Forecasting the Economic Effects of AI*

Ezra Karger[1,*], Otto Kuusela[2,*], Jason Abaluck[3], Kevin Bryan[4], Basil Halperin[5], Todd Jones[6], Connacher Murphy[7], Phil Trammell[7], Matt Reynolds[2], Dan Mayland[2], Ria Viswanathan[2], Ananaya Mittal[2], Rebecca Ceppas de Castro[2], Josh Rosenberg[2], and Philip E. Tetlock[8]

[1]Federal Reserve Bank of Chicago
[2]Forecasting Research Institute
[3]Yale School of Management
[4]University of Toronto
[5]University of Virginia
[6]Mississippi State University
[7]Stanford University
[8]University of Pennsylvania

March 2026

Abstract

We elicit forecasts of how AI will affect the U.S. economy, comparing the beliefs of five groups: academic economists, employees at AI companies, policy researchers focused on AI, highly accurate forecasters, and the general public. The median respondent in each group expects substantial advances in AI capabilities by 2030, small declines in labor force participation consistent with demographic shifts, and an annual GDP growth rate of 2.5%, which exceeds both the typical medium-run (2.0%) and long-run (1.7%) baseline forecasts from government agencies and private-sector forecasters. Conditional on a "rapid" AI progress scenario, in which AI systems surpass human performance on many cognitive and physical tasks, experts forecast substantial, though not historically unprecedented, economic shifts: annualized GDP growth rising to around 4% and the labor force participation rate falling from its current level of 62% to 55% by 2050, with roughly half of that decline—equivalent to around 10 million lost jobs—attributable to AI. A variance decomposition suggests that expert disagreement about these effects is driven primarily by different beliefs about the economic effects of highly capable AI systems rather than by disagreement about the pace of AI progress. These forecasts map onto notably different policy preferences across groups: experts strongly favor targeted measures such as worker retraining, whereas the general public supports both targeted programs and broader interventions, including a job guarantee and universal basic income.

*This research was funded by a grant from Open Philanthropy (now known as Coefficient Giving). Karger and Kuusela are joint first authors. The views expressed in this paper do not necessarily reflect the views of the Federal Reserve Bank of Chicago or the Federal Reserve System. We thank seminar attendees at the Congressional Budget Office for thoughtful feedback on this project. We also thank Morgane Bascle, Oskari Luoma, Aashish Reddy, Sam Holton, and Victoria Schmidt for outstanding research assistance. Corresponding author: Ezra Karger, ezra.karger@chi.frb.org

1. Introduction

1.1 Background

The diffusion of generative artificial intelligence into workplaces, consumer products, and public services has renewed a familiar set of economic questions: Will automation raise productivity enough to change the economy's long-run growth path? What will happen to work—employment, participation, wages, and occupational structure—as machines become capable of performing an increasingly broad set of cognitive tasks? And if the economic gains from AI are large, will they be broadly shared or concentrated among owners of capital and workers whose skills complement AI?

Despite intense attention, the evidence on AI's economic effects to date remains mixed. Recent work finds signs of labor-market adjustment concentrated among the parts of the workforce most exposed to generative AI: Brynjolfsson, Chandar, and Chen (2025) document a sizable decline in early-career employment in AI-exposed occupations following the widespread rollout of generative AI, with limited effects on older workers and less-exposed fields. Complementary evidence, however, complicates this interpretation. Humlum and Vestergaard (2025) find similar early-career declines in Danish data, but do not find that the declines are strongly linked to firm-level adoption of generative AI, raising the possibility that measured effects reflect broader changes in demand, task organization, or labor supply. Davis (2026) adds further context to these findings, showing that while employment in highly AI-exposed sectors has lagged the rest of the economy since late 2022, wages in those same sectors have not fallen. Related evidence in Gimbel et al. (2025) likewise points to limited near-term aggregate impacts. Taken together, the emerging empirical record suggests that some groups of workers and occupations may already be experiencing measurable effects from AI, but the aggregate macroeconomic signal remains difficult to isolate from typical fluctuations in a dynamic economy.

At the same time, prominent voices in business and the AI industry warn of transformative upheaval: Jamie Dimon, CEO of JPMorgan Chase, argues that AI "will eliminate jobs" and that "people should stop sticking their head[s] in the sand" (Gerut, 2025); Sam Altman, CEO and cofounder of OpenAI, predicts that "whole classes of jobs" will disappear even as unprecedented wealth is created; and Dario Amodei, CEO and cofounder of Anthropic, suggests that AI could push overall unemployment to 10–20% within the next five years (Altman, 2025; VandeHei and Allen, 2025). Quantitative analyses span a similarly broad range. Arnon (2025), using the Wharton Budget Model, projects AI-driven productivity and GDP gains (in levels) of just 1.5% by 2035 and 3.7% by 2075—modest figures that translate to less than 0.04 percentage points of additional annual productivity growth in the long run. The OECD, by contrast, estimates that AI could add 0.4–1.3 percentage points to annual aggregate labor productivity growth over a ten-year horizon in high-exposure countries (Filippucci et al., 2025). The gap between these assessments is wide, and the policy stakes are correspondingly high.

A central challenge in debates about the economic effects of AI is that such forecasts are, unavoidably, joint forecasts about the capabilities of AI systems and the diffusion of AI-related technology into the economy. In practice, these discussions often combine answers to three distinct questions into one. First, will AI capabilities advance meaningfully, such that

AI systems become capable of independently performing, or assisting with, a large quantity of economically valuable work? Second, if such progress occurs, what will happen to key macroeconomic outcomes, including GDP growth, productivity, labor-force participation, and inequality? And third, given predictions and uncertainty about the effects of AI on the economy, what are the optimal policy responses?

The first question about the progression of AI capabilities is primarily addressed by two research fields: (1) AI benchmarking, where computer scientists develop tasks that track the limits of AI systems' capabilities over time in work such as Russakovsky et al. (2015), Hendrycks et al. (2020), and Jain et al. (2024); and (2) capability forecasting, where researchers collect predictions about AI capabilities in projects like Grace et al. (2024) and the Longitudinal Expert AI Panel (Murphy et al., 2025). The second question on how AI diffuses into the economy is the core focus of a large and growing economics literature, as discussed above, yet standard models yield ambiguous predictions: the impact of rapid technological change on employment is theoretically indeterminate in the short run and neutral in the long run under canonical frameworks (Aghion, B. F. Jones, and C. I. Jones, 2019; Agrawal, Gans, and Goldfarb, 2018), in part because automating some human tasks often augments the value of others (Agrawal, Gans, and Goldfarb, 2022). Diffusion and adoption introduce further uncertainty, as even the most powerful technologies can take decades to reshape aggregate outcomes (Comin and Hobijn, 2010). On the third question—which policies to optimally pursue—progress is difficult because of unresolved disagreement about the answers to the first two questions, since the optimal policy interventions depend critically on both the pace of technological change and its economic consequences.

1.2 This paper

We elicit expert beliefs on all three of these questions simultaneously, surveying four carefully selected expert groups alongside a general public sample. We draw our expert economist panel from those publishing on the intersection of AI and economics, speakers at major conferences about AI and the economy, and faculty at top-100 economics departments—with a dedicated sub-sample of prominent economists. We recruit AI industry professionals from the organizations behind frontier AI models, and we sample AI policy professionals from U.S.-based think tanks and research institutions. We draw highly accurate forecasters (superforecasters) from a set of individuals with a verified track record of exceptional predictive accuracy.[1] See Section 2.1 for more information about our survey respondents.

First, we collect unconditional (all-things-considered) forecasts of key U.S. economic variables—such as annual GDP growth, total factor productivity (TFP) growth, the labor-force participation rate (LFPR), and wealth inequality—at both near-term (2030) and long-term (2050) horizons. These forecasts reflect each respondent's current beliefs about the likely trajectory of the economy given their overall views about both AI and other trends and shocks. Second, we elicit forecasts of the same variables conditional on three AI-progress scenarios by 2030—slow, moderate, and rapid—and each respondent's subjective probability that the world will end up in each of these scenarios. This conditional structure allows us

[1] The term 'superforecaster' was coined in early research on subjective probability elicitation in a geopolitical context, as described in Mellers et al. (2014).

to separate disagreement about AI capabilities from disagreement about economic impacts, given a particular level of capabilities. Third, we ask respondents to predict the marginal effect of six specific policy proposals on GDP and LFPR under both unconditional and rapid-progress conditions, and to indicate their normative support for each policy. This multi-layered design allows us to trace out how beliefs about AI progress propagate through to economic forecasts and, ultimately, to policy preferences.

The three scenarios for AI progress describe capabilities progress achieved by 2030, across the domains of research, problem-solving, creativity, agency, and robotics. While the full scenarios are described in Appendix H.2.1, to summarize:

1. In the "slow" scenario, AI is a capable assisting technology for humans: writing literature reviews at the level of a capable PhD student, handling half of all freelance software-engineering jobs that would take an experienced human a day to complete, topping up your online grocery cart, and physically being able to unload dishwashers in some homes.

2. In the "moderate" scenario, AI is an effective collaborator across domains: autonomous lab systems can make rapid advances in solar-cell technology; almost all freelance software-engineering jobs requiring 5 days of effort from an experienced human are automatable; robots can do dishes as quickly as humans; robo-taxis can drive anywhere that humans can.

