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ADAPTING TO AI: RETHINKING LABOR INCOME AND RETIREMENT DESIGN IN A CHANGING ECONOMY

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In this paper, we discuss how artificial intelligence (AI) could impact lifetime income through the channel of occupational tasks and wages. We first derive a life-cycle model of consumption, then incorporate AI as a shock to income and longevity. We find that AI-derived impacts on labor income and longevity can influence wealth accumulation and consumption over an individual's lifetime. We test a key input to this model in which occupations that experienced a net drop in tasks demanded of workers suffer declines in total wages. We then use a large language model to estimate how susceptible occupations can be to task reduction from automation. Our results suggest that most occupations will be affected by AI-driven automation but with a wide dispersion across jobs and industries. We conclude with a discussion on why AI-driven changes in the labor market should prompt new approaches to retirement and explore how financial planning can help workers adjust to an AI-enhanced economy.

1 Introduction

Rapid advances in artificial intelligence (AI) are reshaping industries and redefining the future of work. As AI becomes increasingly embedded in production and decision-making, its influence on employment patterns, productivity, and wages is expected to grow significantly. While many studies have explored AI's impact on the shape of industries and economic growth, there remains a pressing need to quantify how these changes might affect lifetime income trajectories of labor across industries. Such an understanding may help individuals, policymakers, and organizations navigate the economic opportunities and potential disruptions brought by AI.

To explore the relationship between retirement and automation, this paper estimates the potential impact of AI on lifetime income across occupations and wages. We do so by introducing a lifecycle investment model to assess how AI-driven changes in wages could impact retirement income, followed by an empirical analysis

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to assess the likelihood of AI-driven wage shocks across various jobs and tasks.

We begin by introducing a standard lifecycle savings-and-consumption model focused on two key inputs susceptible to AI: labor income during earning years, which determines an investor's savings capacity, and survival probability of the investor at each age, which determines the length of retirement. Given the vast dispersion of AI impact on total wages across jobs, we consider the sensitivity of the lifecycle model to both positive and negative labor-income shocks as well as a set of scenarios for the speed of AI's impact in the labor market and how various investors might respond.

Our theoretical model shows that workers whose tasks may be disrupted by AI could potentially experience lower overall consumption over their lifetime. The speed of AI's integration into jobs makes savings choices appear more consequential than risk or equity level choices for investors, due to compounding. Similarly, if longevity is enhanced by AI, then longer retirement periods could require greater focus on saving and investing early in one's career.

Next, our empirical section evaluates the impact of AI on wage and employment outcomes through the changes in occupational tasks. We build on Acemoglu and Restrepo's (2019) framework decomposing jobs into a series of tasks by using the Occupation Information Network (O*NET) database to categorize tasks and estimate task evolutions over a 10-year period, starting with a baseline number of tasks per occupation in 2011. We then derive sensitivity estimates of wage changes to shifts in tasks associated with occupations by using employment- and wage-level statistics from the BLS Occupational Employment and Wage Statistics (BLS OEWS).

We observe that when more tasks are added than removed to an occupation due to technological change, total wages, defined as the number of employees in an occupation multiplied by the average wage, tend to increase. Total wages can fall when a greater number of jobs are removed than added as the quantity of workers drops; however, when an occupation experiences an uptick in a significant number of new tasks, average wages tend to increase as the occupation becomes more complex.

We then use OpenAI's GPT4.0 large language model (LLM) to estimate how AI might impact tasks over a cross-section of today's occupations. For the first step, we map the tasks in the O*NET database into three categories based on the job description to reflect whether these tasks will be automated, unaffected, or complemented using AI technologies. We then bootstrap the estimated expected share of tasks changes using our regression coefficients from the previous decade.

We find that AI technologies could have an impact across most occupations—some positive, and others with potentially negative effects. Additionally, we find that there may be meaningful wage dispersion between jobs that require little vs. extensive preparation. The impact on total wages is expected to be skewed though again pointing to significant variability across occupations.

We conclude the paper by suggesting ways to mitigate the financial costs of automation to workers' retirement. We propose several options based on our analysis, including planning for income shocks from AI, and we explore various investment choices.

The remainder of the paper is organized as follows. Section 2 describes the relevant background literature for both the empirical and lifecycle-design sections. Section 3 describes the lifecycle analysis that incorporates the potential AI-driven income shocks over alternate horizons. Section 4 discusses the empirical historical study and LLM-based projection to today's occupations. Finally, Section 5 discusses potential mitigants and implications for investor decision-making and evolving policies.

2 Background

2.1 AI and employment and wages

Generative AI is expected to drive significant productivity gains across the economy, but the pace and extent of these improvements appear to depend on three features: adoption rates, the professions affected, and task-level changes. Acemoglu (2019) emphasizes that while productivity growth can increase labor demand, it may also lead to job displacement and wage reductions, partially offset by labor-reinstatement effects. Eloundou *et al*. (2024) estimate that 19% of jobs will have 50% of their tasks impacted by AI, and 80% of jobs will see at least 10% of tasks affected—indicating that AI could enhance workflows rather than replace most jobs entirely.

High-skill fields such as medicine may experience a growth of new intellectual property alongside automation of existing tasks within a job. Fleming (2018) highlights AI's role in accelerating drug discovery, while Esteva *et al*. (2017) and Rajkomar *et al*. (2018) demonstrate its impact on improving disease diagnostics and enabling early risk prediction, respectively. However, challenges persist, including algorithmic bias (Obermeyer *et al*., 2019) and regulatory hurdles (Yang *et al*., 2017).

At the macro level, estimates of AI-driven productivity growth vary. Acemoglu (2024) estimates growth of 0.55% annually over a decade while Baily *et al*. (2023) and Briggs and Kodnani (2023) foresee potential annual labor productivity growth of up to 1.5%, comparable to past technological revolutions. Rao and Verweij (2017) estimates that AI could contribute USD $15.7 trillion to global GDP by 2030 through automation, labor augmentation, and improved consumer offerings. Similarly, Chui *et al*. (2023) suggest generative AI could drive annual productivity growth of 0.1–0.6% through 2040, spurred by increased investment in AI after the 2022 ChatGPT launch. Overall, we find that growth impacts range from approximately 0% to 2% across academic and industry estimates.

Cazzaniga *et al.* (2024) argue that 40% of global employment is exposed to innovations in AI, but with material differences between countries and within occupations: 60% of advanced economy jobs are estimated to be impacted by AI, compared to 40% in emerging markets. Further, high-wage earners are most likely at risk of AI displacement, but jobs that are more complementary to AI enhancements may benefit. BNP (2023) ranks developed markets as leaders in AI readiness but highlights emerging economies like Singapore and South Korea as strong contenders. These findings underscore AI's transformative potential, while highlighting the importance of addressing challenges to ensure sustainable growth across industries and regions.

There has also been speculation that AI may lead to an increase in longevity, further impacting the labor market and retirement. Marino *et al.* (2023) outline several ways in which machine learning/AI (ML/AI) approaches may impact aging and longevity research with examples such as improving data extraction in genomic instability, generation of epigenetic data, and modeling telomere changes to improve aging biomarkers. Zhavoronkov *et al.* (2019) underscore the role deep learning can play in identifying biomarkers, improving the understanding of the pathways for aging, and advancing anti-aging drug discovery.

In a survey of AI-based ageing literature, Bernal *et al.* (2024) classify research into six domains where AI has been explored including biomarkers, as well as cognitive, physical, and socio demographic change.

2.2 *Lifecycle consumption and portfolio choice*

There is a significant body of research focused on the optimal consumption and portfolio decisions under uncertainty over the course of a lifetime. Cocco *et al*. (2005) provide an example of a well-calibrated model that examines lifetime consumption and portfolio choices with uncertain labor income. Similarly, O'Hara and Daverman (2015) propose a study that uses a comparable model to develop optimal target–date–fund glidepaths.

There are numerous extensions and variations of the basic lifecycle model presented by Cocco *et al.* (2005). For instance, Gomes and Michaelides (2005) account for fixed costs of participating in the equity market and include internal habit formation in individual preferences. Chai *et al.* (2011) introduce flexibility in work hours, the timing of retirement, and examine the effects of including annuities in the set of investment options. Gálvez and Paz-Pardo (2023) further expand on this by providing a more detailed and flexible representation of labor-income risk. Lastly, Daverman *et al.* (2024) expand a life-cycle model of consumption to include interruptions to income from scenarios such as extreme-weather events.

There has so far been little work done on how AI might impact the lifetime-consumption problem. To the extent that there has been work done at the intersection of AI and retirement, it has mostly been focused on how AI has led to digital-finance tools like robo-advisors and personalized spending plans. Several papers also analyze the impact of technology on labor markets, including Autor *et al.* (2003), which shows that automation and technology are driving labor market polarization and increased labor-income uncertainty. To our knowledge, this paper is the first to analyze the impact of AI from the perspective of lifecycle investing.

3 A Lifecycle Model for Consumption and Equity

In this section we propose a model for how AI's impact on wages might shift lifetime consumption and equity-allocation decisions. Along with labor-income or wage changes, we also examine how increased longevity through AI-enhanced healthcare could influence optimal saving and investment decisions throughout an individual's lifecycle.

3.1 *The model*

We start by using the lifecycle model of consumption and portfolio choice from Cocco *et al.*, to estimate optimal consumption decisions and equity allocations over an individual's lifetime. A key input to this model is defining labor income as a function of age during the accumulation period. The model-solution process happens in three steps:

- First, using a baseline set of assumptions for labor income, mortality characteristics, and capital market assumptions, a set of policy functions that prescribes optimal savings and equity allocation is estimated.
- Second, labor-income and capital-market-return paths are simulated to estimate savings and equity allocations over an investor's lifetime. Statistical estimates of expected values, volatilities, and other distributional characteristics are computed for savings contributions, equity allocations, and spending outcomes

across these paths. This baseline model returns estimates for lifetime savings and spending outcomes against which AI-impacted labor-income estimates can be compared.

- Third, we then introduce an AI-impacted labor-income shock to estimate changes to lifetime savings, risk taking, and spending outcomes. By comparing the baseline averages to those calculated with the AI-driven income curves, we seek to estimate how AI is expected to impact lifetime consumption and investment decisions. The result from this analysis is presented in Sections 3.1 and 3.2. We conclude by incorporating a longevity shock to the model.

The model formulation and baseline model assumptions can be found in Appendix A

3.2 *Benchmark model results*

The lifecycle model, as outlined in Equations (A.1) to (A.8), is solved as follows:

(1) **Step 1** (*Policy function step*): First, we estimate the policy functions, which tabulate the proposed optimal consumption and equity-allocation decisions conditional on age and wealth, using a dynamic program-solution process that employs backward

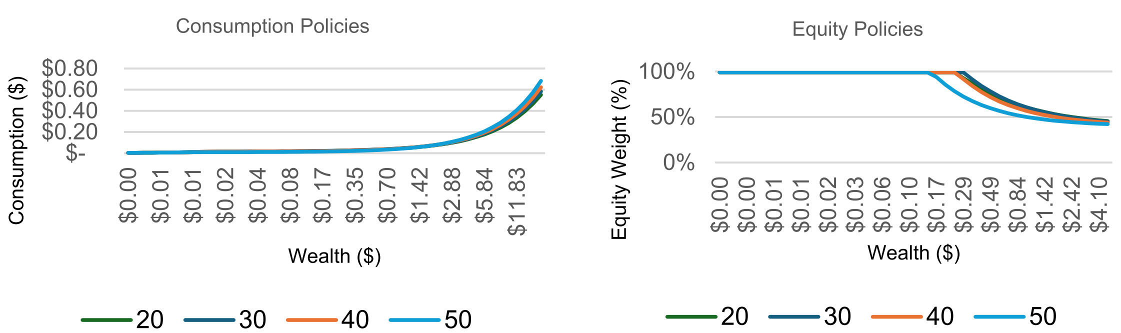

Figure 1 Consumption and equity allocation as a function of wealth for select ages.

Source: BlackRock. As of August 2025.

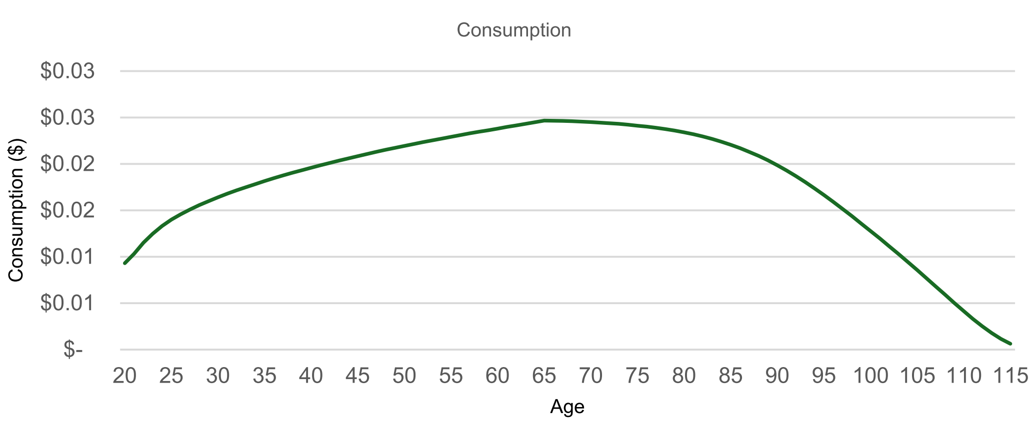

Figure 2 Average consumption in the benchmark case.

Source: BlackRock. As of August 2025.

induction. Sample policy functions for a few select ages are shown in Figure 1.

(2) **Step 2** (*Simulation step*): Next, we estimate investor consumption, equity, and wealth paths by simulating labor income and financial returns. The investor is guided in these choices of consumption and equity at every step by the optimally computed policy-function tables. We use 10,000 sample paths in this step.

(3) **Step 3** (*Averaging step*): We compute the mean values for these estimates across the sample paths generated in Step 2, which gives us the average consumption, equity, and wealth by age. The average curves for the baseline model are shown in Figure 2–4. We would note several key observations based on these average-level estimates:

(a) For a given age, optimal consumption is an increasing function of wealth.
(b) For a given age, optimal equity is a decreasing function of wealth.

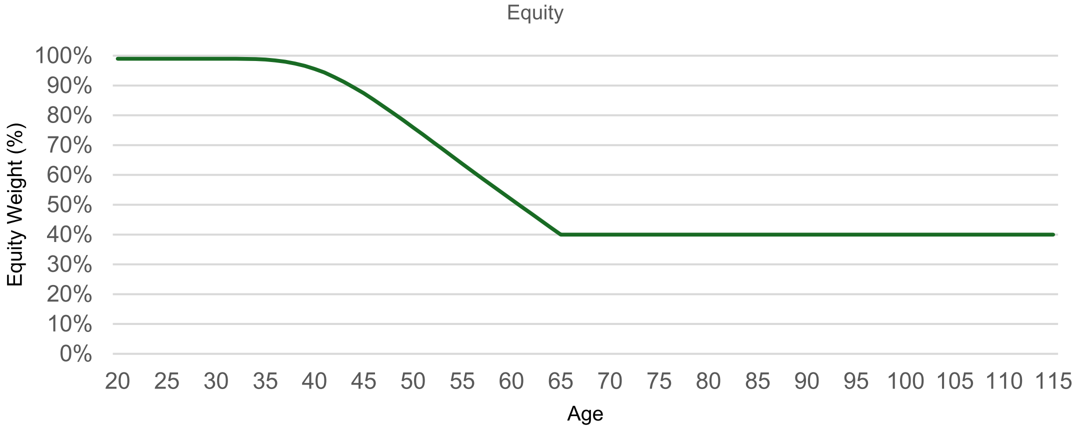

Figure 3 Average equity allocation in the benchmark case.

Source: BlackRock. As of August 2025.

Figure 4 Average wealth in the benchmark case.

Source: BlackRock. As of August 2025.

Table 1 Description of different labor-income shocks applied to lifecycle model.

	Description	Rationale	Step of lifecycle computer process impacted
Case 1	Shock entire income curve by a constant.	Captures how level shifts in the labor-income curve impact spending in accumulation and retirement.	Steps 2 and 3
Case 2	Shock entire income curve but assume that the impact of AI on wages takes 10 years to be fully realized and that this shock is not incorporated into optimal decisions.	Likely to take time for AI to be adopted, meaning the impact on wages is also likely to happen slowly. Implicit assumption is that the change is unexpected/not incorporated in optimal decisions.	Steps 2 and 3
Case 3	Shock entire income curve but assume that the impact of AI on wages takes 10 years to be fully realized. Also, assume that this shock is incorporated into optimal decisions.	Same as Case 2 but assume that impact is understood well enough that individuals anticipate the change to their wages and recalibrate their optimal choices to reflect it.	Steps 1, 2, and 3

Source: BlackRock. As of August 2025.

(c) For a given level of wealth, optimal consumption decreases with age.
(d) For a given level of wealth, optimal equity decreases with age.

3.3 *Incorporating AI-induced labor income shocks into the lifecycle model*

In this section, we will explore how both the average curves and the policy functions change when labor income is shocked in the lifecycle model. We explore three methods of incorporating AI-induced income shocks into the lifecycle model: shocking income by a constant to account for the impact of AI on wages immediately, allowing the shock to accumulate over a decade, and allowing investors to anticipate the shock and incorporate the expectation into proposed optimal portfolio decisions. Table 1 summarizes the methods and the corresponding steps used in this process.

