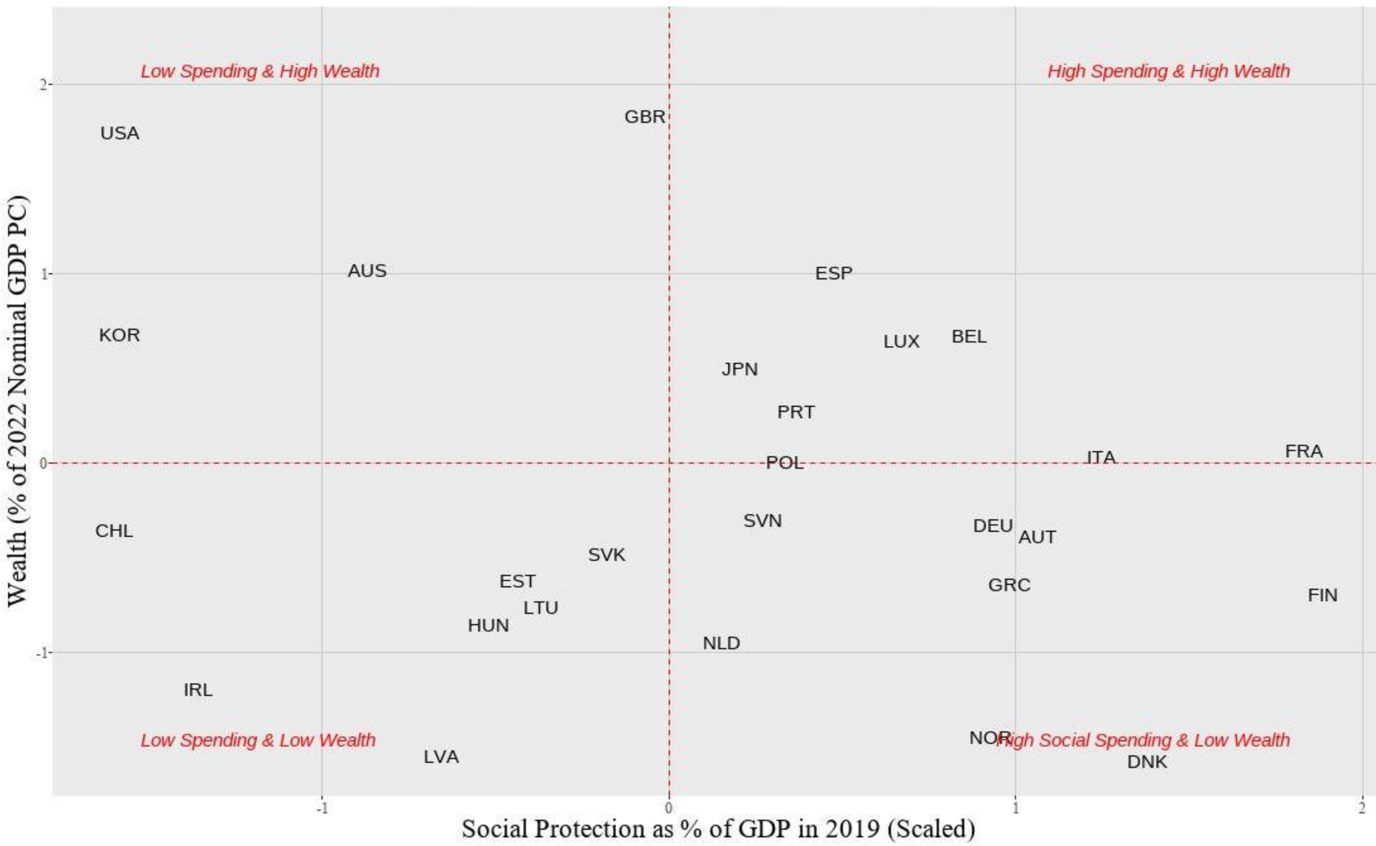