3. In the "rapid" scenario, AI systems surpass humans in most cognitive and physical tasks. Autonomous researchers can collapse years-long research timelines into months or even days. AI systems can surpass all freelance software engineers, customer service agents, paralegals, and clerical workers. Models can write 2025-Pulitzer-caliber books—and negotiate the resulting book contract. Robots can assist in an arbitrary home or factory anywhere in the world.

In addition, forecasters were advised that the scenarios above were intended to describe AI capabilities, not adoption, and that they should consider that regulation, social norms, or integration challenges could delay real-world deployment of systems with these capabilities. They were further advised that reasonable people may disagree with our characterization of what constitutes slow, moderate, or rapid AI progress and may expect slow progress in some AI capabilities alongside moderate or rapid progress in others. Nevertheless, they were asked to select the scenario that, on balance, best represented their views. Finally, capabilities were defined as "achieved" only if they could be done by an AI system as inexpensively and as reliably as humans today.

1.3 Key findings

A detailed analysis of the resulting forecasts yields six key findings:

A majority of survey respondents predicted significant AI progress by 2030. All five groups surveyed anticipate substantial AI capability advances—even if real-world adoption lags—with the average economist assigning a 61.4% probability to moderate or rapid progress.

Despite expecting significant AI progress, unconditional economic forecasts are close to historical trends. Although economists' unconditional GDP forecasts exceed almost all government and private-sector projections, most do not forecast major departures from recent macroeconomic baselines, citing historical base rates, adoption lags, demographic headwinds, policy responses, potential infrastructure bottlenecks, and longstanding patterns in how general-purpose technologies affect the economy.

Conditional on the rapid scenario, economists expect significant economic shifts, but not the transformative acceleration some have predicted. If the rapid scenario materializes, economists forecast GDP growth of 3.5%, LFPR falling to 55.0%, and the fraction of wealth held by the wealthiest 10% of households rising to 80.0% by 2050—large shifts, but with historical parallels, such as to GDP growth post-WWII, the LFPR before women entered the workforce en masse, or pre-WWII inequality.

Unconditional consensus masks significant uncertainty about rapid scenario outcomes. Economists' unconditional forecasts are relatively tightly clustered, but under the rapid scenario the range of plausible outcomes expands, suggesting that experts have far less confidence about what would happen if AI proves truly transformative.

Between-group differences are small relative to within-group disagreement, and most disagreement reflects uncertainty about economic effects rather than AI capabilities. In contrast to the view, articulated most clearly by Cunningham (2025), that the primary source of disagreement about AI's economic effects is disagreement about the pace of AI capability progress, a variance decomposition suggests that expert disagreement about long-run macroeconomic outcomes is primarily driven by different beliefs about the economic effects of highly capable AI systems rather than disagreement about the pace of AI development itself.

Economists and the general public disagree on how to respond to AI's economic impacts. Economists strongly favor targeted policy interventions such as AI-focused worker retraining (71.8% support) over broad structural interventions like job guarantees (13.7%) or universal basic income (37.4%), whereas the general public supports both targeted and broad interventions.

1.4 Prior Work

A growing body of economic research examines how advanced AI may reshape productivity and growth, labor markets, and inequality. While there is near-universal agreement that more capable AI tends to raise productivity, the magnitude and timing of this and other effects are contested. The core disagreement reflects a debate about two previously discussed questions: how fast will AI capabilities progress, and how fast will capable AI systems diffuse through the economy? This paper elicits expert beliefs on both dimensions, as well as on policy responses, and our survey design maps directly onto this debate.

Productivity and Growth

When it comes to productivity and growth, the research largely falls into three schools of thought, each defined by how broadly they believe AI can replace human labor across economic tasks. At the most optimistic end, Trammell and Korinek (2023) review theoretical models which suggest that, if AI can automate both production and research and development, self-reinforcing feedback between capital accumulation and idea generation could produce double-exponential or hyperbolic growth, marking a structural break from the near-linear growth of the past two centuries. Erdil and Besiroglu (2024) synthesize the arguments for "explosive growth," which refers to economic growth rates significantly higher than recent historical trends, and assign roughly 50% odds of this occurring by 2100 if AI capable of broadly substituting for human labor is developed, while acknowledging the many potential regulatory, physical, and alignment constraints that create wide uncertainty in this forecast.

A more moderate view anticipates meaningful but smaller bumps in productivity and economic growth from AI. Based on Eloundou et al. (2024) estimates of the tasks GPT-4 could perform with scaffolding, Aghion and Bunel (2024) estimate annual TFP gains of 0.5–1.3 percentage points depending on assumptions about adoption and the share of tasks that are profitably automatable, noting that gains are likely transitory unless AI also automates idea production. Filippucci, Gal, and Schief (2024) embed sector-level AI exposure in a general equilibrium model and find a similar 0.25–0.6 percentage point increase in TFP, while highlighting that Baumol Cost-related effects from sectors with limited AI penetration may constrain aggregate gains.[2] Beraja and Zorzi (2022) add an important caveat to this discussion by explaining that when private incentives diverge from social welfare, which often happens in the rollout of a new technology, automation may be inefficiently allocated, slowing welfare gains even when measured productivity rises.

The most skeptical view is described by Acemoglu (2024), who uses task-based growth accounting calibrated to data to conclude that what he considers to be realistic near-term AI adoption adds only around 0.07 percentage points per year to TFP growth. His key finding is that most currently exposed tasks are either low-value, not yet reliably automatable, or both. Consistent with this view, Comunale and Manera (2024) confirm that firm-level productivity effects are positive, but that macro magnitude remains highly sensitive to adoption speed and institutional context. This "productivity without prosperity" framing has broader implications: income for many may fall, since even if aggregate output rises, labor's share of that output may fall, concentrating gains at the top of the income or wealth distribution.

Labor Markets

The empirical labor market literature has struggled to keep pace with a technology diffusing faster than standard data-collection cycles can capture. Brynjolfsson, Chandar, and Chen (2025) document a 13% relative employment decline for early-career workers (ages 22–25) in the most AI-exposed occupations following the widespread rollout of generative AI. This may be evidence of concentrated displacement of entry-level workers; an early indicator of eventual macroeconomic effects. In this analysis, the mechanism appears to resemble a negative labor demand shock rather than simple labor substitution. Wages in exposed roles rose alongside

[2] For more on Baumol's Cost Disease, see Baumol (2012).

employment declines, consistent with firms using fewer, more experienced workers rather than replacing all workers with AI. In contrast, Gimbel et al. (2025) find the overall occupational mix (by AI exposure) to be broadly stable, and Humlum and Vestergaard (2025) look for and find Brynjolfsson, Chandar, and Chen's employment decline in a Danish sample, but show that the decline is uncorrelated with firm-level generative AI adoption, raising questions about potential confounders.

These conflicting early results are consistent with an economics literature that often struggles to find technological displacement in aggregate data over short time horizons. Frey and Osborne (2017), whose framework pre-dates generative AI, remains the standard baseline for classifying occupations as being exposed to automation from computerization; they summarize the literature finding such effects in data from the prior decades. On the other hand, Korinek and Juelfs (2022) provide a theoretical counterpoint to pessimism about displacement. They argue that a utilitarian social planner would phase out work gradually and only for workers with low productivity and weak non-monetary attachment to employment. The implication is that the appropriate response to automation is a managed transition rather than resistance.

Inequality

A recurring concern in the literature is that AI's productivity gains will be distributed unequally, potentially decoupling aggregate economic growth from broad-based welfare improvement for most people. Acemoglu (2024) argues that rising TFP alongside a falling labor share is the most plausible scenario given task-based substitution patterns. Korinek (2024) extends this argument, modeling a post-AGI economy[3] in which productivity growth could exceed 18% annually while workers' wages collapse unless there is active redistribution. This model motivates a set of interconnected policy responses that the authors propose, ranging from UBI to global AI governance. Korinek and Stiglitz (2021) echoes this inequality concern on a global scale, arguing that AI strengthens superstar-firm dynamics and concentrates rents in the most developed economies, weakening the development pathways that allowed developing countries to grow quite fast in the 20th century. Lastly, Abbott and Bogenschneider (2018) identify a mechanism that could amplify these trends: existing tax systems treat automation-related capital as deductible while taxing labor, creating a potential bias toward over-automation that erodes the labor tax base.

Policy Responses

Several studies emphasize that optimal policy responses to AI (or technological innovation more generally) depend on assumptions about the pace and breadth of AI adoption. Slow, uneven diffusion may imply that targeted worker adjustment programs are optimal; rapid, broad-based automation may require structural reforms to taxation and redistribution at a scale with no peacetime precedent. Comunale and Manera (2024) and the OECD (OECD, 2023) both catalog existing regulatory approaches and stress that optimal interventions vary

[3] AGI stands for Artificial General Intelligence and refers to a world where AI systems can perform tasks and bundles of tasks at a level that exceeds the vast majority of current workers, especially for white-collar workers whose jobs are not particularly physical in nature.

sharply with assumptions about adoption speed and displacement risk.