3.3.1 *Case* 1: *Incorporating AI-induced labor parameters within the simulations by shocking the entire curve*

In this section, we show results from Case 1, where we only adjust labor income while sampling in Steps 2 and 3. For simplicity we shock the entire labor-income curve, i.e., if our labor income model is given by Equations (A.3) and (A.4) we add a labor-income multiplier κ, so that labor income becomes:

$$\log(Y_{i,t}) = f(t) + \eta_i + v_{i,t} + \epsilon_{i,t} + \kappa. \qquad (1)$$

All parameters are as outlined in Table A.1. Labor-income curves are computed for different values of κ, such that $\exp(\kappa) = -0.05, -0.025, 0.025$, and 0.05. Since Equation (1) gives the equation for log wages, $\exp(\kappa)$ can be understood as a shock that shifts the entire wage curve up or down. Said differently, we are multiplying the

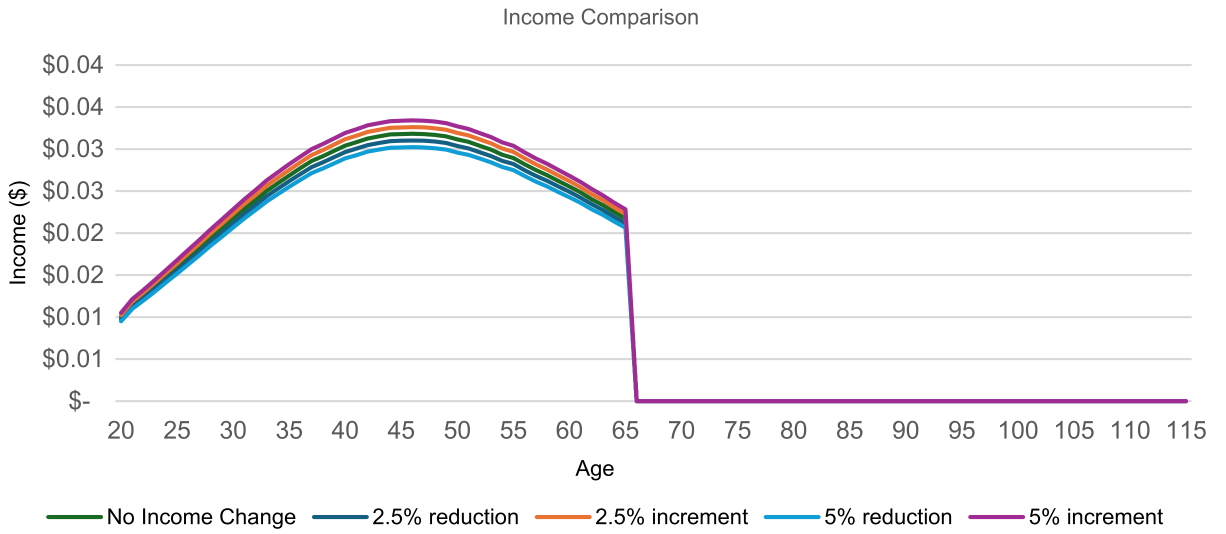

Figure 5 Income by age for different values of κ.

Source: BlackRock. As of August 2025.

entire wage curve by $\exp(\kappa)$. We keep Step 1 the same as the baseline case, i.e., we use the policy functions derived from the baseline model. We run Step 2 using labor-income samples for each κ specified above. That is, we run four sets of simulations, one for each value of κ. The different income curves we use are shown in Figure 5.

Next, Step 3 is run for each set of simulations. The average consumption, equity allocation, and

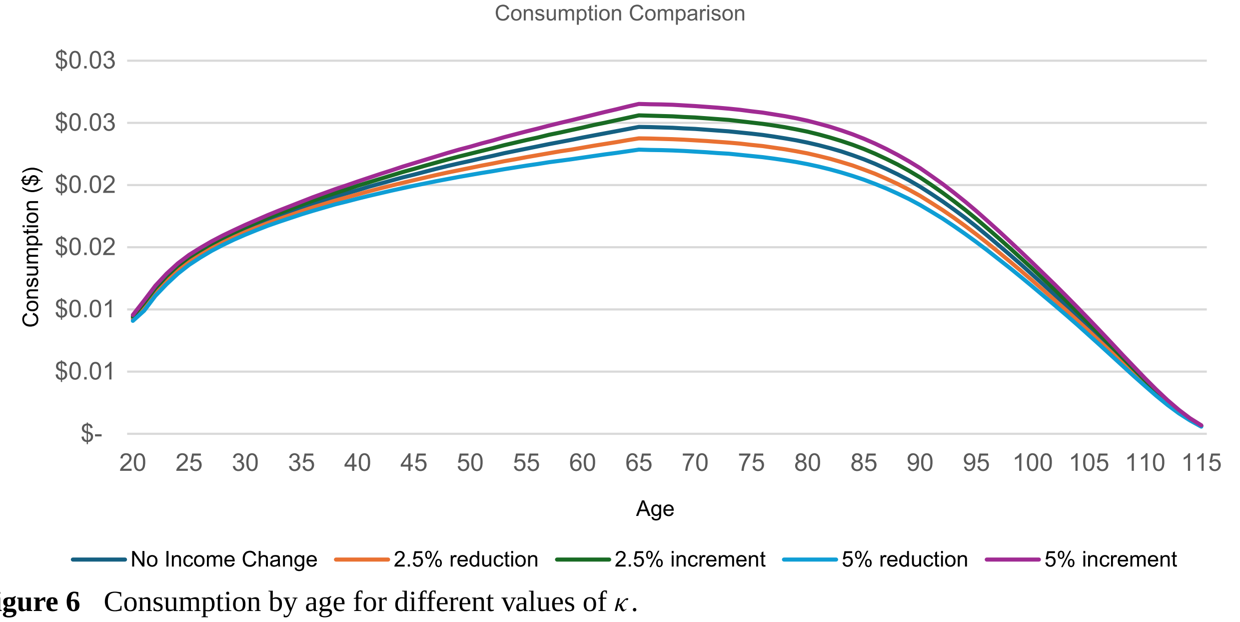

Figure 6 Consumption by age for different values of κ.

Source: BlackRock. As of August 2025.

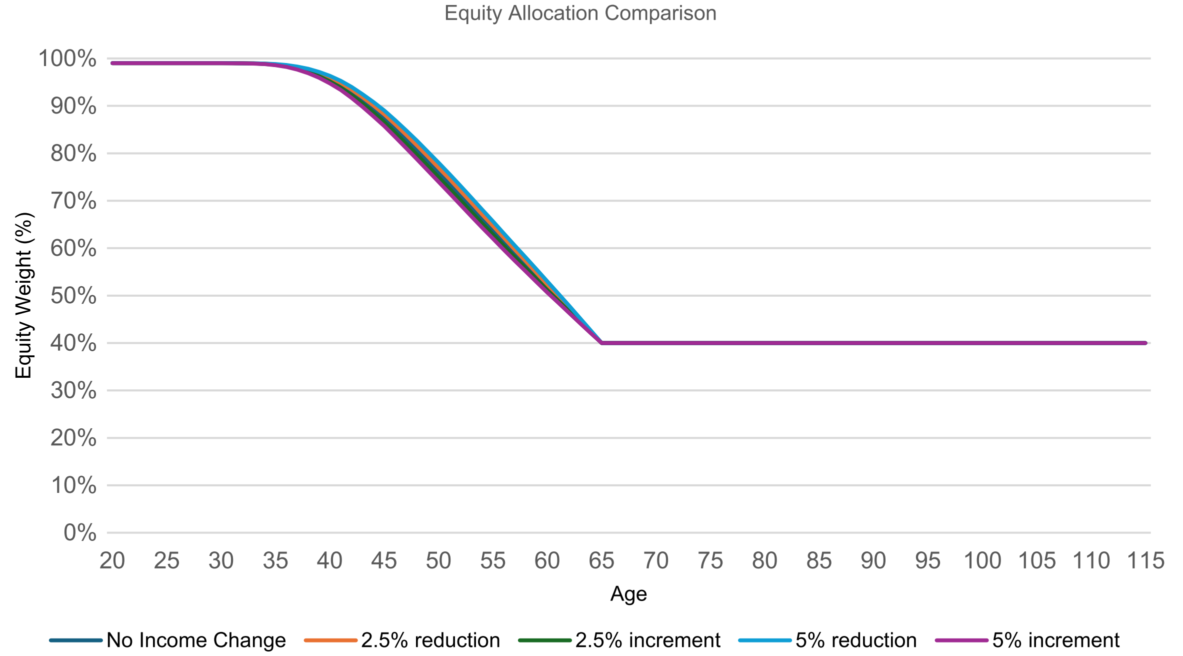

Figure 7 Equity allocation by age for different values of κ.

Source: BlackRock. As of August 2025.

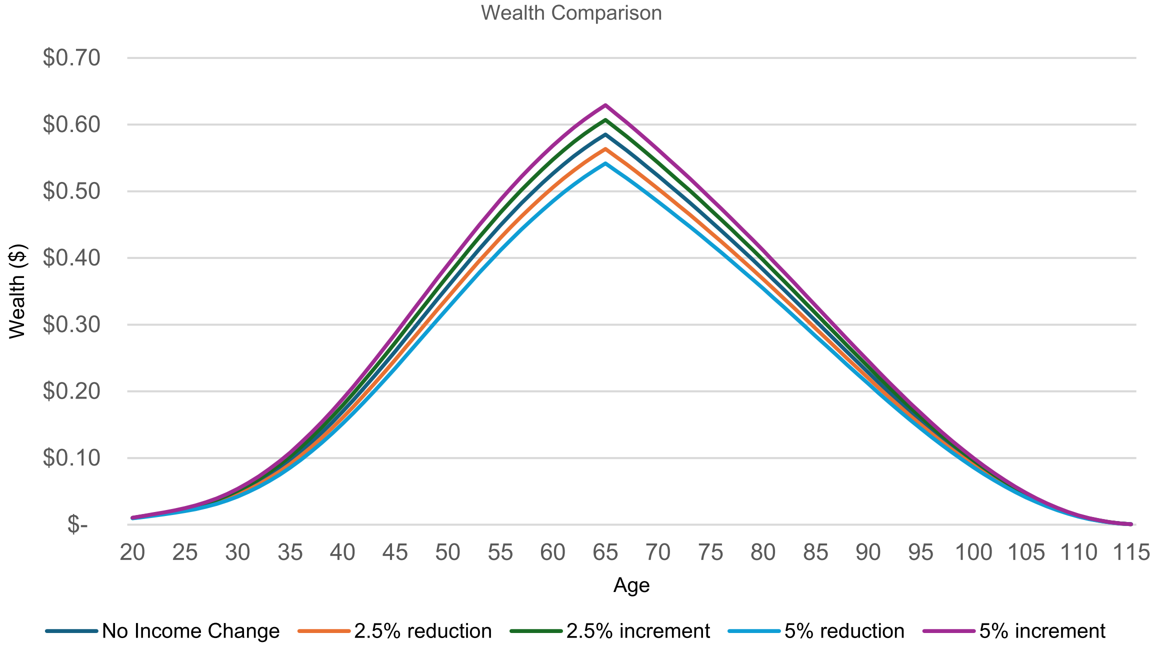

Figure 8 Wealth by age for different values of κ.

Source: BlackRock. As of August 2025.

wealth outcomes for each set of simulations are in Figures 6–8. A few key inferences from these results follow:

(1) Positive labor-income shocks result in higher average consumption and wealth, while negative labor-income shocks result in lower average consumption and wealth, when compared to the baseline case. Higher income levels also result in higher aggregate saving through the investor's lifetime.
(2) Negative labor-income shocks results in higher equity allocations through the accumulation phase. This follows the key observations made in Section 3.1. Namely, based on our framework, wealth is lower than in the baseline case, and, all else equal, as wealth decreases, the optimal equity allocation increases for a given age. The individual must take additional risk to enable a level of spending over his or her lifetime.

Finally, Figure 9 shows how total average spending in retirement compares to the baseline case. The figure shows percent change in spending compared to baseline spending for each of these cases. Since the comparisons are at the total spending level, the changes are nonlinear.

3.3.2 *Case* 2: *Incorporating AI-induced labor shocks within the simulations with a 10-year ramp up/ramp down period*

In this section, we estimate the impact on consumption, wealth, and equity allocations if the wage changes happen over 10 years. We test two cases:

(1) First, AI results in a 5% increase that takes 10 years to be fully realized.
(2) Second, AI results in a 5% decrease that takes 10 years to be fully realized.

More specifically, the income curve impact for the positive case is given by:

$$\log(Y_{i,t}) = f(t) + \eta_i + v_{i,t} + \epsilon_{i,t} + \kappa_t$$

$$\exp(\kappa_t) = \begin{cases} 0.005t & \text{for } t < 10 \\ 0.05 & \text{for } t \geq 10 \end{cases} \tag{2}$$

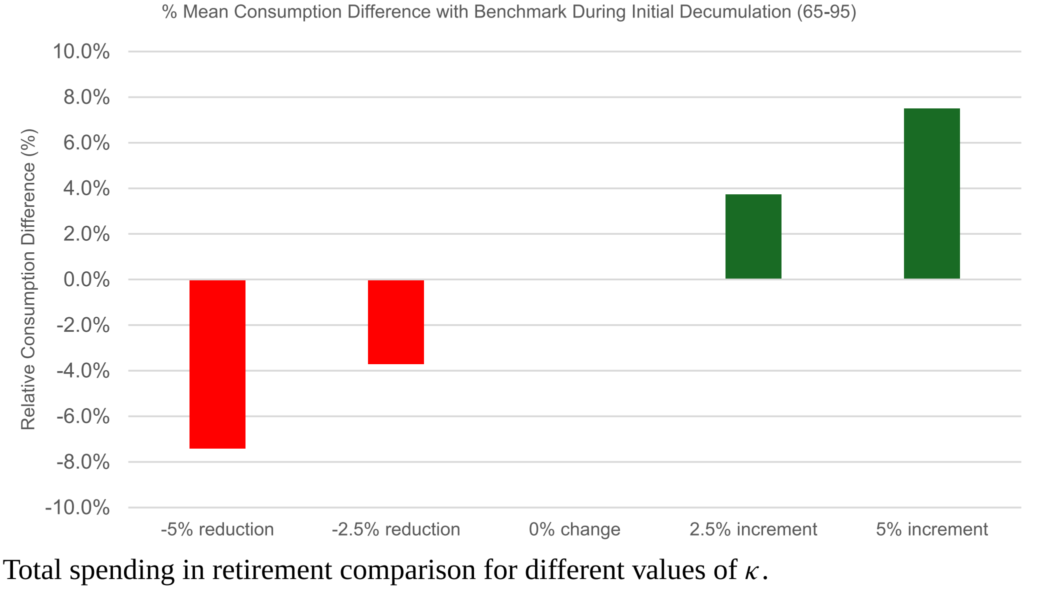

Figure 9 Total spending in retirement comparison for different values of κ.

Source: BlackRock. As of August 2025.

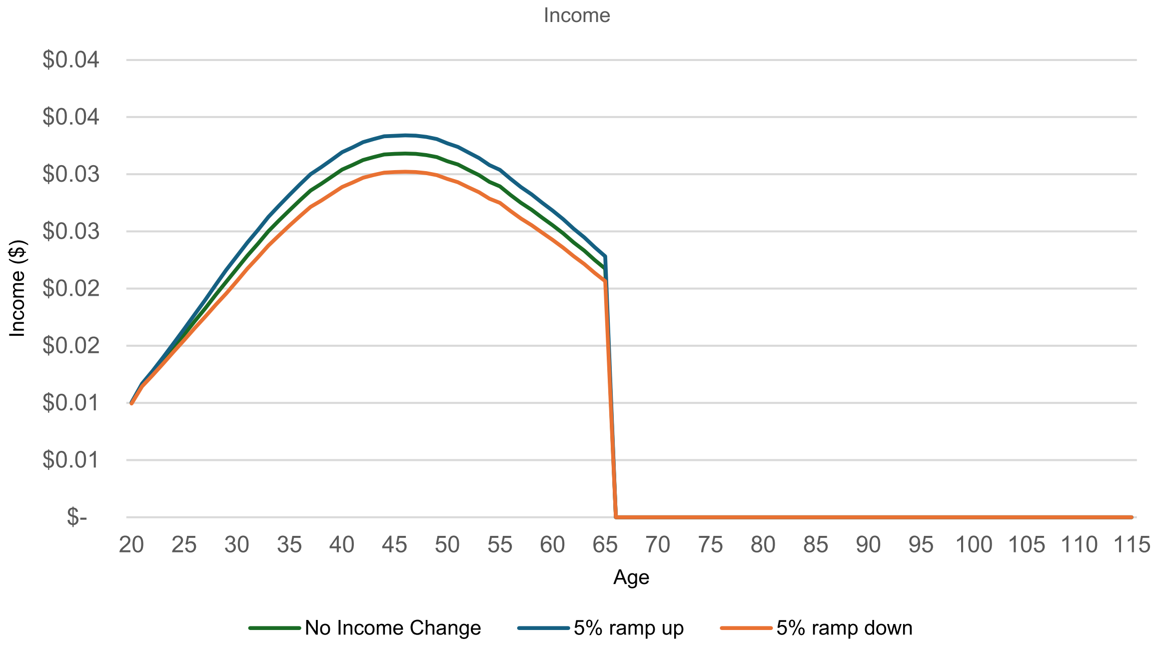

Figure 10 Income by age for different ramp-up and ramp-down cases using benchmark policy functions.

Source: BlackRock. As of August 2025.