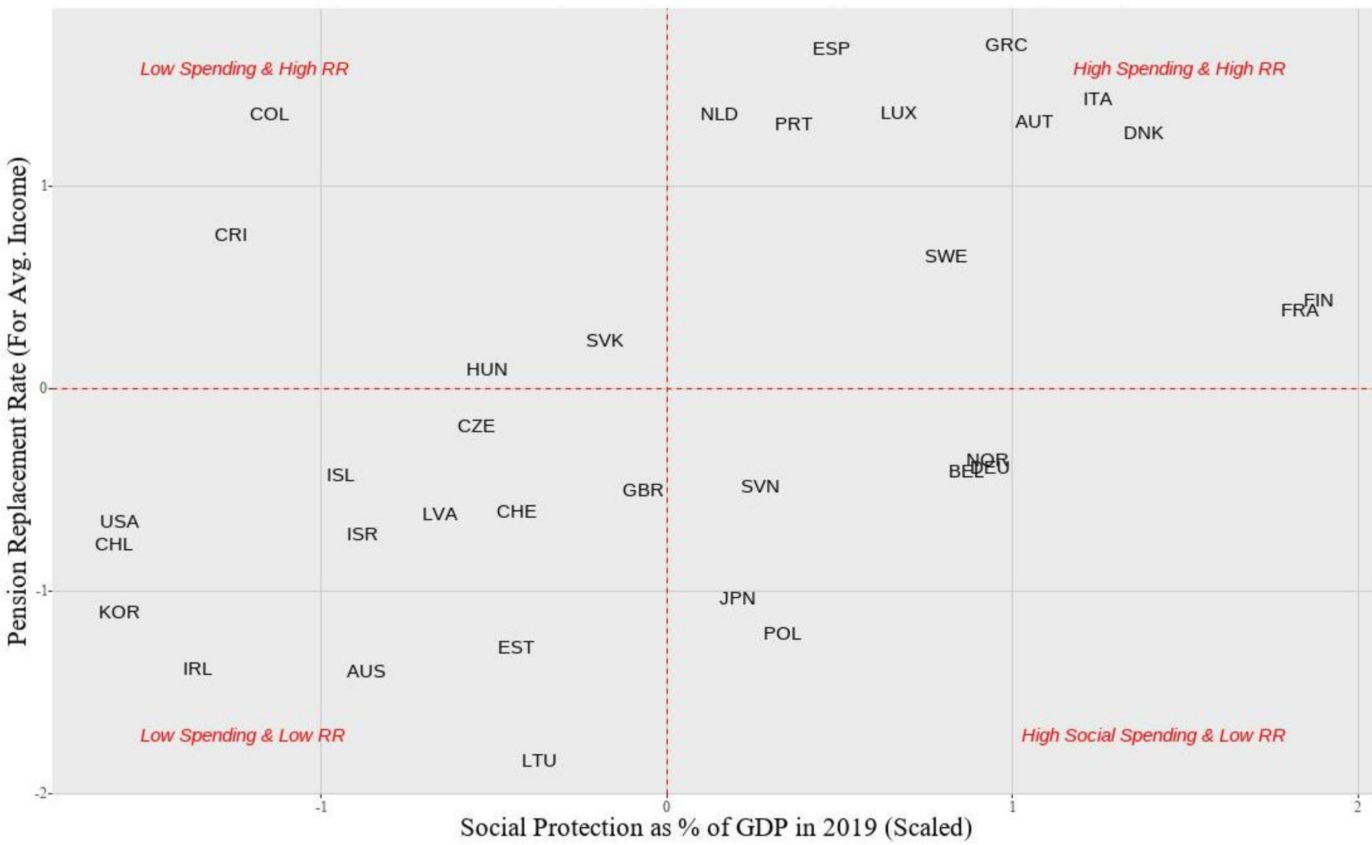