On the labor-market adjustment side, Hyman, Kovak, and Leive (2024) use a regression discontinuity in the U.S. Trade Adjustment Assistance program to show that this type of program shortens unemployment spells by 1.26 quarters on average, raises cumulative earnings by over $18,000, and is self-financing once one accounts for fiscal externalities from affected workers. This result speaks directly to the debate about modernized unemployment insurance. Korinek and Juelfs (2022) argue that broader institutional reform is ultimately needed, shifting social insurance from work-conditioned benefits to unconditional income support as automation capital replaces labor income.

On the tax and redistribution side, Abbott and Bogenschneider (2018) propose neutralizing the current potential bias towards capital (and against labor) by taxing capital income at the same rate as labor income, instead of at an implicitly lower rate. Bastani and Waldenström (2024) provide a more systematic optimal-tax approach, concluding that capital taxation becomes increasingly important as the labor tax base erodes, though they note practical constraints on feasibility in open economies. At the far end of the spectrum, Korinek (2024) and Anthropic (2025) advance comprehensive policy frameworks organized by scenario severity, from modest workforce training grants to sovereign wealth funds and new revenue structures, an approach that directly motivates this survey's conditional policy questions.

Prior Surveys

Several prior surveys have elicited expert beliefs about AI capabilities and economic impacts. Grace et al. (2024) survey 2,778 AI researchers on their predictions about the pace of AI progress, finding a median estimate that AI will outperform humans at all tasks by 2047, with substantial disagreement across respondents. The Clark Center's US Economic Experts Panel (Clark Center Forum, 2025) has polled leading economists on whether AI adoption will substantially increase growth rates or unemployment over the next decade, with most economists expressing uncertainty about the magnitude though agreeing on the direction of productivity effects. Murphy et al. (2025) establish the Longitudinal Expert AI Panel (LEAP), a three-year panel survey tracking the views of computer scientists, economists, AI industry professionals, and policy researchers through monthly surveys, providing a dynamic alternative to one-time cross-sectional surveys. (We compare our results directly to LEAP's in Appendix C.) Our survey differs from these prior studies in three key ways: (1) we elicit forecasts of specific quantitative outcomes rather than qualitative agreement or disagreement; (2) we condition on explicit AI-progress scenarios, thereby allowing us to separate beliefs about capabilities from beliefs about economic effects; (3) and finally, we simultaneously collect forecasts and normative policy preferences, allowing us to link empirical expectations to policy support.

The Source of Disagreement and Our Contribution

A key open question that our survey is designed to address is whether disagreement about future economic outcomes is primarily about AI capabilities progress or about economic mechanisms conditional on that progress. Cunningham (2025) argues it is predominantly the former: forecasters largely agree on the economic logic but diverge on whether transformative AI capabilities will actually arrive. This view is consistent with the observation that Acemoglu's skepticism and Trammell and Korinek's optimism are in part reconcilable as they agree on the theoretical mechanisms, but apply to very different scenarios for AI capabilities and adoption. Here, we examine forecasts based on scenarios that span a wide range of AI development. Contra Cunningham, we find that disagreement centered on whether new AI capabilities will have an economic impact, rather than disagreement over whether such capabilities will arise.

2. Methods

This section describes the strategy for recruiting survey participants, the survey instrument, and the data processing procedures used in this study. The survey was launched in October 2025 and concluded in February 2026.

2.1 Participant Recruitment

We surveyed a diverse panel of experts and non-experts. Our sampling strategy targeted five participant groups: (i) economists, (ii) AI industry professionals, (iii) AI policy professionals, (iv) superforecasters, and (v) members of the general public. These groups were selected to capture complementary forms of expertise relevant to forecasting technological progress, economic outcomes of that progress, and policy responses. For ease of presentation, in most analyses, we group AI industry and policy professionals under 'AI experts'.

In total, we contacted 4,866 experts, 54 superforecasters, and 1,395 members of the general public. Of the invited, 90 economists, 30 AI industry professionals, 27 AI policy professionals, 38 superforecasters and 401 members of the general public completed the survey. After filtering our expert respondents to ensure they meet our population criteria, our final sample contains 69 economists, 27 AI industry professionals, and 25 AI policy professionals. For details on participant recruitment, see Appendix A.

Economists, AI industry professionals and AI policy professionals were compensated at \$100/hour for a minimum of five and a maximum of ten (self-reported) hours. Superforecasters were paid \$60/hour, with the same time limits on compensation. Participants from the general public were initially paid \$30 for completing the survey, but this was increased to \$40 for later batches of participants. In addition to these payments, we incentivized participants to give insightful rationales by promising to award ten \$500 prizes among the expert participants, two \$500 prizes among superforecasters, and twenty \$100 prizes among the general public to participants with the highest-quality rationales.

Economists

Our primary population of interest was economists, who are best positioned to understand and provide quantitative forecasts of macroeconomic outcomes. We further subdivided this target population into three sub-populations: (i) economists working on AI-related topics, (ii) economists working on economic growth and technological changes more broadly, and (iii) well-known economists, such as Nobel prize winners. In the final sample, these groups

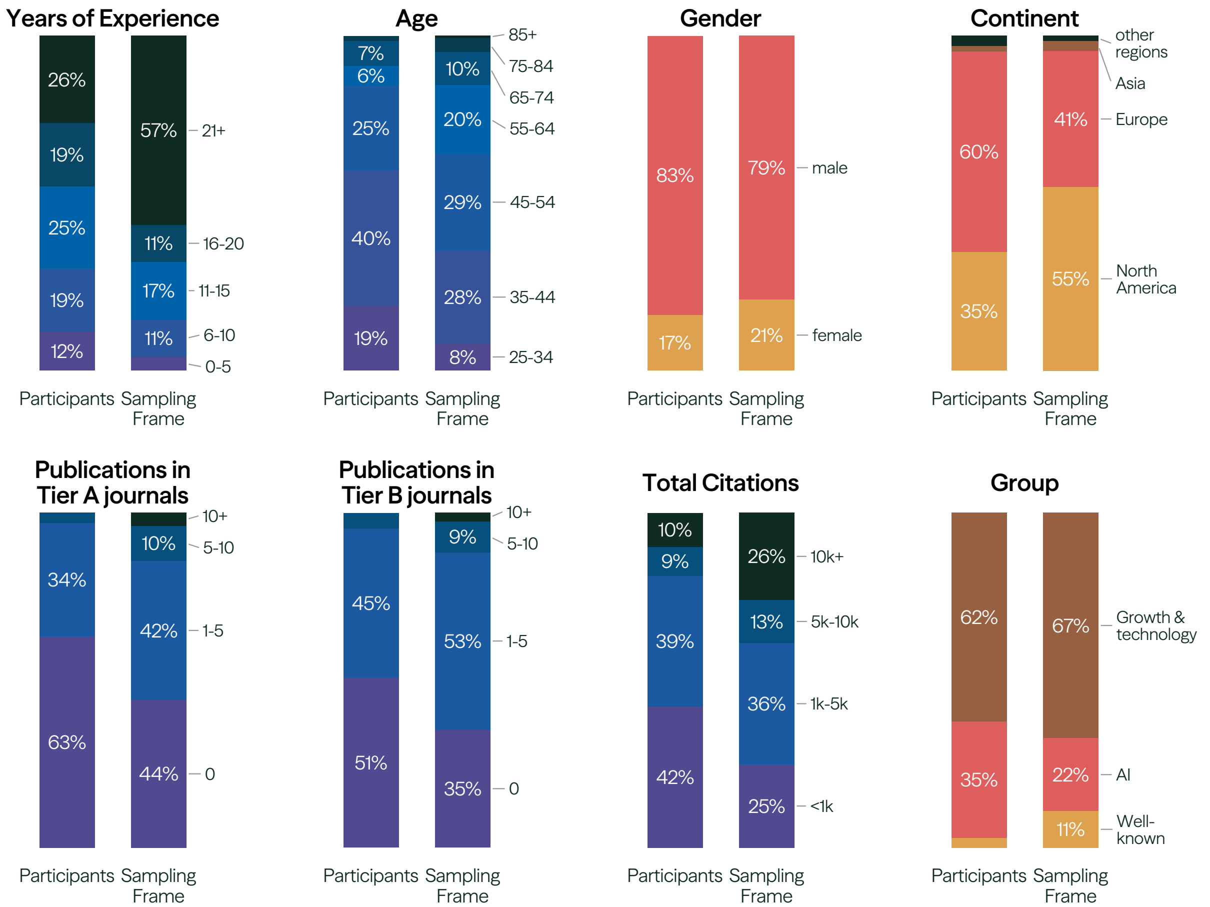


Figure 1: *Summary statistics of the economist sample.* The bars on the left show the distribution for participants, and the bars on the right show the distribution in our sampling frame (both participants and non-participants). The figure is based on publicly available information collected by human assistants and an AI-based system. Tier A and B publications are defined in Table 58.

have 24, 43, and 2 respondents, respectively. Figure 1 shows summary statistics about our economist respondents. Our respondents were younger, less experienced, more male, and more European than the sampling frame. They also had fewer high-quality publications and were less likely to have high levels of citations. That being said, we still have significant coverage across the less represented groups in our participant set. For example, 45% of our respondents had at least 16 years of experience, 38% were age 45 and older, 17% were female, 35% were from North America, 37% had at least one Tier A publication (a so-called 'top-5' publication in economics), and 58% had at least 1,000 citations. In our main results, we reweight the participants on experience and geography to match the sampling frame. This has minimal effects on our results (see Appendix G).