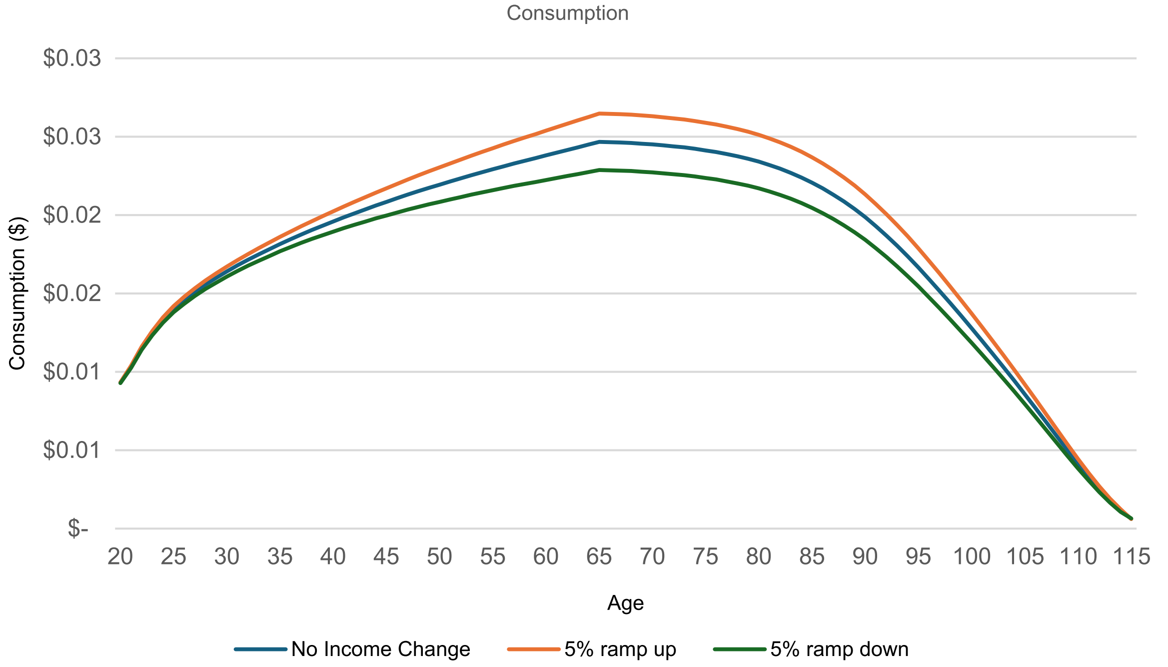

Figure 11 Consumption by age for ramp-up and ramp-down cases using benchmark policy functions.

Source: BlackRock. As of August 2025.

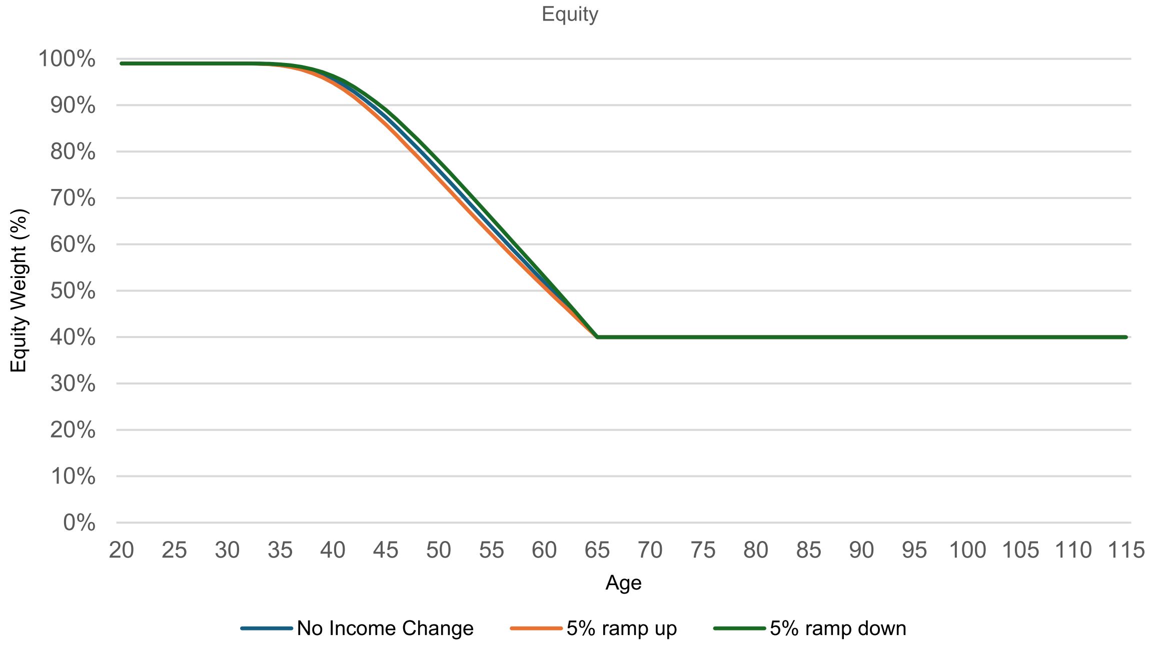

Figure 12 Equity allocation by age for ramp-up and ramp-down cases, using benchmark policy functions.

Source: BlackRock. As of August 2025.

Figure 13 Wealth by age for ramp-up and ramp-down cases, using benchmark policy functions.

Source: BlackRock. As of August 2025.

and the negative impact case is given by:

$$\log(Y_{i,t}) = f(t) + \eta_i + v_{i,t} + \epsilon_{i,t} - \kappa_t$$
$$\exp(\kappa_t) = \begin{cases} 0.005t & \text{for } t < 10 \\ 0.05 & \text{for } t \geq 10 \end{cases}. \tag{3}$$

The shocked income curves are plotted in Figure 10. Note that beyond age 30, the curves are identical to the positive and negative 5% shock cases shown in Section 3.2.1 where we shock the entire income curve. For ages 20–30, the income curves are scaled linearly in log scale as mentioned above.

As in Case 1 presented in Section 3.2.1, we keep the policy-function estimation step the same as the baseline case. We then run the simulation step using labor-income samples for each of the values of κ. That is, we run two sets of simulations, one where we are ramping up and one where we are ramping down.

The results of running Monte Carlo simulations[1] and taking the averages are in Figures 11–13. The results and intuition are as in the previous section. The impact of labor-income changes is realized over a 10-year ramp-up period, which results in a slower and muted impact when it comes to the savings, equity allocation, and total spending over the lifetime. For example, comparing the results shown in Figure 14 to those in Figure 9, we can see the consumption impact when the entire curve is shifted up and down by 5% is larger than the ramp-up and ramp-down cases. This means that both Case 1 and Case 2 are directionally consistent, as expected.

3.3.3 *Case* 3: *Incorporating AI-induced labor shocks within the policy functions*

In this section, we recompute the policy-function estimation step using the positively and negatively shocked wage curves given in Equations (2) and (3) and shown in Figure 10; all other

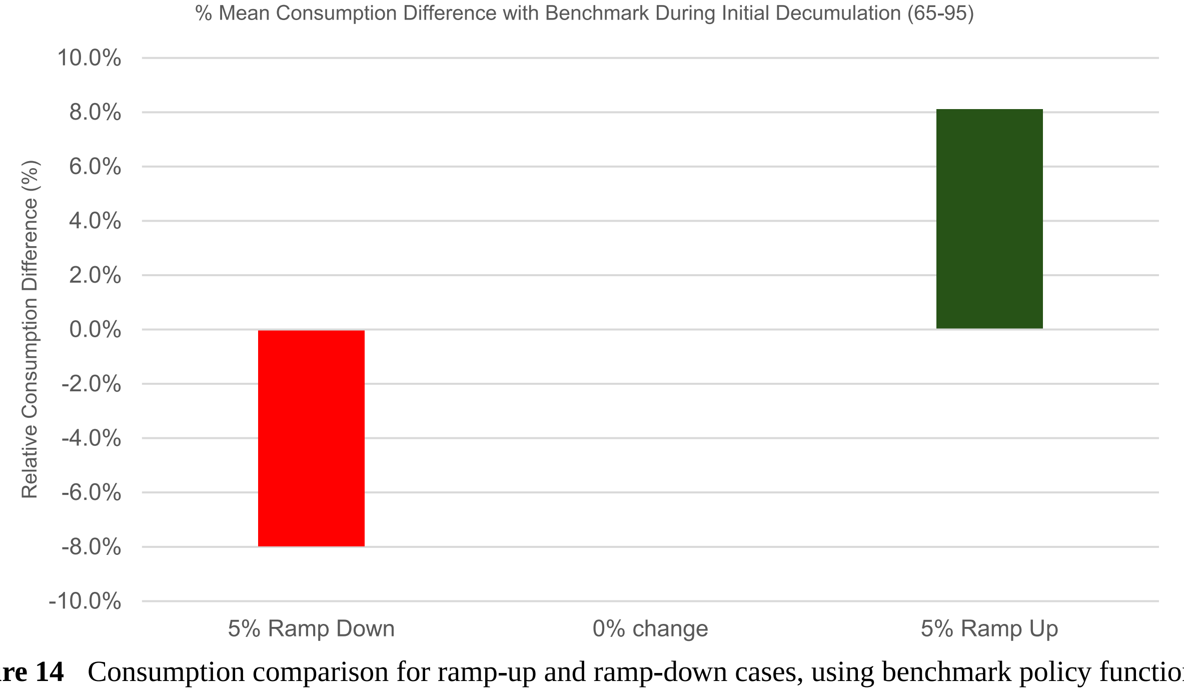

Figure 14 Consumption comparison for ramp-up and ramp-down cases, using benchmark policy functions.

Source: BlackRock. As of August 2025.

parameters are the same as the baseline values as shown in Table A.1. Next, we run the simulation step for each of the two cases: one for each of the ramp-up and ramp-down schedules.

The resulting average consumption, equity allocation, and wealth from running the simulations on the newly computed policy functions are shown in Figures 15–17.[2] There are two key observations

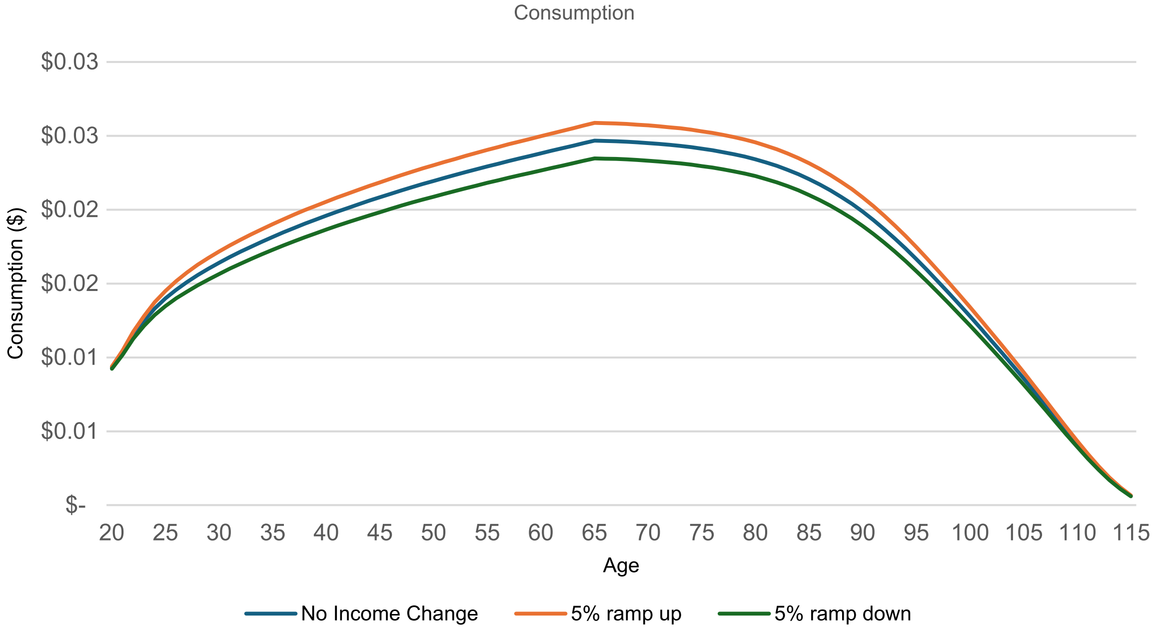

Figure 15 Consumption by age for ramp-up and ramp-down cases, with updated policy functions.

Source: BlackRock. As of August 2025.

Figure 16 Wealth by age for ramp-up and ramp-down cases, with updated policy functions.

Source: BlackRock. As of August 2025.

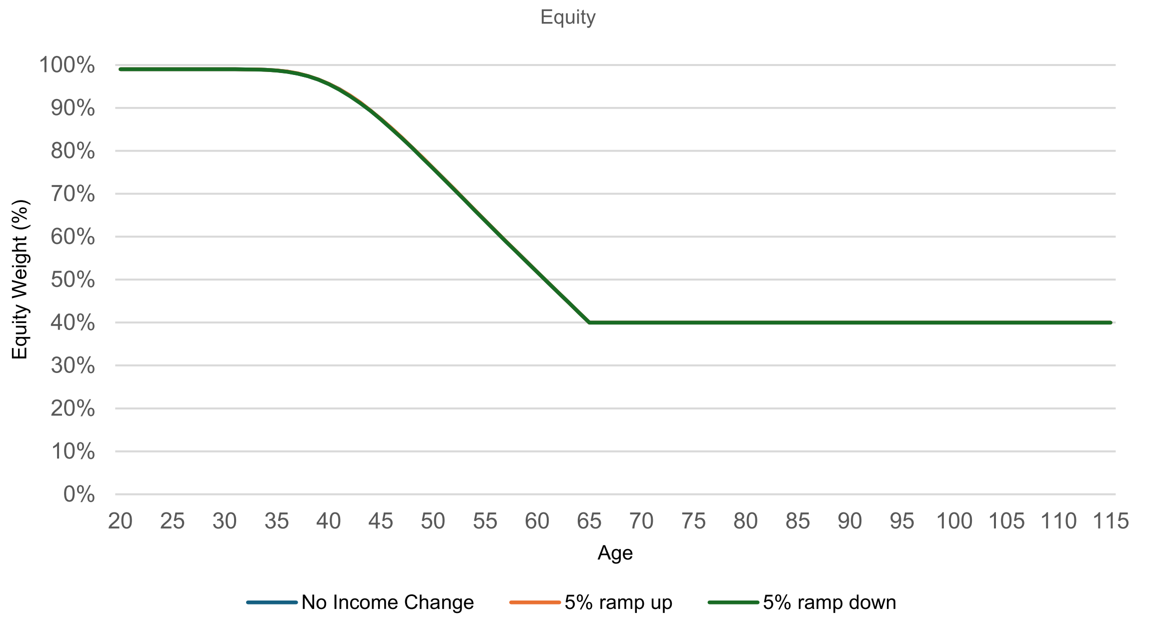

Figure 17 Equity by age for ramp-up and ramp-down cases, with updated policy functions.

Source: BlackRock. As of August 2025.

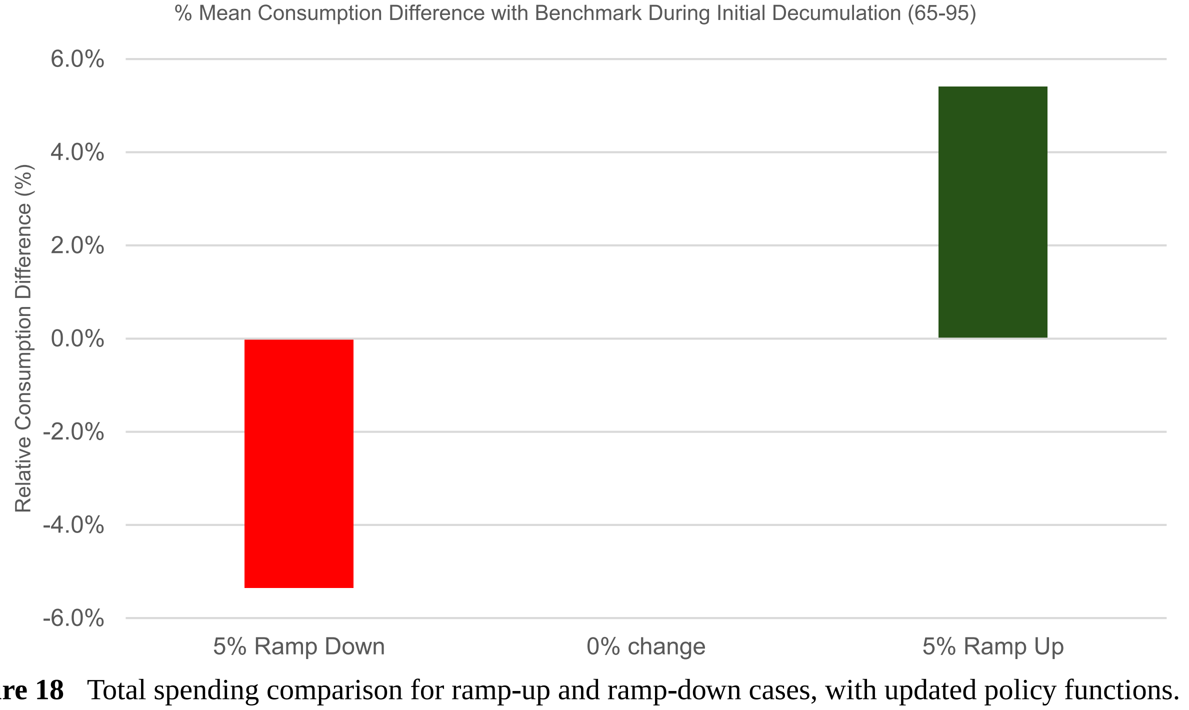

Figure 18 Total spending comparison for ramp-up and ramp-down cases, with updated policy functions.

Source: BlackRock. As of August 2025.

to note here:

(1) As expected, the results show that consumption and wealth are higher in the positive income shock cases—consistent with Case 1 and Case 2.
(2) What is slightly unexpected, however, is that the equity allocations over the lifetime do not seem to show differences, as in Case 1 and Case 2. The difference between Cases 1, 2, and 3 is that we recomputed the underlying policy functions in Case 3, which may have changed the optimal decisions for the investor, conditional on age and wealth.

Figure 19 shows the suggested equity allocations as a function of wealth at various ages. From this we can infer that positive income shocks result in a higher equity allocation for the investor at each wealth level. Since a greater proportion of labor income is earned later in life, the investor has more capacity for risk (and hence equity) earlier in his or her life. However, we do not see a material difference in the equity allocations in Figure 17 because of the wealth effect acting in the opposite direction: higher labor income leads to higher wealth accumulation, which leads to lower equity allocations, per the policy-function tables. These two opposing forces offset each other, thereby reducing the overall equity-allocation impact.