Figure A.3.3—Social Spending vs. Avg. Pension Replacement Rate



A.4 The Positive Correlation between Social Protection and Savings

Figure A.4.1—Social Spending vs. Avg. Scaled Saving Variables (Control for GDP)

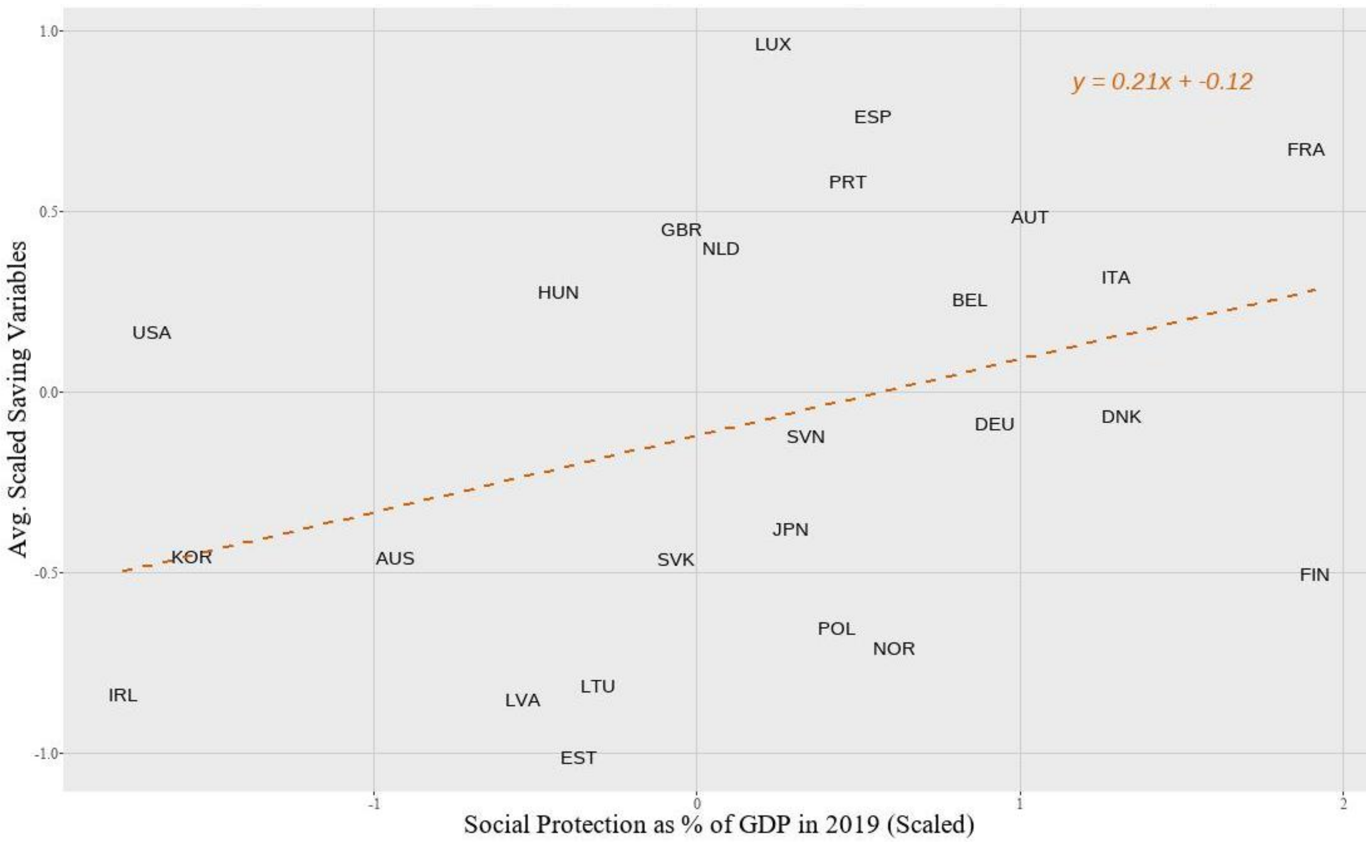


Figure A.4.2—Social Spending vs. Avg. Scaled Saving Variables (Control for Gov. Spending)