Economists working on AI were identified using three primary sampling pools: (i) a literature-based pool of authors publishing on the economics of AI, identified through Research Papers in Economics (RePEc) using relevant Journal of Economic Literature (JEL) codes and AI-related keywords, (ii) an event-based pool of speakers and participants at major academic and policy conferences focused on AI and economic outcomes, and (iii) an institution-based pool targeting top-100 economics institutions according to RePEc. In the literature pool, invitations were extended in descending order of citation counts adjusted by paper age. In other pools, we sampled randomly.

Economists working on growth and technological change were similarly identified through (i) publications indexed in RePEc using JEL codes related to technological innovation and economic growth, and (ii) an institution-based pool. In the literature pool, authors were ranked by age-adjusted citation counts, and invitations were sent in descending order.

Well-known economists were identified using a combination of Nobel Prize recipients, RePEc author rankings, and participation in the Clark Center U.S. Economic Experts Panel. Invitations were extended to all individuals meeting these criteria.

AI Industry Professionals

AI industry professionals were sampled from companies developing or applying frontier AI models. We constructed sampling pools using three sources: (i) institutions associated with frontier models ranked by training compute, (ii) institutions associated with organizations producing top-performing models on public evaluation leaderboards, and (iii) highly funded AI startups identified via fundraising databases. Within each institution, we randomly sampled research and engineering staff. Sampling was stratified to ensure maximum coverage across chosen organizations.

AI Policy Professionals

AI policy experts were sampled from U.S.-based think tanks, research institutions, and government-affiliated organizations engaged in AI governance and technology policy. Participants were identified via institutional staff directories and professional networking platforms, focusing on researchers and policy practitioners working directly on AI governance.

Superforecasters

Superforecasters were recruited through our existing connections. All individuals in this pool have a demonstrated track record of forecasting accuracy.

Forecasters are denoted "superforecasters" if they (1) were in the top 2% of the accuracy distribution in a given year of the Intelligence Advanced Research Projects Activity (IARPA) Aggregative Contingent Estimation (ACE) tournament (IARPA, 2011; Mellers et al., 2014) or (2) they were a highly accurate performer on Good Judgment Open, an online continuous geopolitical forecasting tournament. Good Judgment Inc., which runs Good Judgment Open, then adds these top forecasters to the "superforecaster" pool. Most superforecasters come from the first selection criterion. Mellers et al. (2015) find persistent performance of these superforecasters across several years of geopolitical forecasting.

General Public

We included a general public sample to compare expert beliefs against the broader public's expectations. Members of the general public were recruited through CloudResearch Connect (Hartman et al., 2023).

2.2 Survey Instrument

The survey instrument elicited probabilistic forecasts of AI progress, economic growth, labor-market outcomes, inequality, and policy effects over medium- and long-term horizons (by 2030 and 2050). Respondents provided both unconditional forecasts and conditional forecasts under three AI development scenarios—slow, moderate, and rapid progress, defined using concrete capability benchmarks.

For forecasts of economic outcomes, participants reported 50th-percentile forecasts and, for selected questions, 10th- and 90th-percentile forecasts. The survey also collected qualitative rationales to capture underlying reasoning and mechanisms. Participants received background information, historical data, and detailed resolution criteria for all forecasting questions. The survey instrument was administered online and required 8 hours for completion, on average. The survey questions are shown in Appendix H and the forecasting interface in Figure 80.

2.3 Data Processing

Coherence Checks

To ensure forecasts were both logically coherent and representative of participants' intended forecasts, we applied a series of consistency checks to each participant's forecasts. These include verifying that scenario probabilities summed to one and that conditional forecasts were not inconsistent with the unconditional forecasts for a given economic outcome. We reached out to participants to give them the opportunity to update their forecasts if their forecasts were flagged by these checks. In all analyses, we present results using these updated forecasts. If participants did not update their forecasts, we removed their forecasts for some checks, while we left them in place for others. For a full list of these checks, see Appendix F. The appendix also describes the impact of the coherence check process on aggregate forecasts: differences between pre- and post-intervention results are small.

Reweighting

We assign each participant in the economist group a weight to correct for non-response bias in participant recruitment. This ensures that the sample we derive our results from is representative of those we invited. We reweighted on years of relevant expertise and continent (North America, Europe, other), since our sample was biased towards European and more junior participants compared to the sampling frame (see Figure 1). These weights are used in all results presented below. For a full list of variables we considered for reweighting, see Appendix G. The appendix also compares key results with and without reweighting. The procedure does not systematically make results more conservative or extreme: reweighted GDP growth aggregate forecasts are more conservative (small-to-moderate differences) and

LFPR forecasts more extreme (moderate-to-large differences). Even the larger differences, observed for longer-horizon LFPR forecasts, are well within aggregate uncertainty bounds.

For the remaining groups, sample sizes are smaller and reweighting has not been applied; results for these groups should accordingly be interpreted as characterizing the recruited samples rather than their broader populations.

Aggregation

We use two approaches for aggregating forecasts. For our main results, we calculate a weighted (using the participant weights) median for each percentile separately. We see these as our main results, since this aggregates the noisy estimates of the underlying 50th, 10th, and 90th percentiles to arrive at a more accurate estimate.

To understand forecaster disagreement, we additionally performed an alternative aggregation procedure for questions where the additional 10th and 90th percentile forecasts were available. We first fit a distribution to an individual participant's quantile forecasts (separately for unconditional forecasts and forecasts conditional on the rapid scenario) and then calculated a weighted average over the participants. This has the benefit of showing disagreement among participants. Section 4.3 contains more details about this procedure. For a comparison of these two aggregation approaches and evidence that the former may lead to more accurate forecasts, see Lichtendahl, Grushka-Cockayne, and Winkler (2013).

Rationale Analysis

We used an LLM to extract the key drivers mentioned in rationales accompanying forecasts for the four main results (GDP, TFP, LFPR and wealth inequality). We supplemented these LLM-curated drivers with a manual analysis of the rationales, checking for inconsistencies and adjusting the identified drivers to fully capture those offered in the rationales. We then used a second LLM agent to tag each occurrence of the identified drivers, and then analyzed the frequency with which different drivers were mentioned by various groupings of participants.

The rationales accompanying the policy results received similar treatment. An initial partial human review identified the likely main drivers and checked for systemic inconsistencies or question misinterpretations; this was supplemented by LLM analyses to confirm and expand upon these drivers, roughly quantify the frequency of driver mentions across participant groups, and extract rationales that best exemplified each driver.

See Appendix D.2 and Appendix I for more details on rationale analysis.

3. Results

3.1 AI Progress

In the survey, we elicited participants' beliefs about the pace and scope of AI capability progress by the end of 2030 using three descriptive scenarios: slow, moderate, and rapid progress. These scenarios, described in full in Appendix H.2.1, are intended as broad benchmarks rather than precise descriptions of how the world will unfold. Participants were asked to judge which scenario a panel of experts would judge as the best overall match to the true state of AI capabilities, recognizing that progress may be uneven across domains. Across all groups, we find that a majority of respondents place most of their probability weight on the moderate or rapid progress scenarios, expecting AI capabilities to advance significantly by 2030 even if real-world adoption lags.

Figure 2 summarizes the scenario descriptions and participants' probability forecasts. On average, economists assigned the highest probability to the moderate scenario (47.4%), with the remaining probability split between the slow (38.6%) and rapid (14.0%) scenarios. The rapid scenario was judged to be the least likely according to all groups, including AI policy and industry professionals (here grouped together under 'AI experts'), superforecasters, and the general public. Superforecasters placed more weight on slow progress when compared to economists, assigning 45.0% to the slow scenario, and were also the most skeptical about the rapid scenario, assigning it 12.6% on average. In contrast, the general public's probabilities were more evenly distributed across scenarios (40.8% slow, 41.0% moderate, 18.1% rapid).

Figure 3 summarizes the distribution of scenario probability forecasts across expertise groups. The slow scenario category demonstrates the highest variance among respondents, most pronounced among AI experts, whose interquartile range (IQR) stretches from 16.5–60.0%. Variance was slightly lower for the moderate scenario probabilities, with economists having the widest interquartile range, stretching from 31.5–64.5%. Variance across respondent groups was lowest for the rapid scenario, with interquartile ranges across groups spanning from 10 percentage points (superforecasters) to 20 percentage points (the general public).

3.2 Growth

Gross Domestic Product (GDP)

Figure 4 compares historical measures of GDP growth (shown in black) to respondents' forecasts of annualized GDP growth over the five years leading to 2030 and 2050. Participants provided unconditional forecasts, reflecting their overall views, as well as forecasts conditional on the three AI progress scenarios described throughout the survey. Across all groups, unconditional forecasts for 2030 were clustered tightly around the current rates, spanning from 2.4% to 2.5%. By 2050, unconditional medians remain in roughly the same range, ranging from the economists' prediction of 2.5% to AI experts' prediction of 3.0%. However, disagreement between groups, as well as uncertainty within groups, slightly increases (as reflected in the shaded regions). These forecasts suggest that most respondents do not expect strong trends of acceleration in GDP growth absent major shifts.