We also compare Cases 2 and 3 to demonstrate the potential benefits of updating the policy function in anticipation of income shocks due to AI.

While both Case 2 and Case 3 assume a gradual ramp-up period for AI-induced labor-income shocks to be realized, Case 3 anticipates these shocks and accordingly adjusts the savings, equity allocation, and spending schedules by recalibrating the policy frames seeking to ensure optimal consumption for the investor at all times. In the −5% ramp-down shock, for example, Case 2 shows an 8% decrease in spending, compared to a decrease of only 5% in Case 3 (see Figure 14 for Case 2 and Figure 18 for Case 3). With the +5% ramp-up shock, the impact is reversed.

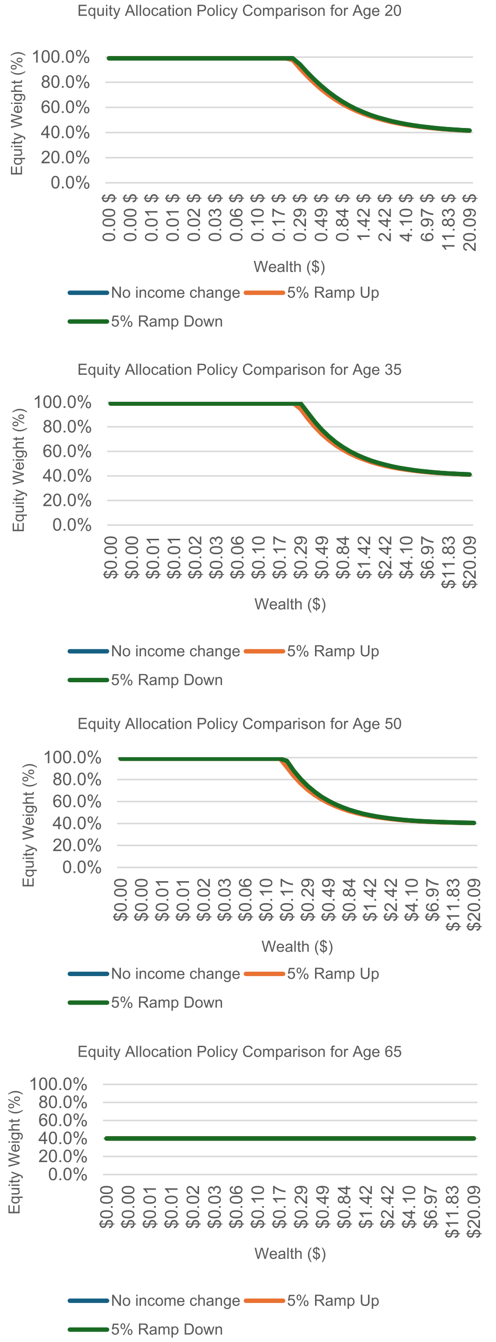

Figure 19 Policy function comparison.

Source: BlackRock. As of August 2025.

Table 2 Summary of results.

	Description	Equity impact	Consumption impact	Main takeaway
Case 1	Shock entire income curve by a constant	A positive (negative) shock results in lower (higher) equity allocations at all ages	A positive (negative) shock results in higher (lower) consumption at all ages	When a negative income shock is unexpected and no extra saving is incorporated within the policy functions, equity allocations are higher to help make up for the shortfall
Case 2	Shock entire income curve but assume that the impact of AI on wages takes 10 years to be fully realized and that this shock is not incorporated into optimal decisions	A "ramped-up" positive (negative) shock results in lower (higher) equity allocations at all ages	A "ramped-up" positive (negative) shock results in higher (lower) consumption at all ages	Same takeaway as Case 1, but the impact is smaller because the impact of the shock on aggregate income is less. So if the impact of AI takes longer to be realized, the overall impact on equity and consumption will be smaller
Case 3	Shock entire income curve but assume that the impact of AI on wages takes 10 years to be fully realized. Assume that this shock is incorporated into optimal decisions	An anticipated "ramped-up" positive (negative) shock results in higher (lower) equity allocations within the policy functions, but does not ultimately change the mean equity allocations across all ages	An anticipated "ramped-up" positive (negative) shock results in higher (lower) consumption at all ages	The equity impact of an anticipated change in income is nuanced because both the shape of the income curve (more specifically, when income is earned) and the wealth effect determine equity allocations. As a general rule, the analysis suggests that it is more optimal for savings rates to be the lever that is pulled to finance retirement spending, not equity allocations. Consumption and wealth also increase due to the planning for AI-induced income shocks being incorporated into the policy function

For the same −5% ramp-down shock, peak-wealth changes compared to base-case values are a 3.5% drop for Case 3, compared to a 6.8% drop for Case 2 (see Figure 13 for Case 2 and Figure 16 for Case 3). There does not seem to be a significant change in equity allocation between these two cases. The peak-consumption drop for the same −5% ramp-down shock of labor income is also marginally better for Case 3 than Case 2: 10% lower peak consumption compared to base case for Case 2, compared to 8% lower peak consumption in Case 3 (see Figure 11 for Case 2 and Figure 15 for Case 3).

3.3.4 Summary

At a high level, AI-induced-labor income shocks have a material impact on how individuals may be saving and investing for retirement. The magnitude and direction of the shock could determine how much saving and equity-allocation decisions may change. This is evident from outcomes we looked at by shocking the labor-income input in the lifecycle model (see Summary Table 2).

3.4 Incorporating AI-induced longevity shocks

The final set of shocks we apply are to mortality assumptions, which are used to derive an investor's survival probability over his or her lifetime. We believe that alongside impacting occupations and wages, AI may contribute to healthcare advances that will extend human life. Absent delaying the age of retirement, living longer will likely add years of consumption to retirement. It is difficult to precisely estimate the magnitude of the increase in longevity, so the analysis in this section is focused on estimating the directional impact the increase in longevity would have on optimal consumption and equity allocations over the investor's lifetime.

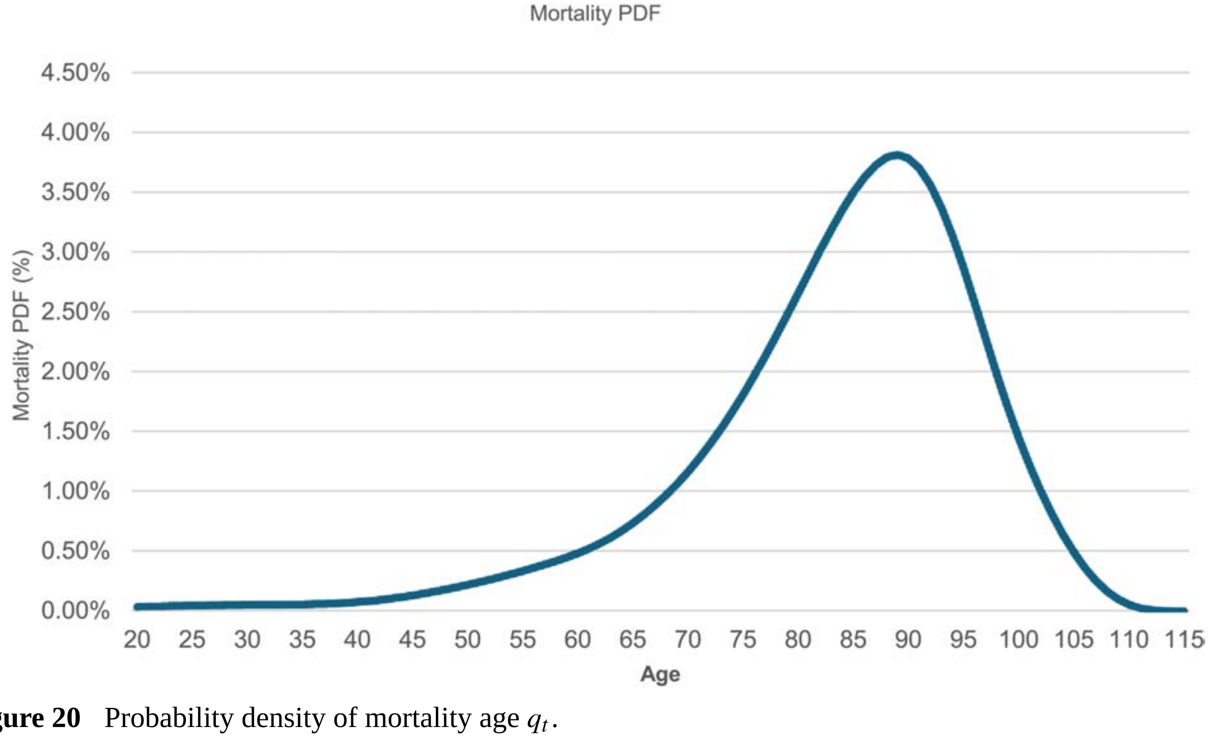

Figure 20 Probability density of mortality age q_t.

Source: BlackRock. As of August 2025.

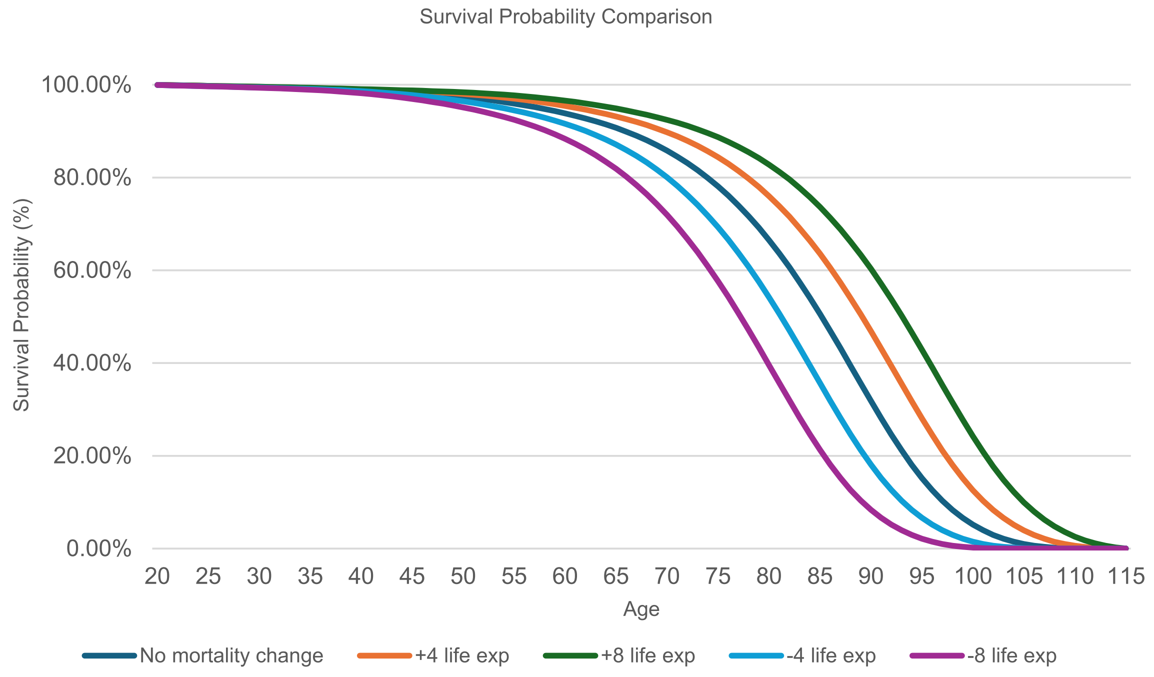

Figure 21 Survival probabilities for different shocks to overall life expectancy.

3.4.1 *Shocking the mortality tables*

The mortality model used in this analysis is shown in Appendix B. The probability density of mortality age q_t shown in Equation (B.2) is plotted in Figure 20.

There are many ways to shock mortality to reduce or increase life expectancy. For simplicity, in this analysis we only adjust mean life expectancy, while keeping the higher distributional characteristics, all other moments, fixed. Essentially, this amounts to shifting the entire probability density of mortality age plotted in Figure 20 to the right.[3] Using the shifted probability-density function for mortality age, we obtain the survival probabilities p_t for $t = 20, \ldots, 115$. These are plotted in Figure 21 for different changes in life expectancy.

3.4.2 *Shocking mortality within the lifecycle model*

To understand the impact increased longevity has on decision-making, we follow the lifecycle-model execution similar to Case 3 in the labor-income section. The difference here is that we shock only the survival-probability values and not the labor-income curves. We first recompute the first policy function step for each set of shocked survival probabilities plotted in

Table 3 Description of mortality shocks.

	Description	Rationale	Step of lifecycle process impacted
Central case	Shock mortality tables	Captures how increases or decreases in life expectancy impact optimal decision making	Steps 1, 2, and 3

Figure 21. Next, we repeat Steps 2 and 3—simulation and averaging—to generate average consumption, equity, and wealth curves. Table 3 summarizes the shocks and the associated estimation steps.

Average consumption, equity, and wealth curves are plotted in Figures 22–24. The following observations can be made based on these results:

(1) The green lines in Figure 22 show that when life expectancy is higher, consumption is lower during the accumulation phase and through the first decade of retirement, when compared to the baseline case. There is greater need to save for a lengthier-than-baseline retirement period.
(2) Consumption is higher than the baseline case beginning around age 75. This is mainly because the individual has a higher probability of living at these ages, compared to the baseline case, hence there is a greater consumption need in later years.
(3) Equity allocations appear lower, compared to the baseline case, in Figure 22. Higher spending needs do not necessarily mean investing in higher-return assets. To gain a better understanding of why this is, we again look at the policy functions, which are shown in Figure 25.[4] We make the following two observations:

    (a) For a given age and level of wealth, it is better to take more risk when life expectancy is higher. Note that the magnitude of the difference across the different life expectancies tested is small and basically disappears with age.
    (b) For a given age and level of wealth, it is more prudent to consume less (i.e., save more) when life expectancy is higher.

Comparing different shifts in life expectancy shows a greater differentiation in consumption policies (e.g., savings rates) than in equity policies

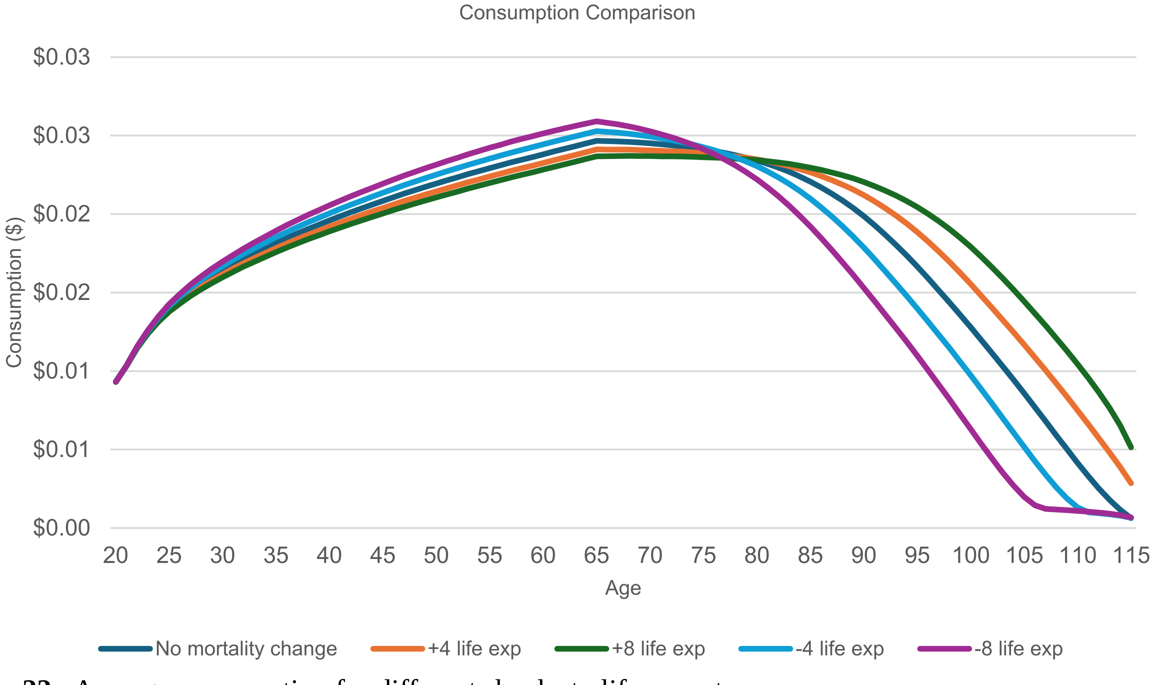

Figure 22 Average consumption for different shocks to life expectancy.

Source: BlackRock. As of August 2025.