In contrast, the rapid scenario is associated with significantly higher expected GDP growth for both time horizons. For 2025–2029, the median economist predicted annual GDP growth to be around 3.3% (with median 10th and 90th percentile forecasts of 1.2% and 5.5%), and superforecasters showed a similar median (3.7%, 2.0–6.0%). AI experts' rapid scenario median is slightly higher in this period, at 3.7%. The divergence between groups is wider by the 2045–2049 period, with annual GDP growth reaching 3.5% for economists (1.0–7.0%), 4.0% for superforecasters (1.0–7.0%), 5.3% for AI experts (2.3–9.3%), and 4.5% for the general public (2.5–7.1%). The moderate scenario falls between unconditional and rapid.

Figure 5 summarizes uncertainty using pooled distributions, shown for the unconditional

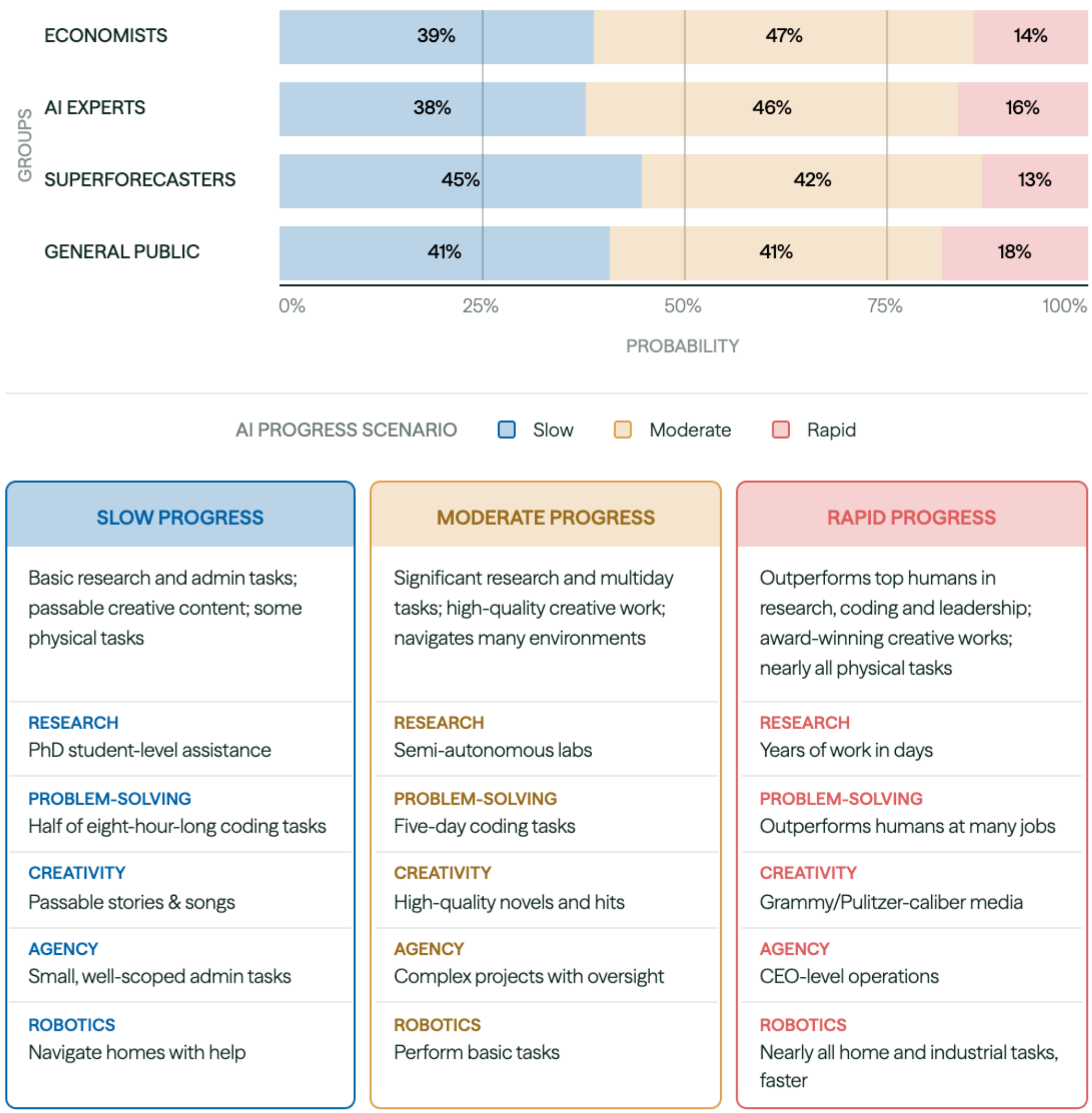


Figure 2: *Average probability of AI progress scenarios by 2030.* The average probability assigned by respondents in each group to the likelihood of a given AI progress scenario most closely describing the real world in 2030. The full scenario definitions can be found in Appendix H.2.1.

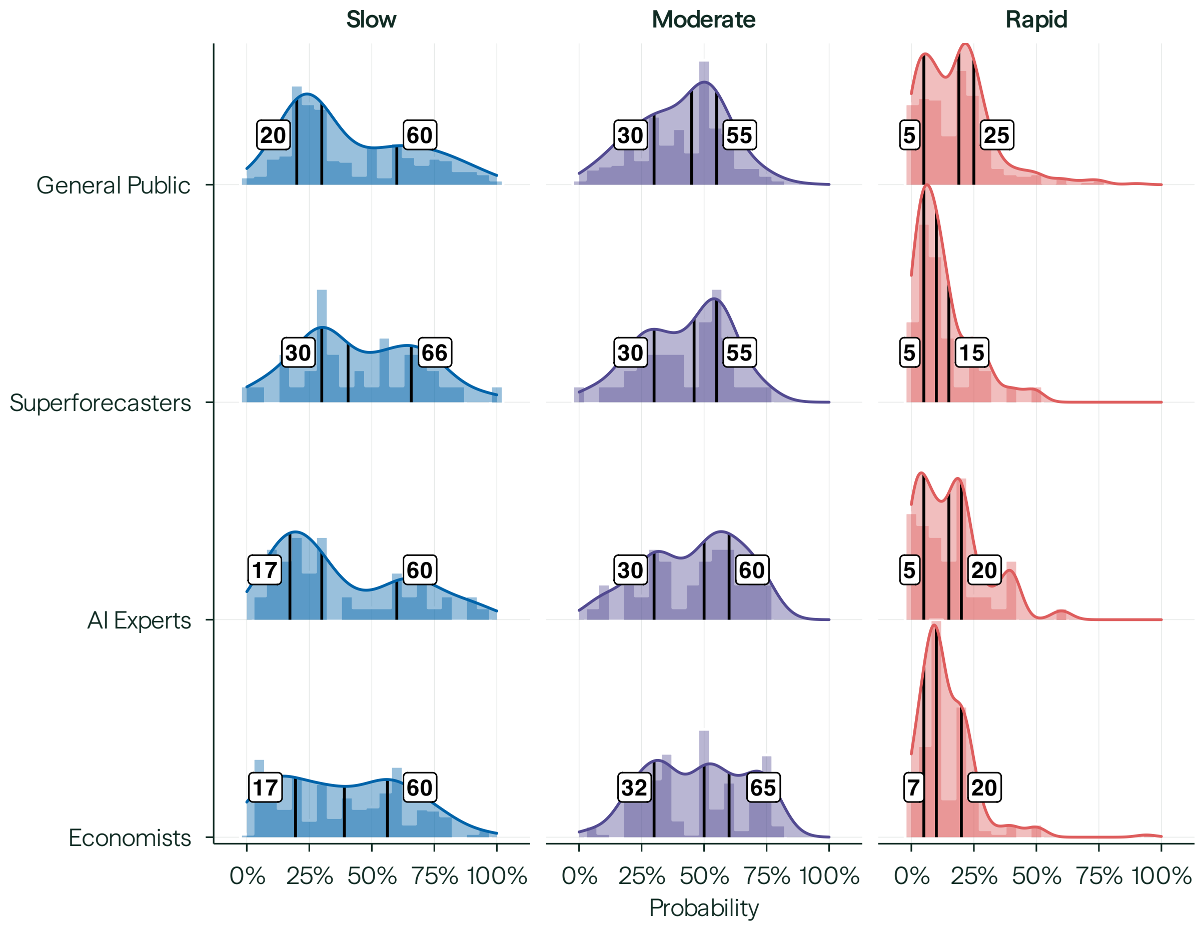


Figure 3: *Distribution of AI progress scenario forecasts.* Vertical lines show the 25th, 50th, and 75th percentiles of the scenario forecasts. The 25th and 75th percentiles are labeled. The distribution is shown in two ways: as a histogram and as a density estimate.

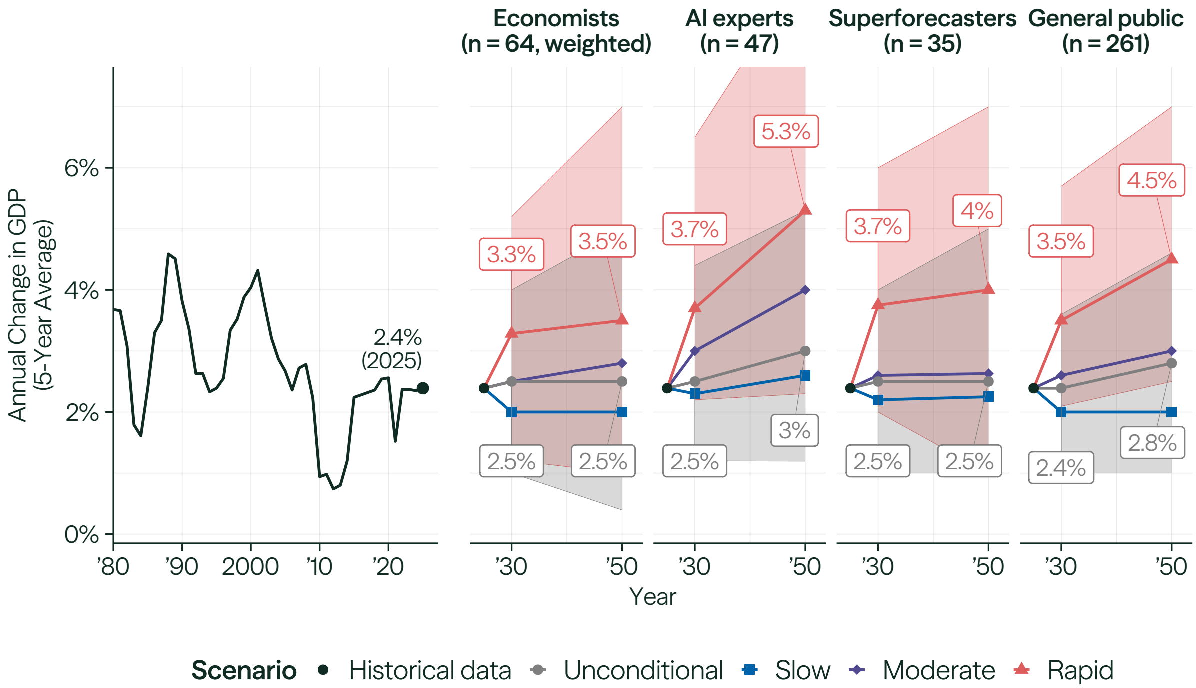


Figure 4: *Forecasts for five-year annualized change in the Gross Domestic Product (GDP).* Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10^{th} to the median 90^{th} percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3). See Appendix H.4.1 for question details and the source of the historical data.

and rapid scenarios, for which participants provided 10th and 90th percentile predictions in addition to their best-guess 50th percentile predictions. Variance increases at the longer time horizon (see Table 10), consistent with greater uncertainty about growth outcomes, and with this broadening happening especially under the rapid scenario. For example, economists' pooled distribution for GDP growth in 2030 under the rapid scenario spans 1.21%–6.420% (10^{th}–90^{th} percentile), compared to 0.73%–4.56% for the unconditional scenario. Similar patterns hold for other groups. Notably, the 90th percentiles of the 2030 and 2050 pooled distributions for AI experts reach the 10% winsorization cap (a bound applied to the distribution tails to prevent outlier forecasts from disproportionately skewing the pooled variance) and some experts forecast growth well above our cap. While superforecasters' medians once more fall close to economists', they assign higher weight to >10% growth in the rapid scenario, even in 2030.

We compare the median of economists' 50^{th} percentile GDP forecasts to other forecasts in Figure 6.[4] Our economist sample's estimate for 2025–2029 of 2.5% is higher than eight of

[4]These forecasts are: FOMC (Federal Reserve (FOMC), 2025), CBO (Congressional Budget Office, 2026), OMB (Office of Management & Budget (OMB), 2025), IMF (International Monetary Fund, 2025), SPF (Survey of Professional Forecasters, 2025; Survey of Professional Forecasters, 2026), OECD (OECD, 2025), Goldman Sachs (Goldman Sachs, 2025), The Conference Board (The Conference Board, 2026), and Deloitte

Figure 5: *Distribution of forecasts for five-year annualized change in Gross Domestic Product (GDP).* Distribution is pooled across participants to summarize the full distribution of participant beliefs. Tail mass outside of figure bounds shown as ball-and-stick at 0% and 10%, with numbers in boxes indicating the proportion of the pooled distribution that lies below 0% or above 10%. Interior points show $10^{\text{th}}/50^{\text{th}}/90^{\text{th}}$ percentiles of the distribution. See Appendix H.4.1 for question details.

the nine other forecasts we consider, which range from 1.9% to 2.1%. The only forecast that is higher is OMB's of 2.8%. When we consider 2045–2049, this paper's estimate of 2.5% is higher than both other estimates (1.3% and 1.6%).

Compounded over decades, small differences in growth rates can produce large differences in prosperity; see Figure 7. Consider the 3.5% growth rate in the rapid forecast possesses a doubling time of 20 years versus 28 years for the 2.5% growth in the unconditional forecast. Extrapolating to 2050, the rapid scenario produces a real GDP of $54.7T, 25% larger than $43.7T in the unconditional scenario.[5] This is roughly equivalent to the GDP difference between 2016 and today.

Towards the end of the forecast period, growth approaches the post-World War 2 economic boom. From 1951-1973, growth averaged 4.06%, close to the rapid scenario; because population growth today is lower than during the postwar era, this suggests the rapid scenario could meaningfully exceed the per capita growth experienced from 1951-1973.

Total Factor Productivity

As a separate measure of economic growth, participants were asked to provide forecasts for the annualized change in total factor productivity (TFP) over 5 years. Figure 8 compares participant forecasts to historical measures of this outcome. Median forecasts are homogenous across groups, clustering tightly for the unconditional scenario around 1.0% (superforecasters and the general public)–1.2% (economists and AI experts) for 2030 and 1.0%–1.7% for 2050, with economists at 1.5%.[6] Under the rapid scenario, forecasts roughly double relative to the unconditional baseline, growing to 1.9%–2.0% for 2030 and 2.2%–2.5% for 2050.

Key finding: Despite expecting significant AI progress, most unconditional economic forecasts are close to historical trends

The results above reveal an apparent tension: economists assign a 61.4% probability to moderate or rapid AI progress by 2030 (see Figure 2), yet their unconditional GDP and TFP forecasts do not substantially depart from recent baselines. The median unconditional GDP forecast of 2.5% for both 2030 and 2050 is only marginally above the 2021–2025 baseline of 2.39%, and TFP forecasts of 1.2% for 2030 and 1.5% for 2050 similarly represent noticeable, but incremental, gains relative to the 2025 baseline of 0.97%. While it is true that these forecasts are not quite as conservative as they may first appear when considered in the context of the medium- and long-run projections we report in Figure 6, the implied AI-driven productivity acceleration is modest by historical standards: the IT boom of the late 1990s arguably led to an additional 0.65 p.p. jump in annual TFP in the late 1990s (Jorgenson and Stiroh, 2017), and the economists' forecasts of TFP growth in our study imply an acceleration in growth from AI that is roughly half that size by 2030 and on par with it by 2050.

(Deloitte, 2025). We focus on the baseline estimates; some forecasts consider other cases, such as Deloitte's "Downside" and "Upside" scenarios and OECD's "Energy Transition" scenarios.

[5] These estimates assume growth rates in 2030-2045 are linearly interpolated between the 2025–2029 and 2045–2049 forecasts, as in Figure 7.

[6] For comparison, the average CBO forecast of TFP between 2025 and 2029 is 0.82%, and between 2044 and 2049 it is 1.1% (Congressional Budget Office, 2026).