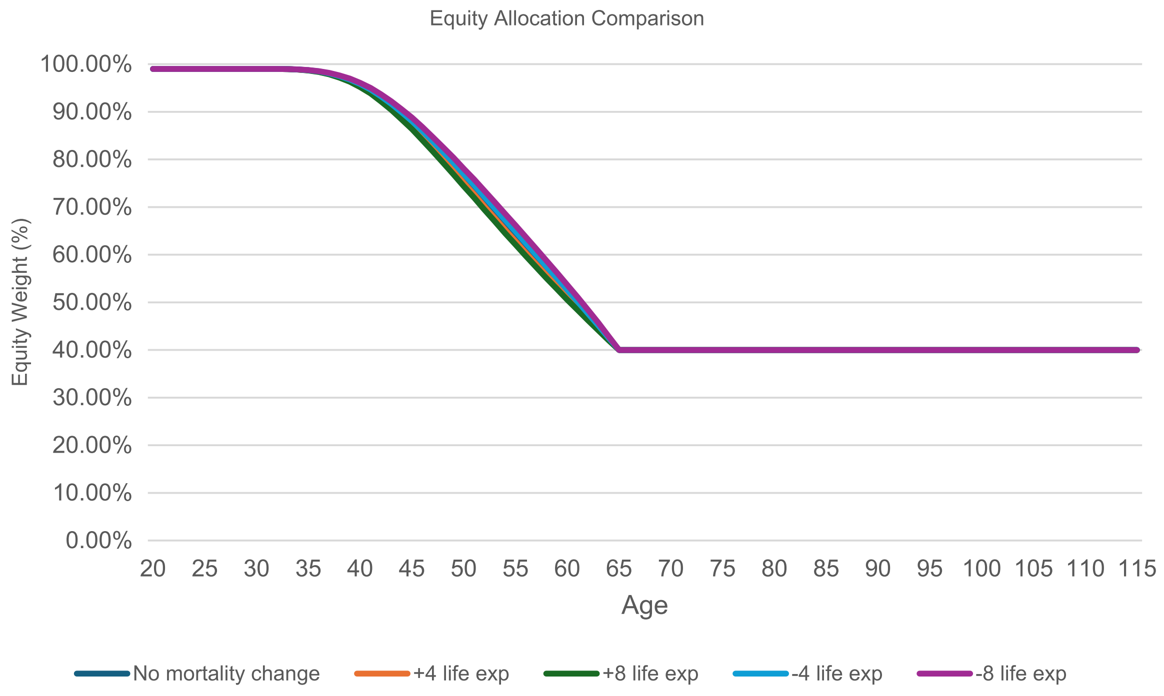

Figure 23 Average equity allocation for different shocks to life expectancy.

Source: BlackRock. As of August 2025.

Figure 24 Average wealth for different shocks to life expectancy.

Source: BlackRock. As of August 2025.

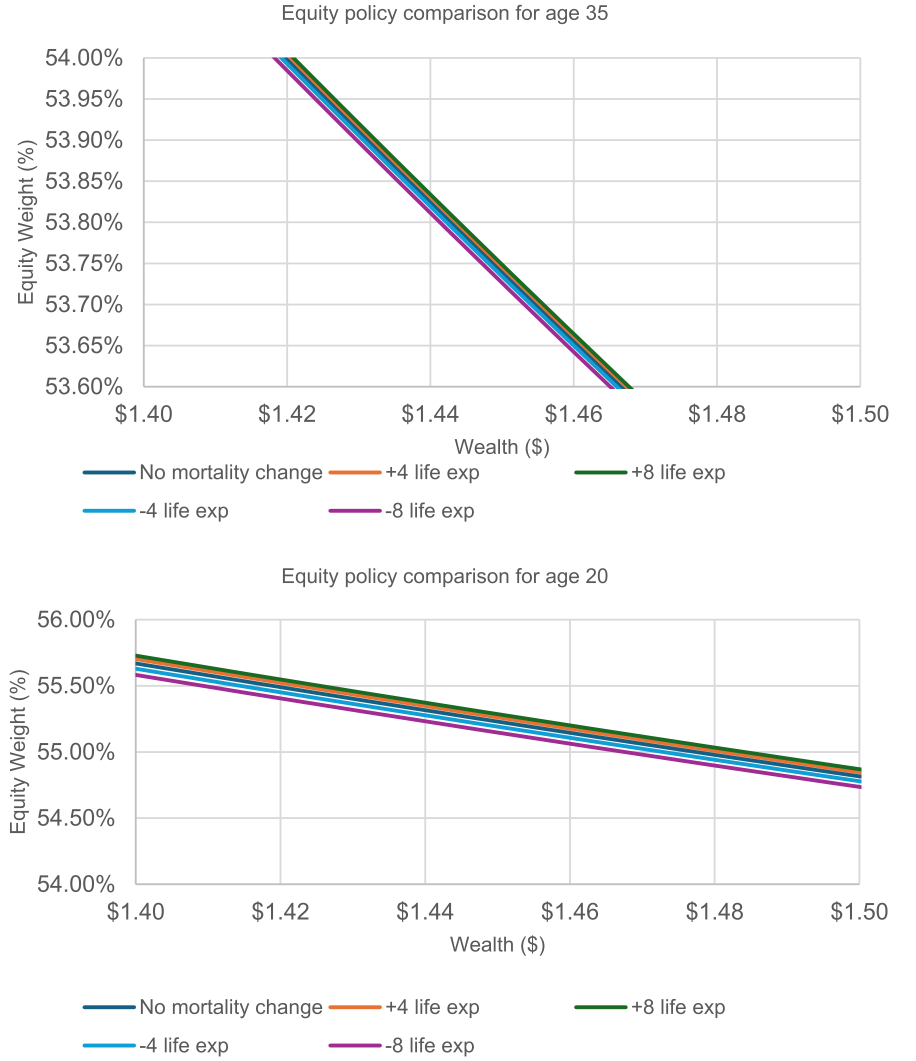

Figure 25 Policy as functions of age for different shocks to life expectancy.

Source: BlackRock. As of August 2025.

(i.e., risk-taking over lifetime). This means that the saving-rate changes are more impactful in helping the investor finance retirement consumption when life expectancy increases. While higher life expectancy does suggest higher equity allocations, this increase is marginal. As savings rates rises with rising life expectancy, wealth accumulates more quickly than the baseline case. This leads to a tug-of-war between increases in wealth lowering the equity allocation and increases in life expectancy raising the equity allocation. While these two effects both impact equity, the glidepaths in Figure 24 show that the wealth effect is dominating.

3.5 Closing the consumption gap

In the previous sections we saw how AI-induced changes to labor income and longevity could impact wealth accumulation over an individual's lifetime. In this section, we detail various options an individual may have to mitigate penalties to lifetime consumption. We focus on how appropriate planning, along with adding alpha, can mitigate the consumption shortfall that results from unanticipated negative income shocks.

Below, we plot the consumption, wealth, and equity curves for four different cases[5]:

- *Case 1*: Our standard baseline case assuming no impact from AI on either labor income or longevity.
- *Case 2*: Negative income shocks that are not anticipated and therefore not planned for. This reflects a case where investors do not take any mitigating actions to address the potential for consumption headwinds from adoption of AI. Specifically, we focus on the negative 5% shock that takes 10 years to be fully realized.
- *Case 3*: Negative income shocks that are anticipated and therefore incorporated when solving for saving and investment decisions. More specifically, in this case we are solving for a new set of policy functions that considers the −5% total shock that takes 10 years to be fully realized.
- *Case 4*: Negative income shocks that are anticipated, along with the incorporation of alpha. In this case, we apply the new set of policy functions from Case 3 and introduce a modest hypothetical adjustment of +0.3% active return and +0.6% active risk to the equity and fixed income assets within the simulations.

The consumption curves in Figure 26 demonstrate the positive impact that planning and adding alpha can have on consumption. Focusing first on the planning dimension, we see that the mere act of planning for a negative income shock results in notably higher consumption in retirement; this is because the model anticipates the income changes and recommends higher savings rates at younger ages. As a result, wealth accumulates more quickly and ends up 3% higher at the point of retirement. We can see through Figure 27 that we end up with this result even without increasing risk (i.e., the equity allocations

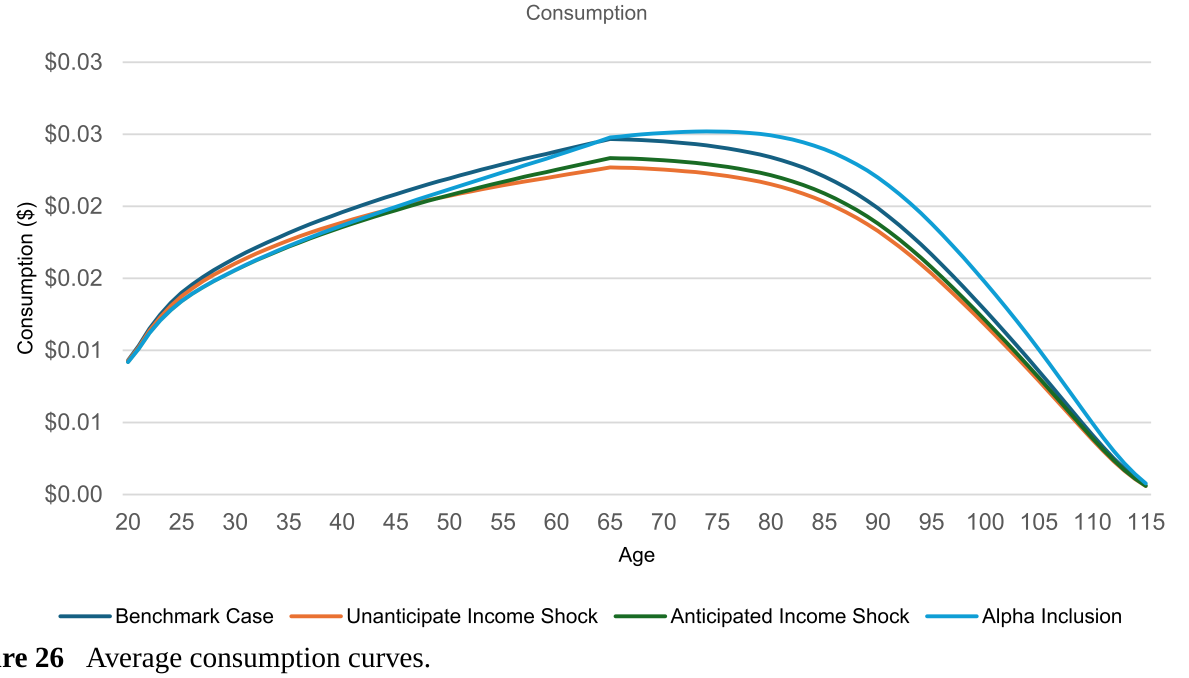

Figure 26 Average consumption curves.

Source: BlackRock. As of August 2025.

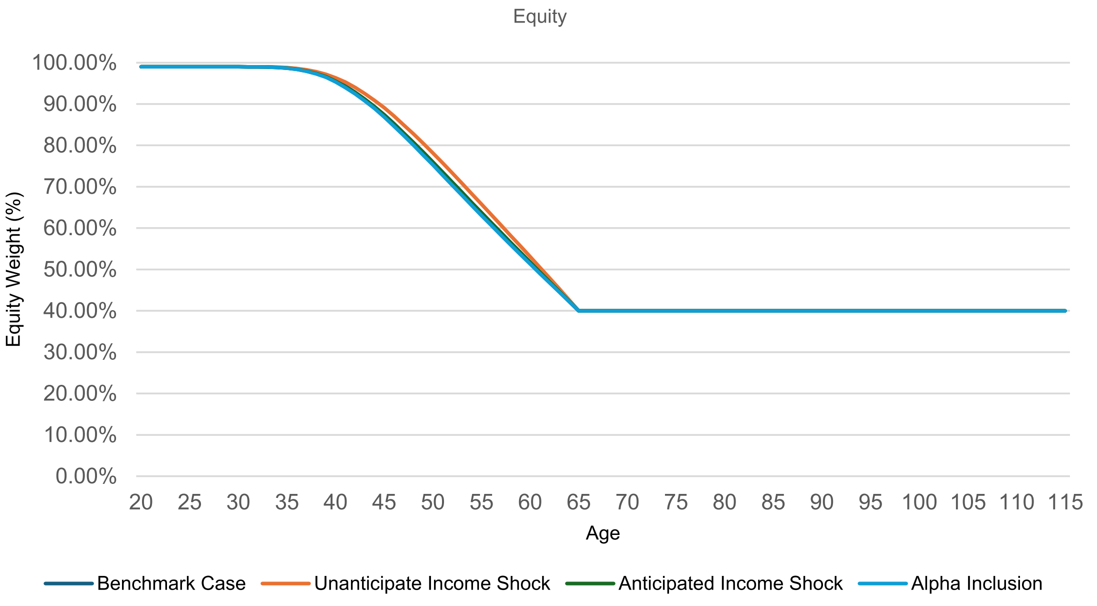

Figure 27 Average equity curves.

Source: BlackRock. As of August 2025.

are lower when negative income shocks are incorporated). So, through a bit of additional savings early on that maximizes savings efficiency, we have narrowed the consumption shortfall.

The final case we show demonstrates that by including alpha we can further narrow the consumption shortfall. Specifically, in this case we add 0.3% of active return and 0.6% active risk

Figure 28 Average wealth curves.

Source: BlackRock. As of August 2025.

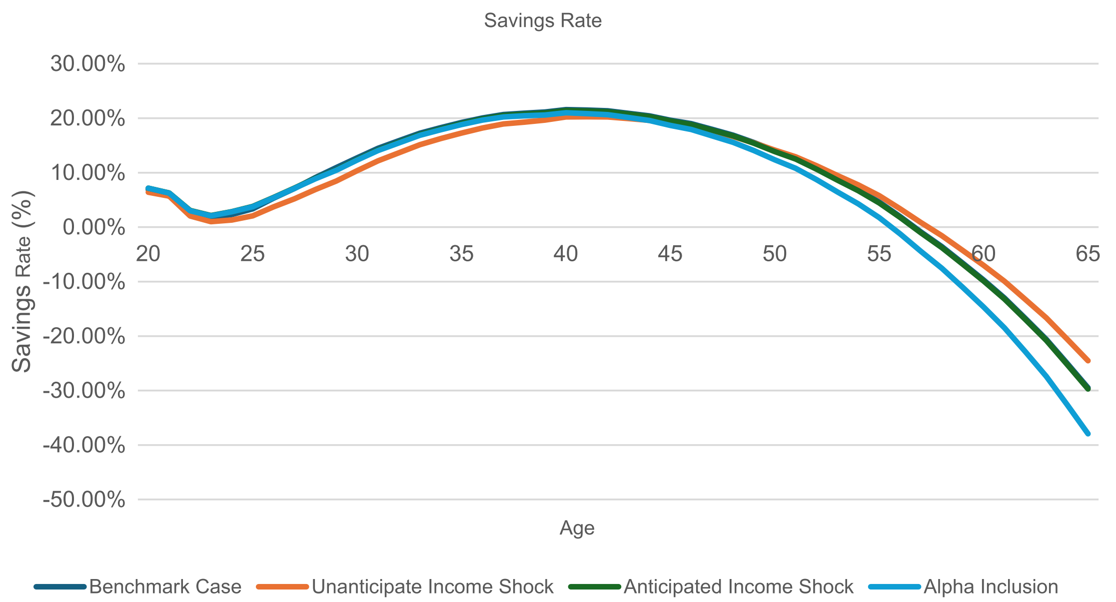

Figure 29 Average saving rates.

Source: BlackRock. As of August 2025.

to the equity and fixed income assets within the simulations.[6] We also assume no correlation between the alpha stream and the equity and fixed income assets, meaning we are increasing return and only modestly increasing risk given the uncorrelated nature of the alpha. Figure 43 shows that including 0.3% of consistent alpha results in higher consumption in retirement, thereby fully closing the consumption shortfall. The wealth curves in Figure 28 demonstrate that at the point of retirement, wealth in the base case and the alpha-inclusion case are effectively equal. This is because the individual continues to earn this extra return on his or her assets through retirement. It is also notable that we have achieved these higher levels of consumption without increasing our equity allocation.

Our stress scenarios in this section offer a powerful conclusion because they demonstrate that both effective planning and additional alpha streams can play key roles in helping to mitigate any adverse consumption effects from an AI-induced income shock. This has implications for plan design and fund selection, as employers and policymakers work to help workers navigate retirement in a world that is increasingly disrupted by AI.

4 Empirical Approach

Having explored a theoretical model of how AI can shift lifetime consumption and equity-allocation decisions, we propose to test one of these channels directly by empirically measuring the impact of automation on income. In this section, we will build a statistical analysis of historical impacts of task changes on occupational wages, then use a LLM to extrapolate the susceptibility and earnings impact of AI on a current cross-section of occupations in the U.S. labor market.

4.1 A framework for understanding the impact of AI on wages

To better understand the potential future impacts of AI on labor and wages, we build an empirical model developed around task content of production. Among other papers, Acemoglu and Restrepo (2019) present the idea that all jobs can be decomposed into a series of tasks done for their completion. This framework evaluates the impact of technological change on wage and employment outcomes through changes in the tasks done by labor.

In the simplest form, there are four key effects to consider:

(1) All else equal, technological change boosts labor productivity and in turn wages. In other words, technology makes labor more efficient, allowing it to participate in the benefits of output growth.
(2) When technology automates away tasks, known as displacement, wages tend to decline, due to a reduction in demand for the associated labor.
(3) When novel technologies create new tasks for labor to do, wages and employment rise.
(4) Across the economy, composition effects can shift tasks from one industry to another, negatively impacting wage profiles in the former and improving them in the latter.

Wage impacts from new technologies can be thought of as a combination of these intersecting dynamics. Acemoglu and Restrepo (2019) illustrate this point further by showing the mechanization of agriculture between 1850 and 1910 reduced the need for manual labor in farming, decreasing the agricultural labor share and total wages. However, overall labor demand increased due to the reallocation of workers to the industrial sector and the creation of new, labor-intensive jobs. Using this framework, we can consider the potential future impacts of AI on wages across occupations and industries through the lens of its impact on tasks.