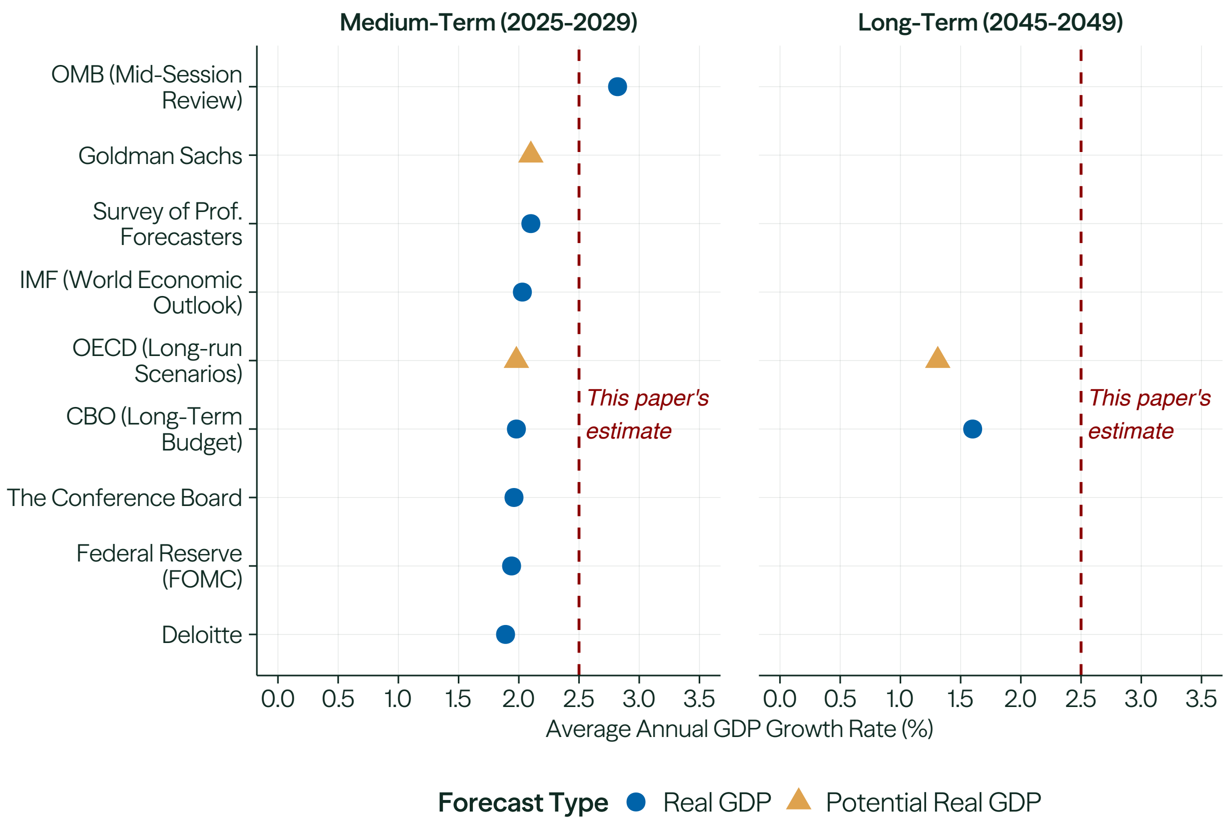


Figure 6: *Comparison of economist GDP growth forecasts to other forecasts.* In this figure, we compare the weighted median forecast for economists, which is indicated by the red dashed line, to nine other forecasts for 2025–2029 (left panel) and to two other forecasts for 2046–2050 (right panel). We use the baseline (or analogous) estimates. Where yearly estimates are given, we average these estimates. Where a single estimate is given for a yearly range, we use this estimate. Exceptions are: 1) for 2025–2029 Federal Reserve, we use the "Longer run" value for 2029; 2) for 2025–2029 Conference Board, we use the 2028–2032 value for 2028 and 2029; 3) for 2025–2029 Deloitte, we linearly interpolate values for 2027–2029 based on the 2026 and 2030 values; 4) for 2025–2029 (2045-2049) OECD, we use the value for the range of 2025–2030 (2045–2050). The type of forecast (real GDP or potential real GDP) is indicated.

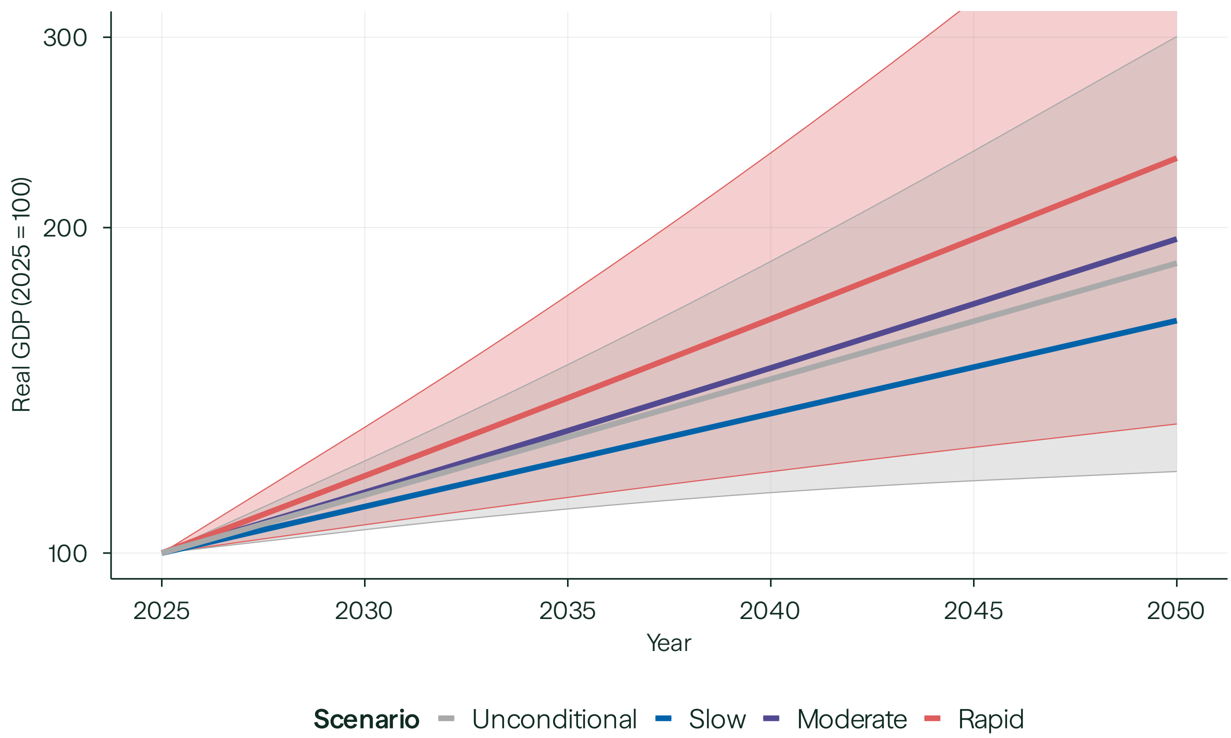


Figure 7: *Projected GDP trajectory under different scenarios.* Based on economists' GDP growth forecasts; growth rates between 2030-2045 are linearly interpolated from 2025–2029 and 2045–2049 forecasts. Shaded areas are determined using 10^{th} and 90^{th} percentile forecasts for the unconditional and rapid-scenario forecasts. Note the logarithmic scale on the y-axis.

Economists' written rationales, however, lend insight into this tension. The most frequently cited reason why transformative technology would translate into only modest economic growth was uneven and time-lagged diffusion, with economists drawing on analogies to electrification, automobiles, and personal computers to argue that multi-decade lags routinely separate a general-purpose technology's arrival from its measurable productivity impact. Geopolitical, structural, and demographic headwinds—including trade wars, climate change, an aging population, and declining immigration—that could offset AI-driven gains were also cited, as were constraints on energy, chips, and data center construction. Collectively, these factors were deemed likely to cap the pace at which AI capabilities could be deployed regardless of how quickly they advance. Under the rapid scenario, the possibility that large-scale workforce exit, societal unrest, or existential risk could become drags on GDP was also considered. A deeper analysis of these rationales can be found in Appendix D.2.1 (GDP growth) and Appendix D.2.3 (TFP growth).

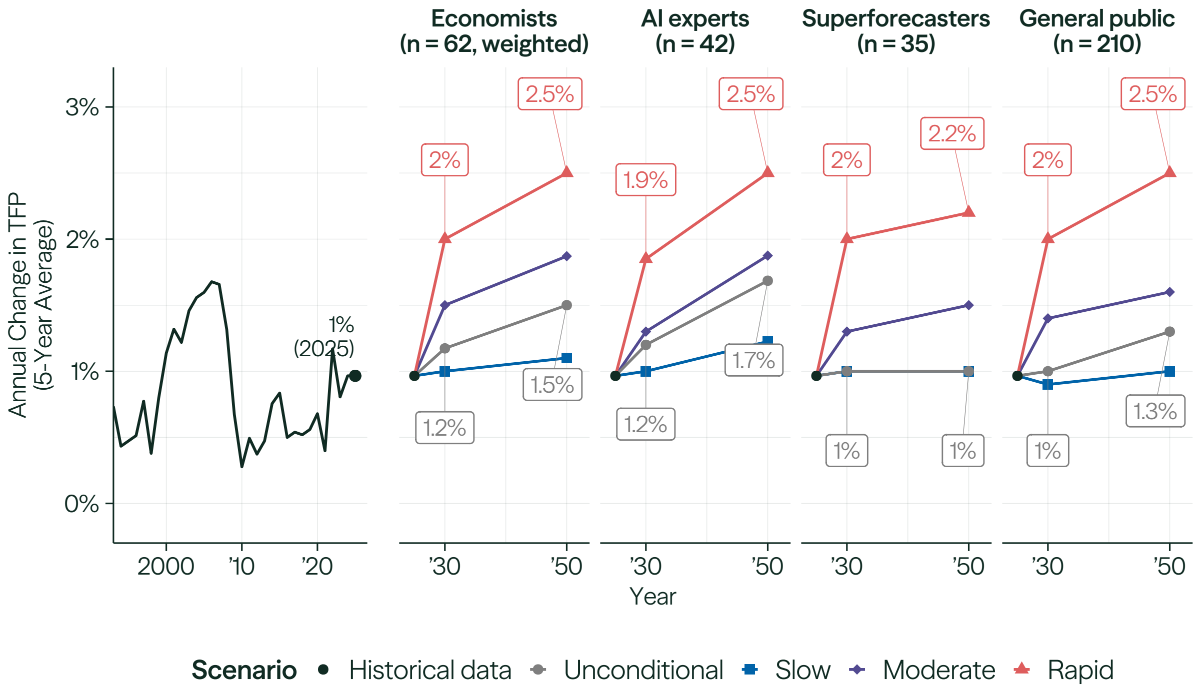


Figure 8: *Forecasts for five-year annualized change in total factor productivity (TFP).* Lines show medians of 50$^{\text{th}}$ percentile forecasts across participants. Because we elicited only 50$^{\text{th}}$ percentile predictions for TFP growth, this figure does not show uncertainty. The results for economists are reweighted to adjust for non-response bias (see Section 2.3). See Appendix H.4.3 for question details and the source of the historical data.