We will focus on estimating relative impacts of AI technologies across occupations rather than the economy in aggregate for two reasons. First, to be able to understand the implications at the economy-wide level, one must make numerous additional assumptions on the impact of AI on investment and take-up. Indeed, when surveying recent studies on the topic, we find a wide variation in such aggregate estimates, with positive productivity impacts ranging from approximately 0% to 1.5% per annum, as shown in Figure 30. Applying the findings from Acemoglu and Restrepo (2019) over the 1987–2017 period, one might expect that much of that may be proportional to increases in the total wage bill. Second, our interest in this paper is on the differences across occupational cohorts. Although there may be an overall increase in population- or

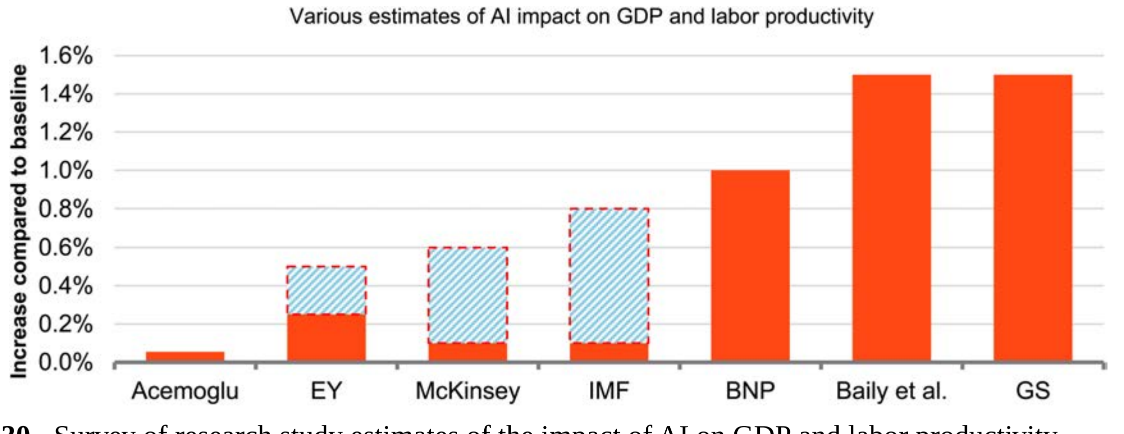

Figure 30 Survey of research study estimates of the impact of AI on GDP and labor productivity.

employment-level wages, the expected or actual impact may vary significantly across different occupations with potential for negative effects.

Our empirical approach will estimate the relative sensitivity of total and average wage changes to the evolution of tasks across occupations through historical analysis. We then use a LLM to tag tasks within existing occupations and estimate the proportion of tasks likely to be positively or negatively impacted by AI. Finally, we combine these estimates to assess the potential impact of AI on wages.

4.2 Data

There are two main data sources for our empirical analysis: the Occupation Information Network (O*NET) and the Bureau of Labor Statistics (BLS). O*NET is an extensive online database that provides detailed information on job descriptions, requirements, and workforce characteristics for various occupations in the United States. The database contains granular descriptions of tasks associated with each occupation. Historically, the database has been updated at least annually. The BLS OEWS database provides comprehensive data on employment and wage estimates across various occupations in the U.S. economy. This database contains both granular information on wages and employment across alternate occupations and industries. OEWS is also updated on an annual basis.

While O*NET provides data at the granular six-digit occupation code, we ultimately aggregate our data to a lower three-digit granularity, leading to a total of 94 occupations across both data sets. The main reason for applying this aggregation is that it helps to reduce the noise from evolutions in some data-collection assumptions across some of the more granular occupations, particularly in the OEWS database.

O*NET-SOC Code	Latest Task ID	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
11-1011	15367	NaN	NaN	NaN	NaN	NaN	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	20461	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	8823	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	8837	NaN	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
11-1021	19501	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	20699	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	933	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	934	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11-1031	15267	NaN	NaN	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
11-2011	15385	NaN	NaN	NaN	NaN	NaN	NaN	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	18586	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	21217	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	1.0	1.0
11-2031	3247	NaN	NaN	1.0	1.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	3255	1.0	1.0	1.0	1.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11-3021	15198	NaN	NaN	NaN	NaN	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
11-3031	8862	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11-3040	985	NaN	1.0	1.0	1.0	1.0	1.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11-3041	3284	1.0	1.0	1.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11-3071	1041	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11-9179	23945	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0
15-2041	8962	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	NaN	NaN	NaN	NaN

Figure 31 Table illustrating granularity of task-by-occupation tracking in the O*NET database, example across occupations and tasks.

4.2.1 O*NET data

The O*NET database indexes both detailed tasks and occupations. We organize the data by year in a simple table, as shown in Figure 31, and keep track of tasks as they evolve over time across each occupation. In aggregate, there are approximately 23,000 tasks that we track in the database.

One challenge is that while O*NET is updated annually, the surveys are not done continuously. For example, Figure 32 shows the total number of updated tasks that we see across occupations in aggregate in each year. The chart makes it clear that updates happen sporadically in large chunks, an issue we expand on in Section 5. For this reason, our empirical analysis will focus on

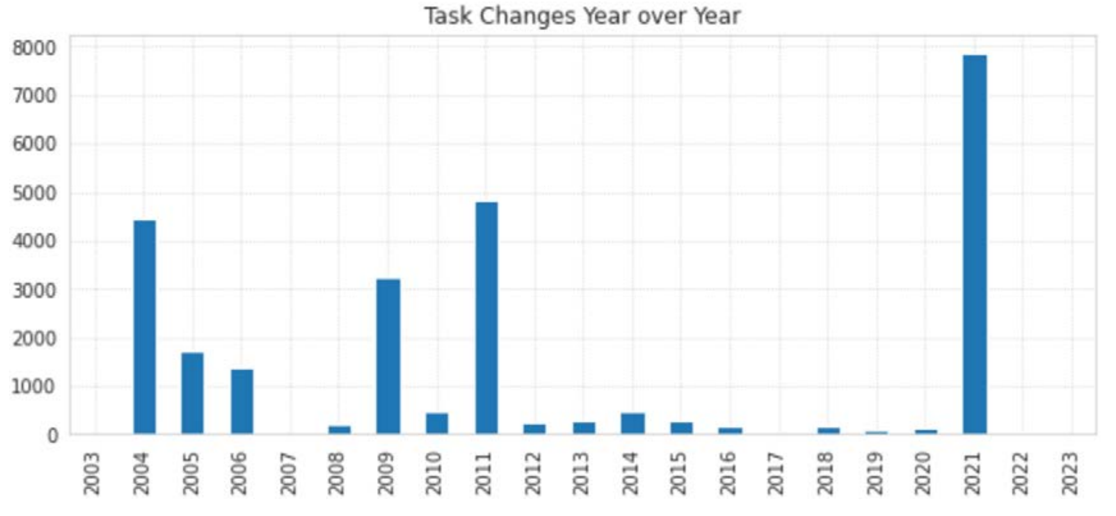

Figure 32 Annual changes in tasks by occupations in the O*NET database.

Source: BlackRock. As of August 2025.

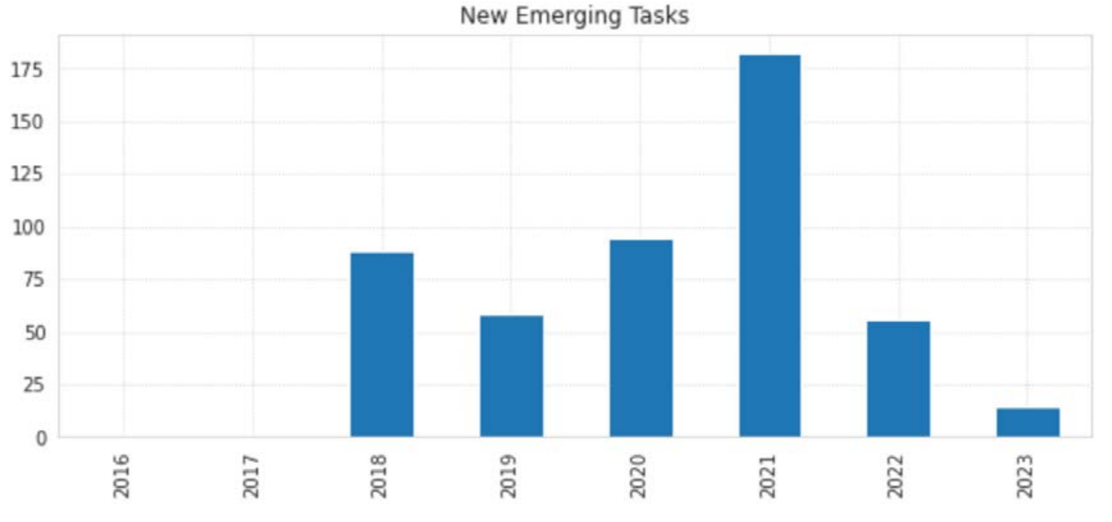

Figure 33 Annual additions of new emerging tasks in the O*NET database.

Source: BlackRock. As of August 2025.

estimating the impact of task changes over a 10-year period from 2011 to 2021 to capture the aggregate effects over the full decade.

We also rely on a table that details emerging tasks, defined as new and evolving duties and responsibilities associated with occupations that arise due to technological advancements, industry changes, and evolving business practices. The updates to this dataset are shown below, which again illustrate that while they are updated relatively continuously, 2021 contains a disproportionate number of updates.

We next compute the impact of task changes by occupation. We start with a baseline of the number of tasks per occupation in 2011, then compute three different metrics for task changes: percent of tasks that have been removed, percent added, and the percent of all tasks in 2011 that have been tagged as emerging. Figure 34 shows some of the variability in these figures by occupation, sorted by the percent of tasks that have been removed.

To provide more context on how tasks evolve across occupations, we explore a few case studies in Table 4. Mathematical science occupations have seen a significant increase in the number of tasks added relative to those removed over the decade. The removed tasks are typically rote activities that have been aided by technology. The added tasks appear to be associated with higher levels of analysis and training.

In contrast, some other occupations have seen an opposite effect—with the proportion of tasks removed exceeding that of new tasks added. For example, some tasks where manufacturing machinery has had an effect of increasing automation include melting, cutting, and cleaning. The added tasks have broadly aligned with duties such as monitoring and maintenance.

In Table 5, we compute the correlation across these variables. We find that there is a meaningful positive correlation between the proportion of tasks removed and added, with low correlations across the emerging tasks and the difference between tasks added and removed.

Running a principal component analysis (PCA) on tasks removed, tasks added, and emerging tasks as the input variables, we find that the first component describes overall changes in non-emerging tasks, the second describes the relative

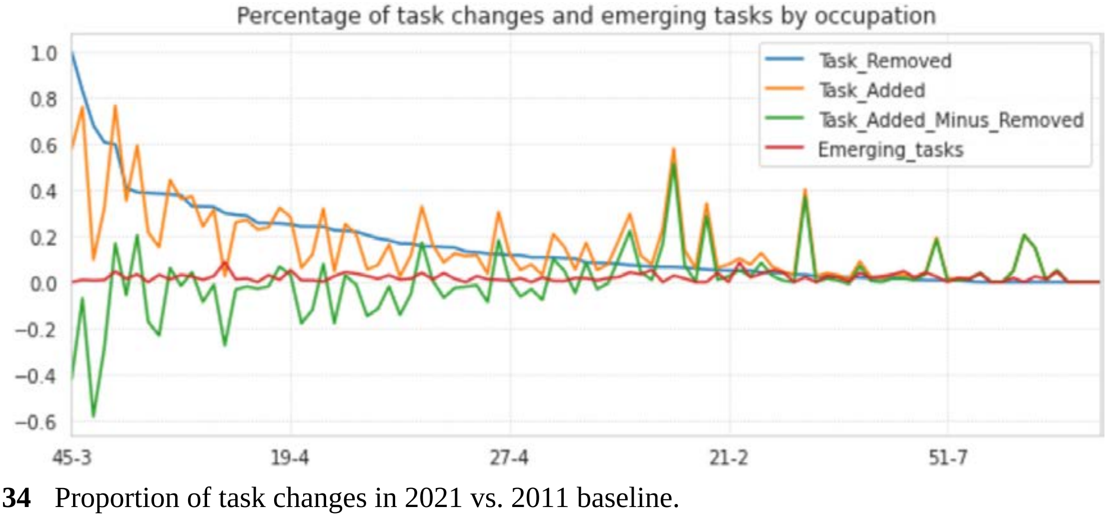

Figure 34 Proportion of task changes in 2021 vs. 2011 baseline.

Source: BlackRock. As of August 2025.

Table 4 Examples of tasks added and removed for selected occupations.

	Example: Tasks Added	Example: Tasks Removed
Example: Mathematical Sciences	Conduct quality analyses of data inputs and resulting analyses or predictions	Apply standardized mathematical formulas, principles, and methodology to the solution of technological problems involving engineering or physical science
	Write computer programs or scripts to be used in querying databases	Modify standard formulas so that they conform to project needs and data-processing methods
	Apply sampling techniques to determine groups to be surveyed or use complete enumeration methods	Reduce raw data to meaningful terms, using the most practical and accurate combination and sequence of computational methods
	Train bioinformatics staff or researchers in the use of databases	
Example: Metal and Plastic Workers	Maintain machine tools in proper operational condition.	Clean machines, tooling, and parts, using solvents or solutions and rags
	Study sample parts, blueprints, drawings, or engineering information to determine methods or sequences of operations needed to fabricate products	Gouge metals using the air-arc gouging process
	Evaluate machining procedures and recommend changes or modifications for improved efficiency or adaptability	Cut metal plates and structural shapes to dimensions, and contour and bevel as specified by blueprints, layouts, work orders, and templates, using powered saws, hand shears, or chipping knives
	Operate forklifts to deliver materials	Melt lead bars, wire, or scrap to add lead to joints or to extrude melted scrap into reusable form
	Diagnose machine tool malfunctions to determine need for adjustments or repairs	

Source: BlackRock, USDOL. As of August 2025.

Table 5 Correlation of task change variables across occupations.

	Task_Removed	Task_Added	Task_Added_Minus_Removed	Emerging_tasks
Task_Removed	1.000000	0.687805	−0.515275	−0.036152
Task_Added	0.687805	1.000000	0.267703	0.043011
Task_Added_Minus_Removed	−0.515275	0.267703	1.000000	0.098767
Emerging_tasks	−0.036152	0.043011	0.098767	1.000000

Source: BlackRock. As of August 2025.

Table 6 Principal component loadings across task change variables.

	Task_Removed	Task_Added	Emerging_Tasks
PC1	0.764271	0.644895	−0.000193
PC2	0.644770	−0.764130	−0.019429
PC3	0.012677	−0.014725	0.999811

Source: BlackRock, USDOL. As of August 2025.

share of tasks removed vs. added, and the third loads solely on emerging tasks.

4.2.2 *BLS occupational employment and wage statistics data*

From the OEWS database, we pull aggregate national employment and wage statistics by occupation. This allows us to calculate the annualized evolution in these figures over the 10-year period (2011–2021). Total wages are highly correlated with total employment, given that total wages equal average wages multiplied by number employed. For this reason, our analysis will focus on total and average wages.

In Figure 36 we plot the changes in total and average wages from 2011 to 2021, sorted by total wages across occupations. As Figure 36 shows, total wages have increased in aggregate far more than average wages. Since total wages are average wages multiplied by total employment, this means that changes in employment levels have been a main driver of the change in total wages in sample. This is important and yet intuitive. Economic growth expands the overall labor force, while changes in demand and productivity across sectors drive employment shifts between industries, redistributing workers from one sector to another.

In Table 7, we report the occupations that have seen the largest and smallest average annualized changes in total and average wages over the 10-year period. In general, there is little overlap between the two categories, with significant

	Total Employment	Total Wages	Average Wages
Total Employment	1.000000	0.990891	-0.139731
Total Wages	0.990891	1.000000	-0.005259
Average Wages	-0.139731	-0.005259	1.000000

Figure 35 Correlation matrix of changes in total employment, total wages, and average wages.

Source: BlackRock, BLS. As of August 2025.

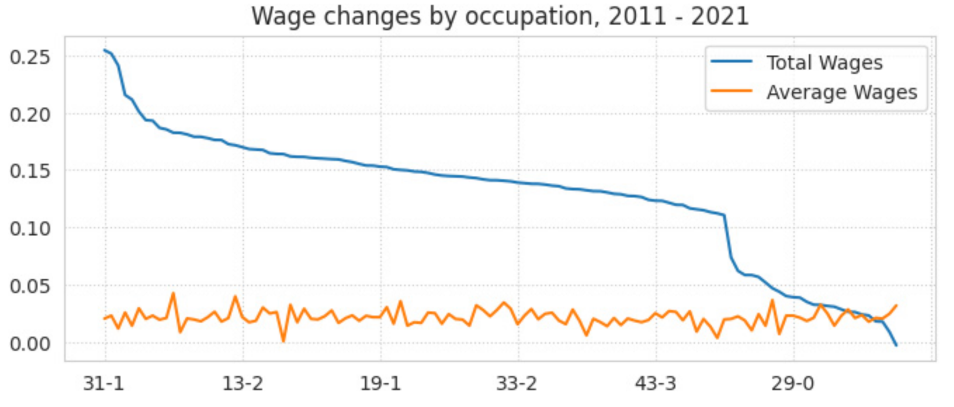

Figure 36 Total and average wage changes, annualized 2011–2021.

Source: BlackRock, BLS. As of August 2025.

Table 7 Occupations with largest and smallest average changes in total and average wages 2011–2021.

	Largest Increase	Largest Decrease
Total Wages	Nursing, Psychiatric and Home Health Aides	Air Transportation
	Mathematical Science	Agriculture
	Supervisors of Transportation	Farming, Fishing and Forestry
	Material Moving	Water Transportation

Source: BlackRock, BLS. As of August 2025.

impact of total employment changes on the overall wage variable.

4.3 *Regression analysis: Relating wages to task evolutions*

Our analysis focuses on estimating the relative importance of changes in the task content of production on total and average wages. To understand the relative impact of tasks added, tasks removed and emerging tasks on shifts in total and average wages, we run a series of regressions using the data outlined in Sections 4.2.1 and 4.2.2. These multi-variate regressions are summarized in Equation (4).

$$\Delta W_o = \alpha + \sum_{k \in K} \beta_k T_{k,o} + \epsilon_o. \tag{4}$$

Here, ΔW_o denotes the change in total wages for occupation o, $T_{k,o}$ is the value of task variable k for occupation o, and K is the subset of task variables included in the regression so that:

$$K \subseteq \{\textit{Tasks Added},\ \textit{Tasks Removed},\ \textit{Tasksadded} - \textit{Tasks Removed},\ \textit{Emerging Tasks}\}. \tag{5}$$

Table 8 gives the results from regressing the change in total wages on different combinations of tasks added, tasks removed, the difference between tasks added and removed, and emerging tasks, all expressed as a proportion of the number of tasks at the start of the period. We note several interesting findings.

First, we find intuitive coefficients: adding tasks increases total wages (column (1)) by 5% for every 1% of tasks added, and when incorporating tasks removed, the coefficient is negative (column (5)).[7] When we just use tasks added—tasks removed (column (3)) the coefficient is also positive, but not statistically significant. However,

Table 8 Regression results: Annualized changes in total wages and average wages on evolution of tasks, 2011–2021

Total Wages	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.14***	0.15***	0.15***	0.15***	0.14***	0.14***	0.14***	0.14***	0.14***	0.14***
	(29.28)	(31.79)	(42.56)	(27.39)	(29.08)	(29.08)	(22.57)	(29.08)	(22.37)	(22.37)
Tasks Added	0.05**				0.07**	0.04*	0.05**		0.07**	0.04*
	(2.14)				(2.31)	(1.77)	(2.12)		(2.26)	(1.76)
Tasks Removed		0.01			−0.03			0.04*	−0.03	
		(0.66)			(−1.09)			(1.77)	(−1.05)	
Tasks Added - Tasks Removed			0.04			0.03		0.07**		0.03
			(1.61)			(1.09)		(2.31)		(1.05)
Emerging Tasks				0.10			0.09		0.07	0.07
				(0.50)			(0.45)		(0.35)	(0.35)
R-Squared	0.05	0	0.03	0	0.06	0.06	0.05	0.06	0.06	0.06
Adj R-Squared	0.04	−0.01	0.02	−0.01	0.04	0.04	0.03	0.04	0.03	0.03
F-Value	4.59	0.43	2.59	0.25	2.89	2.89	2.37	2.89	1.95	1.95
F-P Value	0.03	0.51	0.11	0.62	0.06	0.06	0.1	0.06	0.13	0.13

*Indicates significance at 90% level, **indicates significance at 95% level, and ***indicates significance at 99% level. Figures in parentheses following coefficients indicate t-statistics.
Source: BlackRock. As of August 2025.

when keeping this variable but allowing for some adjustment from overly penalizing removed tasks (column (8)) we find statistical significance in both variables. Emerging tasks is positive in the coefficient, which is aligned with intuition, but is not statistically significant for total wages.

Next, we run the same set of regressions but use average wages as our dependent variable; these regressions are summarized by Equation (6), with K as in Equation (5):

$$\Delta \bar{W}_o = \alpha + \sum_{k \in K} \beta_k T_{k,o} + \epsilon_o. \tag{6}$$

The results for our second regression are very different than what we see for total wages (see Table 9). Since average wages equal total wages divided by total employed, we find that tasks added actually have a slight negative effect on average wages. This means that added tasks pull more employees into the occupation, but, as a result, an increase in the labor supply puts downward pressure on wages.

In contrast, emerging tasks have a very large and significant impact on increase average pay. This is also intuitive: emerging tasks are most likely to be done by existing employees, benefitting their productivity prior to new workers being added to the production process, and thereby increasing individual pay.

The results so far are intuitive. When technological change leads to more tasks added than removed within an occupation, labor demanded increases and hence total wages at the occupation level rise. When technological change leads to innovation and emerging tasks, individuals within the occupation experience more efficiency and the result is higher average wages per worker without an immediate spike in the labor supply.

We rerun the same regressions using our computed-task principal components to completely remove the impacts of multi-collinearity from the independent variable set; the results are in Tables 10 and 11. The conclusions are almost identical: occupations where more tasks are removed than added see a statistically significant decline in total wages, while average wages increase in occupations where emerging tasks are more prevalent.

Table 9 Regression results: Annualized changes in total wages and average wages on evolution of tasks, 2011–2021.

Average Wages	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(22.99)	(24.16)	(28.50)	(17.62)	(22.83)	(22.83)	(16.98)	(22.83)	(16.79)	(16.79)
Task Added	−0.01***				−0.01	−0.01***	−0.01***		−0.01	−0.01***
	(−2.66)				(−1.27)	(−2.82)	(−2.80)		(−1.50)	(−2.90)
Task Removed		−0.01**			−0.01			−0.01***	−0.00	
		(−2.52)			(−0.97)			(−2.82)	(−0.77)	
Task Added - Task Removed			0.00			0.01		−0.01		0.00
			(0.22)			(0.97)		(−1.27)		(0.77)
Emerging Tasks				0.09**			0.09**		0.09**	0.09**
				(2.27)			(2.44)		(2.35)	(2.35)
R-Squared	0.07	0.06	0	0.05	0.08	0.08	0.13	0.08	0.13	0.13
Adj R-Squared	0.06	0.05	−0.01	0.04	0.06	0.06	0.11	0.06	0.11	0.11
F-Value	7.06	6.36	0.05	5.16	4	4	6.7	4	4.65	4.65
F-P Value	0.01	0.01	0.83	0.03	0.02	0.02	0	0.02	0	0

*Indicates significance at 90% level, **indicates significance at 95% level, and ***indicates significance at 99% level. Figures in parentheses following coefficients indicate t-statistics. Source: BlackRock. As of August 2025.

Table 10 Regression results: annualized changes in total wages on principal components of the task evolution variables, 2011–2021

Total Wages	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.15***	0.15***	0.15***	0.14***	0.14***	0.15***	0.14***
	(29.36)	(41.33)	(27.74)	(29.06)	(22.49)	(27.50)	(22.37)
Task Changes	0.02			0.02	0.02		0.02
	(1.40)			(1.42)	(1.39)		(1.42)
Tasks Removed - Tasks Added		0.1351		0.1365		0.1344	0.1358
Emerging Tasks			0.06		0.07	0.06	0.07
			(0.31)		(0.33)	(0.32)	(0.34)
R-Squared	0.02	0.04	0	0.06	0.02	0.04	0.06
Adj R-Squared	0.01	0.03	−0.01	0.04	0	0.02	0.03
F-Value	1.95	3.73	0.1	2.9	1.02	1.9	1.95
F-P Value	0.17	0.06	0.76	0.06	0.37	0.16	0.13

*Indicates significance at 90% level, **indicates significance at 95% level, and ***indicates significance at 99% level. Figures in parentheses following coefficients indicate t-statistics.
Source: BlackRock. As of August 2025.

Having estimated how the evolution of tasks impacts both average and total wages across occupations, we now turn to understanding how tasks across occupations might be impacted by AI.

4.4 *Categorizing O*NET tasks through LLM queries*

To estimate the potential future impact of AI on total and average wages across occupations,

Table 11 Regression results: annualized changes in average wages on principal components of the task evolution variables, 2011–2021

Average Wages	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(23.20)	(27.85)	(17.77)	(22.82)	(16.98)	(17.52)	(16.79)
Task Changes	−0.01***			−0.01***	−0.01***		−0.01***
	(−2.82)			(−2.81)	(−2.86)		(−2.85)
Tasks Removed - Tasks Added		0.00		0.00		0.00	0.00
		(0.31)		(0.32)		(0.31)	(0.33)
Emerging Tasks			0.09**		0.09**	0.09**	0.09**
			(2.31)		(2.37)	(2.30)	(2.35)
R-Squared	0.08	0	0.05	0.08	0.13	0.06	0.13
Adj R-Squared	0.07	−0.01	0.04	0.06	0.11	0.04	0.11
F-Value	7.97	0.09	5.34	4	6.98	2.69	4.65
F-P Value	0.01	0.76	0.02	0.02	0	0.07	0

*Indicates significance at 90% level, **indicates significance at 95% level, and ***indicates significance at a 99% level. Figures in parentheses following coefficients indicate t-statistics.
Source: BlackRock. As of August 2025.

we must first understand how this technological change is likely to impact alternate tasks across occupations going forward. To do so, we follow the approach used in Eloundou *et al.* (2023) and leverage the OpenAI GPT 4 model to tag the approximately 20,000 tasks that exist in the February 2024 O*NET database. To do so, we leverage the Open AI GPT 4[8] model and run the following query[9]:

You are an economist trying to sort out the impact that artificial intelligence (AI), and particularly large language models, will have on the tasks of workers.

You are going through a list of occupations and the tasks that each worker does to determine whether the task is likely to be fully automated by AI (tag: "Automated") by AI so as to reduce need for labor, will be complemented by AI (tag: "Complemented") so as to increase the need for labor, or will be unaffected (tag: "Unaffected") by AI.

If Complemented, please determine whether AI is likely to keep the amount of labor needed but increase the potential output (tag: "Increase Output"), or reduce the amount of labor needed for the task ("Reduce Labor").

Please read following job occupation and task and create a table that indicates whether the task is likely to be fully automated, complemented, or unaffected by AI and whether the task is hard or easy. Please separate sections with semi-colons and provide a rationale.

For example, the output can look like:
AI Impact:Automated;Compexity:Easy;Rationale:The task can be easily done with large language models because it requires programming code.

Occupation: %s
Task: %s

Figure 37 GPT4 query to tag each task and occupation.

In Figure 38, we show some of the tagged projections from our LLM query. First, the results suggests that AI is likely to have an impact on most workers, with some experiencing improved productivity, while in others potentially experiencing some negative effects. It is important to note that this analysis relies on existing tasks and therefore excludes the potential new tasks that will be created due to the advent of AI. In our sensitivity analysis later in this section, we seek to control for this effect by incorporating hypothetical aggregate increases in productivity.

Next, we summarize our task tags by occupation Job Zone in Figure 39. In the O*NET database, Job Zones refer to level of education, experience, and training required to perform the job, with Job Zone 1 indicating “little or no preparation needed”

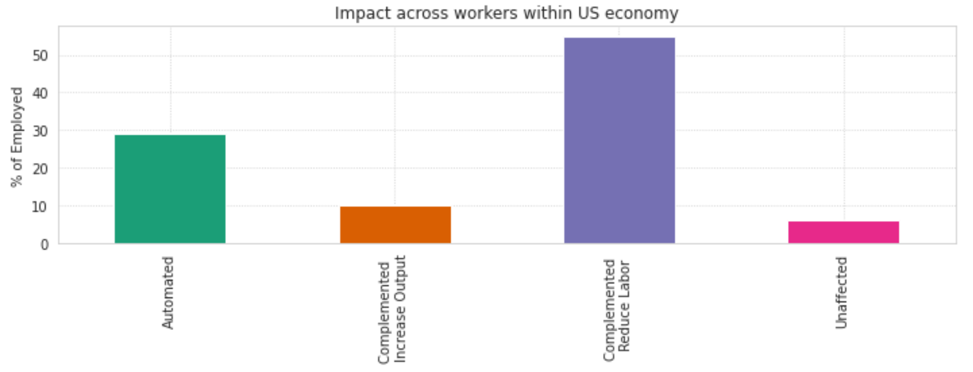

Figure 38 U.S.-economy impact from AI, calculated as the % of employee task shares impacted by AI across the four categories.

Source: BlackRock. As of August 2025.

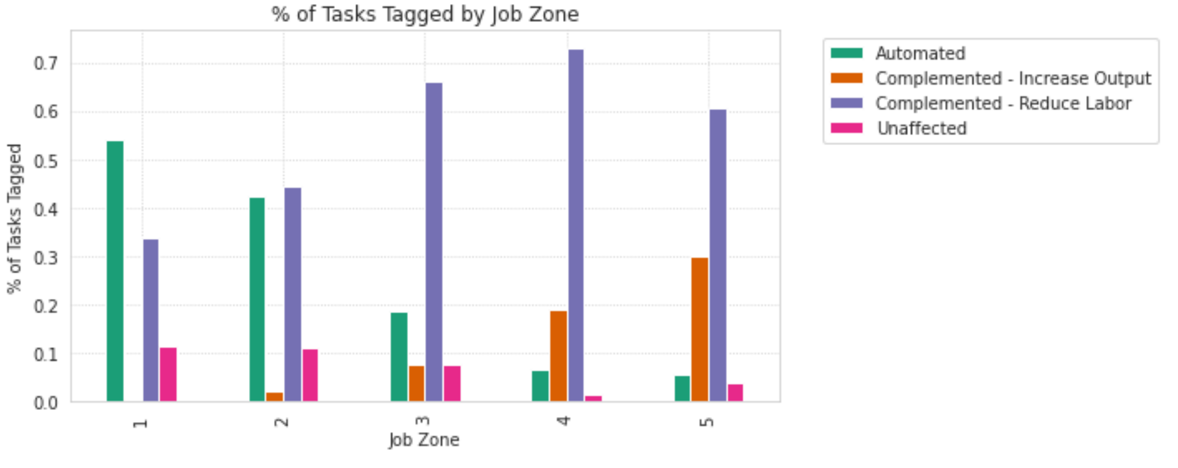

Figure 39 Impact of AI on tasks across job zones.

Source: BlackRock. As of August 2025.

and Job Zone 5 "requiring extensive preparation". Consistent with some of the findings in Elondou *et al.* (2023), we find that AI's labor-reduction through complementary tasks rises with Job Zones but then falls in the highest skilled jobs. Notably, the ability for AI to increase output when complementing tasks is highest in these top Job Zones. Meanwhile, full automation appears intuitively most concentrated at the lowest Job Zones.

Occupations appear to be exposed to AI in two areas: repeated tasks and technological tasks. Based on our experiment, our findings are as follows:

(1) **Full Automation**. Occupations with repeated non-technological tasks are most likely to have their tasks automated (e.g., low-skilled functions that can be substituted by capital, either in software or hardware).
(2) **More with Less**. Occupations with repeated technological tasks are likely more susceptible to AI improving labor productivity while shrinking aggregate labor demand; examples include areas where LLMs can significantly

scale the output of a small number of workers (e.g., computer programming, administrative, and legal tasks).

(3) **More with More**. Occupations with idiosyncratic technological tasks are most likely to be enhanced by AI without adverse impacts on labor market demand; these professions require creative decision-making or drive cutting-edge research (e.g., medical innovation).

(4) **No Automation**. Occupations with idiosyncratic non-technological tasks are least likely to be affected by AI; tasks that require in-person or inter-personal relationships, action, and specialization may be relatively insulated from AI.

We next convert the above mappings into estimates that we can plug into our regression models in the previous section. We assume that the share of likely removed tasks will be equivalent to 100% of the tasks likely to be fully automated and 75% of the tasks likely to be complemented but leading to labor reduction.[10] For added tasks, we assume this is equal to the proportion of tasks where AI can complement labor to increase output without reducing labor output.

4.5 *Estimating potential impact of AI on wages across occupations*

To estimate the potential impact of AI on future total and average wages, we plug in the estimated impacts on tasks added and removed from the previous section into the regression estimates from our empirical study in Section 4.3. In our estimates, we make two important points:

(1) We are interested in understanding the *range of incremental impacts* of AI on wages across different occupations. For this reason, we exclude the intercept estimate, which summarizes the historical average annualized growth in our dependent variables.

(2) We note that while we are not making any assumption on the aggregate incremental impact of AI on overall productivity and hence increased wages, we can leverage the range of estimates from the other academic research papers cited to impact our estimated ranges.

In our total wage regression results, we found that emerging tasks do not appear to have a meaningful impact. For this reason, we apply the coefficients from regression (8) in Table 8 that capture both

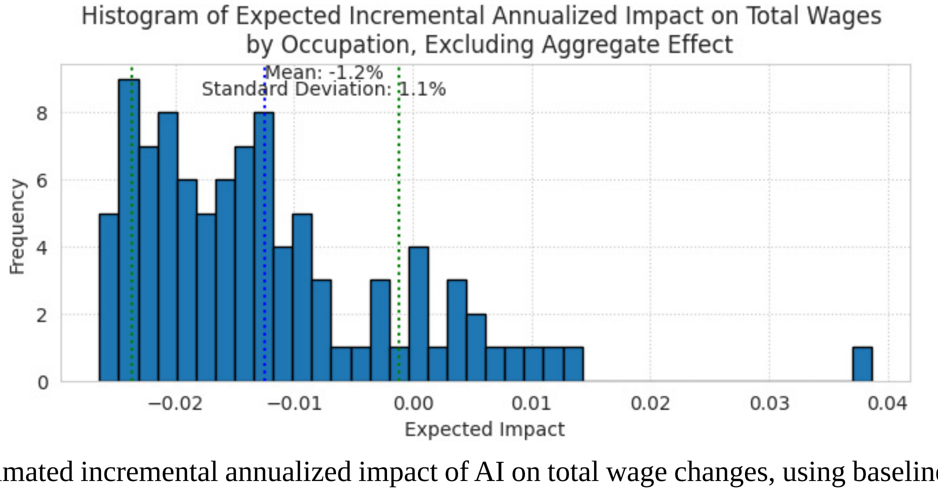

Figure 40 Estimated incremental annualized impact of AI on total wage changes, using baseline assumptions.

Source: BlackRock. As of August 2025.

the difference of tasks removed from tasks added, and the adjustment for just tasks removed.[11]

Figure 40 reports the estimated annualized incremental impact of AI on total wage changes across occupations, ignoring level adjustments. The analysis suggests that there is likely to be meaningful dispersion in the impacts on total wages as a result of AI, with some workers experiencing meaningfully positive effects, while some negative, with a range of approximately −2.5% to +3.5% in annual total wage growth. Notably, this does not yet include aggregate productivity impacts that can raise the entire mean, where we test the sensitivity in Table 12.

To further test our assumptions, we run sensitivity analyses leveraging alternate assumptions around the decline in labor input across tasks tagged as Complemented—Reduce Labor Demand to include alternatives of 25% and 50%, vs. our baseline of 75%. We also add an additional set of cases in Table 12 that shows adjusted values assuming a 1.5% increase in total wages due to labor-productivity impacts, slotting in a value that is at the upper end of the estimates from previously mentioned academic and practitioner studies. Overall, we find that the potential range of impacts across occupations is likely to range from −2.6% to +5.7%. The aggregate means may be slightly negative, or potentially positive if productivity effects increase, especially as AI has the potential to create new tasks, occupations and increase overall output. In general, the dispersion across occupations is likely to be very high, with a difference of approximately 6.5% between the smallest and largest incremental impacts.

We repeat the exercise for our average wage estimates as well. Since emerging tasks appear to explain the majority of changes in average wages, we have simply copied in our task added estimates as emerging tasks estimates as well.[12] Here, using coefficient estimates from Regression (9) from Table 9, we find that, on average, wages are likely to increase (see Figure 41). This result suggests that even in the most negative scenarios where total employment may be negatively impacted in some occupations, the remaining workers are likely to be better off.

Turning to implications for retirement saving, if a worker knew that she was going to keep her position as AI is incorporated into her industry, it would make sense to analyze the retirement-saving impact using the average wage results. However, all new technology, such as AI, raises some uncertainty on the future of existing tasks and level of wages in some occupations. We therefore believe that the estimates of AI's impact on total wage changes are more appropriate to better understand the potential impact on future retirement-strategy design.

Table 12 Estimated incremental annualized impact of AI on total wage changes, with sensitivity analysis.

Assumed increase from labor productivity	No aggregate total wage increase			With 1.5% aggregate total wage increase		
Labor replacement multiplier assumption	25% task reduction	50% task reduction	Baseline (75%)	25% task reduction	50% task reduction	Baseline (75%)
Maximum across occupations	4.2%	4.0%	3.9%	5.7%	5.5%	5.4%
Mean across occupations	−0.4%	−0.8%	−1.2%	1.1%	0.7%	0.3%
Minimum across occupations	−2.2%	−2.4%	−2.6%	−0.7%	−0.9%	−1.1%

Source: BlackRock. As of August 2025.

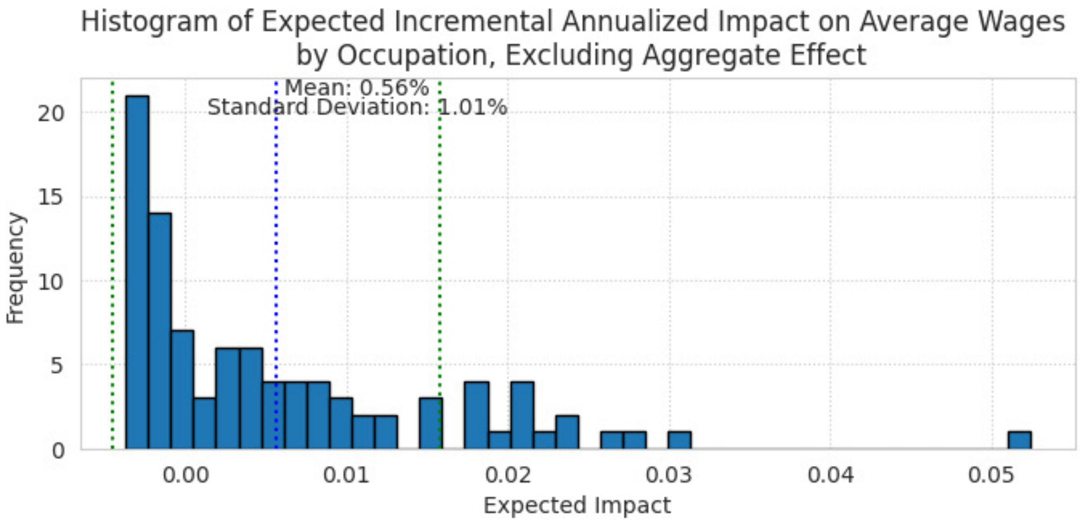

Figure 41 Estimated incremental annualized impact of AI on average wage changes, using baseline assumptions.

Source: BlackRock. As of August 2025.

5 Discussion

The impact of AI on retirement can be estimated through labor income and retirement longevity; the former funds savings during working years while the latter defines the start and duration of retirement.

This paper built a theoretical model exploring how shocks to each can impact lifetime wealth and suggested mitigating strategies to adapt to the likely impact of AI in the labor market. The empirical analysis section drilled into the labor-income segment and showed how wages across various occupations can be impacted by the changing nature of tasks. We concluded the analysis by using an LLM to forecast how occupations in the current labor market might be impacted by AI-driven automation.

We suggest two interventions in line with this paper's findings:

(1) *Helping workers anticipate automation by improving data collection on new technologies*—In this paper's theory section, we show that adjusting savings habits by successfully anticipating AI's impact on labor income can materially improve long-term wealth and consumption. Enhancing the public's access to data that tracks economic activity performed between human and machine can improve research into the impact of AI on labor markets and help workers adjust savings accordingly. Marlar and Gallup (2019) identify gaps in the U.S. Bureau of Labor Statistics data for tracking human vs. machine task measurement, including the frequency of data updates, panel coverage across occupations, and depth of tasks explored. We see this in Figure 3 of O*NET dataset updates, a data offering highlighted by Marlar and Gallup for improvement.

(2) *Portfolio construction and seeking additional excess return*—This paper's theoretical section explores how changes in the composition of an investor's portfolio can impact overall wealth considering AI-driven shocks. We highlighted that finding successful consistent sources of alpha can aid in closing the

consumption gap. Importantly, even modest amounts of alpha can be highly impactful; for example, adding just 0.3% of excess return consistently over time, in addition to proactive adjustments to policy function like altering savings earlier, can meaningfully improve outcomes. In many ways, this recommendation is like those of Daverman *et al.* (2024) when dealing with disaster-based disruptions. Of course, we recognize that alpha is a zero-sum game, limiting its utility as a broad solution to AI's impact on retirement; additionally, finding consistent alpha sources requires additional effort, oversight, and governance.

A combination of these mitigants can have powerful effects for negatively affected cohorts. Lastly, it is worth exploring the balance between income, consumption, and longevity. All else equal, a loss in labor income should result in a drop in consumption—even with precautionary savings or unemployment insurance. Households may pause or even draw-down existing long-term savings to help offset costs from a transitory income shock. If an AI-based productivity shock is sufficiently deflationary for consumer prices, would this drop in costs sufficiently counterbalance interruptions to consumption or savings?

While an AI-driven increase in longevity may allow for longer working years, and might help make up some of the lossed savings and investment returns from AI-impacted job volatility, the loss of compounding savings earlier in ones' career might not be fully replenished by increasing the number of working years (i.e., combining elements of Sections 3.4 and 3.5 in our model). In all scenarios, it is important for households to be equipped with information and financial products to help them navigate the impact of AI in the economy.

6 Conclusion and Future Work

This paper contributes to economics literature by exploring the potential impact of AI on lifetime consumption. We explore this topic from a theoretical perspective using a lifecycle-consumption and portfolio-choice model and an empirical perspective using labor-market data. We suggest several strategies workers can deploy to minimize disruptions to wealth generation and consumption, as well as advice to policymakers on how help the public adapt to an AI-enhanced economy.

One of the key areas for further exploration is in understanding wage impacts across various job profiles, industries, sectors, and subgroups. Combining studies that look at both cross-sectional and longitudinal data to assess these changes could lead to interesting insights for retirement investors. A key, yet hard-to-estimate, parameter for retirees is inflation and the potential disinflationary impact of AI on productivity.

Lastly, there has been an increased focus on retirement spending, specifically guaranteed retirement spending. Additional work on investment strategies that address retirement spending, like using insurance products such as annuities, and their relationship with AI-driven factors may also be useful to help investors navigate the changes due to AI.

Appendix A Lifecycle Model for Consumption and Equity

Let t denote the investor's age at any point in time. We assume the investor lives to age T. Let p_t be the probability that an investor aged t lives to be $t+1$. We will be evaluating this model across a cohort of investors. For this purpose, each investor i's preferences are described by Epstein-Zin utility as follows:

$$V_{i,t}(X_{i,t}, Y_{i,t+1}) = \Big\{(1-\delta)C_{i,t}^{1-1\psi} + \delta E_t\Big[p_t V_{i,t+1}(X_{i,t+1}, Y_{i,t+1})^{1-\gamma}\Big]^{\frac{1-1/\psi}{1-\gamma}}\Big\}^{\frac{1}{1-1/\psi}}. \quad (A.1)$$

Here δ is the discount factor, ψ is the elasticity of intertemporal substitution, and γ is the risk aversion parameter. Consumption at age t is given by $C_{i,t}$, and wealth at time T is given by $X_{i,t}$. Further, we assume each investor's wealth evolves from one time period to the next as follows:

$$X_{i,t+1} = Y_{i,t+1} + (X_{i,t} - C_{i,t}) \times (1 + \alpha_{i,t}R_{t+1}^S + (1-\alpha_{i,t})R_{t+1}^B). \quad (A.2)$$

Next, we look at the labor income during the investor's accumulation years. We assume the investor i's labor income (or wages) in his or her working years at any time t, denoted by $Y_{i,t}$, is given by:

$$\log(Y_{i,t}) = f(t) + \eta_i + v_{i,t} + \epsilon_{i,t}, \quad (A.3)$$

where $f(t)$ is a deterministic function of age. Log (income) is modeled as a third-degree polynomial of age, where if age is given by t then $f(t) = \alpha + \beta_1 t + \beta_2 t^2 + \beta_3 t^3$, $\eta_i \sim N(0, \sigma_\eta^2)$ is an individual specific fixed effect, $\epsilon_i \sim N(0, \sigma_\epsilon^2)$ is a transitory income shock, and $v_{i,t}$ is the cumulative sum of permanent income shocks and is given by:

$$v_{i,t} = v_{i,t-1} + u_{i,t}, \quad (A.4)$$

with $u_i \sim N(0, \sigma_u^2)$. The allocation to equity is given by $\alpha_{i,t}$. The returns on stocks and bonds between periods t and $t+1$ are given by R_{t+1}^S and R_{t+1}^B, respectively, with log returns distributed according to $N(\mu_{RS} - \frac{\sigma_S^2}{2}, \sigma_S^2)$ and $N(\mu_{RB} - \frac{\sigma_B^2}{2}, \sigma_B^2)$. We assume at the terminal age T all wealth is consumed (there is no bequest) and utility is given by:

$$V_{i,T+1}(X_{i,T+1}, Y_{i,T+1}) = (1-\delta)X_{i,T+1}. \quad (A.5)$$

We do not allow short selling and assume no borrowing:

$$0 \le \alpha_{i,t} \le 1. \quad (A.6)$$

And lastly consumption at any time is constrained by the available wealth at that time:

$$C_{i,t} \le X_{i,t}. \quad (A.7)$$

The Optimization Problem

In each period t the investor must decide how much to consume $C_{i,t}$ and how much to invest in the equity asset $\alpha_{i,t}$ conditional on wealth $X_{i,t}$ and labor income $Y_{i,t}$. The optimization problem for the investor is to maximize the expected utility of consumption over the entire lifecycle:

$$\underset{\max\{C_{i,t},\alpha_{i,t}\}_{t=1}^T}{E[v_0]}, \quad (A.8)$$

subject to Equations (A.1) through (A.7). Since an analytical solution to this problem does not exist, we solve the problem using standard numerical solution methods.

Baseline model

For the baseline estimates, we calibrate the labor income curve in Equations (A.3) and (A.4) using data from the Panel Study of Income Dynamics; the average income curve is plotted in Figure A.1. We assume the investor age t begins at 20, and that investors live to a maximum age of $T = 115$. Mortality rates p_t are taken from the Blended

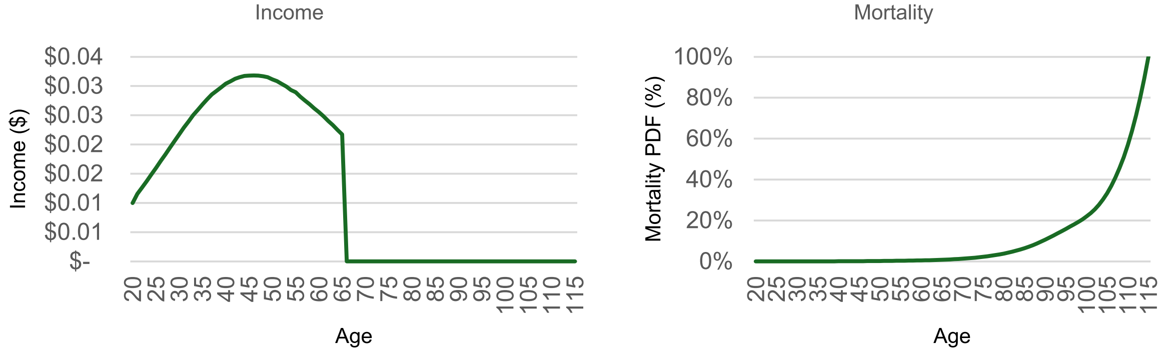

Figure A.1 Baseline income curve and mortality curve.

Source: BlackRock. As of August 2025.

Table A.1 Benchmark parameter values used in lifecycle model.

Parameter	Description	Value
δ	Discount factor	0.96
γ	Risk aversion parameter	3.68
ψ	Elasticity of intertemporal substitution	0.27
μ_S	Expected (real) return on equities	0.0415
σ_S	Standard deviation of equity returns	0.16
μ_B	Expected (real) return on bonds	0.01
σ_B	Standard deviation of bond returns	0.045
σ_η	Standard deviation of individual fixed effect	0.25
σ_ϵ	Standard deviation of transitory income shocks	0.3
σ_u	Standard deviation of permanent income shocks	0.1

Annuity 2000 Mortality table from the Society of Actuaries, as shown in Figure A.1.

Other key parameters and assumptions are in Table A.1.[13]

Appendix B Modeling Mortality Characteristics

For completion, we summarize the estimation process for the survival-probability values, which is a key input to the lifecycle model used in this study. Life expectancy, conditional on living to age 20, is given by the following formula:

$$e_{20} = \sum_{t=20}^{115} t \cdot q_t, \tag{B.1}$$

where q_t is the probability at age 20 that an individual dies at t, and we assume maximum age is 115. These mortality tables give us p_t, the probability that an individual lives to t conditional on being alive at age $t-1$ for $t = 20, \ldots, 115$. From these mortality tables, we can get q_t from the following formula:

$$q_t = \left(\prod_{k=20}^{t-1} p_k\right) \cdot (1 - p_t). \tag{B.2}$$

Endnote

1 For illustrative purposes only. The income, consumption rates and wealth values shown are hypothetical estimates generated using Monte Carlo simulation, which is a statistical modeling technique that forecasts a set of potential future outcomes based on the variability or randomness associated with historical occurrences.

Projections are hypothetical in nature, do not reflect actual investment results and are not guarantees of future results. No representation is made that an investor will achieve results similar to those shown. Actual values could be higher or lower based upon a number of factors and circumstances not addressed herein.

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3 Age in the original mortality table is truncated between 20 and 115, which means that shifting the distribution results in probability mass on ages that are not part of the original lifespan. We therefore adjust the mortality rates to ensure both that there is positive probability weight for ages between 20 and 115, and that the probabilities sum to 1. This adjustment has a very small impact on resulting average life expectancy because the boundary values of the probability-density curve are negligible.

4 For illustrative purposes only. The income, consumption rates and wealth values shown are hypothetical estimates generated using Monte Carlo simulation, which is a statistical modeling technique that forecasts a set of potential future outcomes based on the variability or randomness associated with historical occurrences. Projections are hypothetical in nature, do not reflect actual investment results and are not guarantees of future results. No representation is made that an investor will achieve results similar to those shown. Actual values could be higher or lower based upon a number of factors and circumstances not addressed herein.

5 The hypothetical performance returns are provided for illustrative purposes only and are not meant to be representative of actual performance returns of, or to project or predict returns for, any account, portfolio, strategy or asset allocation. The hypothetical performance period is from August 2025.

*The displayed hypothetical returns are subject to a number of significant limitations. They are illustrative of a product or strategy that does not exist, and therefore do not reflect the deduction of any fees or expenses, including advisory, management and performance fees, as well as brokerage fees, commissions and other expenses that might normally apply. In addition, the allocation decisions reflected in the hypothetical returns were not made under actual market conditions and cannot completely account for the impact of financial risk in actual portfolio management. The aggregate performance of the model is hypothetical and the model is formulated with benefit of hindsight.

There are frequently sharp differences between a hypothetical performance record and the actual record subsequently achieved. Therefore, hypothetical performance records invariably show positive rates of return. Another inherent limitation of these results is that the allocation decisions reflected in the performance record were not made under actual market conditions and, therefore, cannot completely account for the impact of financial risk in actual portfolio management.

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7 Notably just using tasks removed in column (2) has a small positive coefficient, but this is due to the high correlation with the tasks added variable.

8 We call the model from Python, leveraging the gpt-4-32k-0613 model instance.

9 We tested alternate queries, including those where we provided examples, but given the relative simplicity of the task ultimately found that the model does well and produces similar results across alternate approaches. We also tested alternate models, such as GPT 3.5 and found broadly consistent results.

10 While it is difficult to precisely specify the amount of potential labor reduction associated with these tasks,

we start with a 75% baseline that assumes meaningful reduction to estimate the outer limits of potential impacts. In the next section, we show the sensitivity of total and average wage impacts to alternate magnitudes in this assumption. By altering our assumptions, we can produce a range or potential impacts on future total wages across occupations.

[11] We note that this is identical to applying the coefficients from regression (5) in the same table.

[12] We also concede it is difficult to predict what emerging tasks may be created – thus focusing on tasks added is a more conservative choice.

[13] The parameterization of the discount factor δ value is in line with what is used in Cocco *et al.* The risk aversion parameter γ is set so that the equity allocation at the point of retirement is 40%. We set the elasticity of substitution ψ to be the inverse of γ, so, in fact, our utility function collapses to a power utility function. Capital market assumptions are in line with long-term estimates across a range of models. The labor income risk parameters are estimated using the same approach as in Cocco *et al.*, using data from the Panel Study of Income Dynamics.

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