3.3 Labor Markets

Overall Impact

Our main metric for understanding labor market impacts is the Labor Force Participation Rate (LFPR). It measures the fraction of the adult population participating in the labor force, either through employment or active jobseeking. The LFPR has historically been relatively stable, mostly shaped by demographic trends, and is much less cyclical than the unemployment rate. It captures discouragement and long-term exits from the labor force.

Forecasts for the LFPR are shown in Figure 9. Economists expect the decreasing trend of the last two decades to continue. By the beginning of 2030, the median economist forecasts LFPR of 61.0%, a decrease from the January 2025 rate of 62.6%.[7] This forecast has already been affected by economists' expectations about AI capabilities: conditional on the slow scenario, the median forecast is 61.5%, 0.5 p.p. higher. However, when asked to assume the rapid scenario, their forecast drops to 59.3%. If this were to occur, it would be the

[7]For comparison, the average forecast LFPR between 2025 and 2029 for CBO (using the Census Through 2020 Plus CBO Projection) is 62.4% and for Deloitte (after converting unemployment rate and employment-to-population rates to LFPR) is 62.0% (Congressional Budget Office, 2026; Deloitte, 2025).

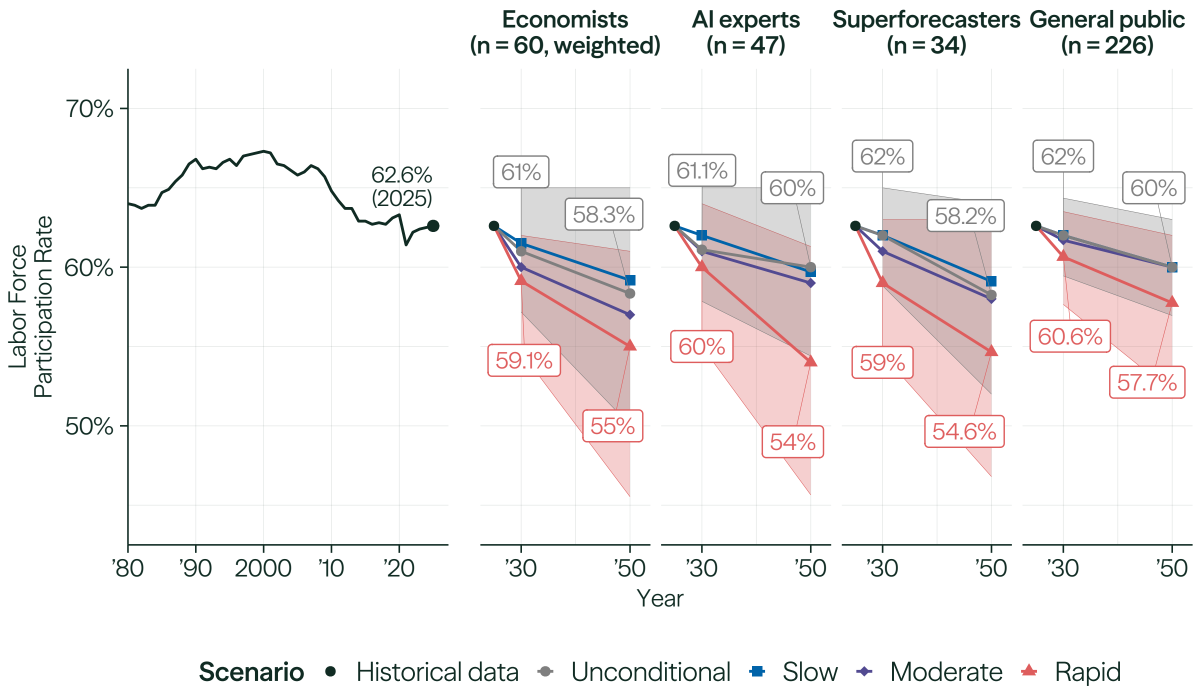


Figure 9: *Forecasts for the labor force participation rate (LFPR).* Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3). See Appendix H.4.4 for question details and the source of the historical data.

first time since the 1970s that a monthly LFPR reading fell below 60% in the U.S., and not since the 1960s has the annual rate fallen below 60%. The potential of AI to influence the LFPR—a difference between the slow and rapid scenarios of 2.2 p.p.—rivals the dip seen during the Covid-19 pandemic (from 63.3% in February 2020 to 60.1% in April 2020), but would reflect a more permanent impact on the labor force. By the beginning of 2050, economists expect a LFPR of 58.3% in the unconditional scenario[8] and 55.0% when assuming the rapid scenario, with roughly half of that decline—equivalent to around 10 million lost jobs—likely attributable to AI rather than demographics and other non-AI trends.[9]

Directionally, all groups agree: faster progress implies lower LFPR values. The general public is slightly more optimistic than economists, with unconditional median forecasts of 62.0% and 60.0% for 2030 and 2050, respectively. Superforecasters are slightly more pessimistic in the long term: unconditionally, they give a median forecast of 58.2% for 2050 and 54.6% assuming the rapid scenario.

In the written rationales economists offered to explain their LFPR forecasts, the most frequently mentioned themes were AI-driven job substitution and loss, reallocation and reskilling, demographic changes, and historical LFPR baselines. A deeper analysis of the rationales can be found in Appendix D.2.4.

Key finding: Unconditional consensus masks significant uncertainty about rapid scenario outcomes

The median LFPR forecasts reported above may give a misleading impression of expert agreement. Across groups, unconditional forecasts cluster in a narrow band—economists at 61.0% for 2030 and 58.3% for 2050, with other groups nearby—and the decline from the current 62.6% baseline looks orderly. But when we examine the distributions underlying these forecasts, particularly under the rapid scenario, the range of plausible outcomes expands.

Figure 10 shows this uncertainty using pooled distributions for the unconditional and rapid scenarios, for which participants provided 10th and 90th percentile predictions in addition to their best-guess 50th percentile predictions. The pooled distribution represents

[8] For comparison, the average forecast LFPR between 2046 and 2050 for CBO is 62.1% (Congressional Budget Office, 2026).

[9] Both estimates are derived by comparing slow and rapid scenario LFPR forecasts. Under the rapid scenario, economists forecast a 7 p.p. decrease in the LFPR from the February 2026 reading of 62% to the 2050 median prediction of 55.0%. Under the slow scenario, where AI-driven displacement considerations are likely to be minimal, the decrease is forecasted to be 2.8 p.p., from 62% to 59.2%. This implies that $(7 - 2.8)/7 \approx 60\%$ of the projected rapid-scenario decline is attributable to AI rather than demographics or other non-AI trends. The AI-attributable share of the decline is thus roughly 4.2 p.p. (the difference between the rapid-scenario forecast of 55.0% and the slow-scenario forecast of 59.2%). Applying this to the current U.S. civilian non-institutional population aged 16 and over of approximately 270 million yields roughly 11 million fewer labor force participants. We round to 10 million to reflect the imprecision inherent in this calculation, including uncertainty about the size of the 2050 population and the simplifying assumption that the slow scenario captures all non-AI sources of LFPR decline. We also note that worlds with rapid AI progress likely differ from worlds with slow progress in ways that extend beyond AI capabilities themselves, so this gap should be understood as the estimated effect of moving between scenarios that are focused on AI rather than a cleanly identified causal effect of AI capabilities alone. That said, the U.S. civilian population is projected to grow through 2050, which would increase the number of displaced workers, making this estimate conservative.

Figure 10: *Distribution of forecasts for labor force participation rate (LFPR).* Distribution is pooled across participants to summarize the full distribution of participant beliefs. Tail mass outside of figure bounds shown as ball-and-stick at 45% and 70%, with numbers in boxes indicating the proportion of the pooled distribution that lies below 45% or above 70%. Interior points show 10th/50th/90th percentiles of the distribution. See Appendix H.4.4 for question details.

both within-forecaster uncertainty and between-forecaster disagreement. The variance of the distribution (shown in detail in Table 10) increased at the longer time horizon and in the rapid scenario, consistent with the pattern observed for GDP growth. While economists' pooled distribution for LFPR in 2030 spans 56.9–65.16% (10^{th}–90^{th} percentile) in the unconditional scenario, it widens to 53.09–64.4% in the rapid scenario. Variance increases even more in the 2050 rapid scenario, spanning 44.77–64.69%, with a significant amount of probability mass (14.3%) below the 45% winsorization floor (note that the 10th percentile falls below the winsorization floor), indicating that, in aggregate, economists predict a non-trivial chance of extreme low-LFPR outcomes. An LFPR at or near the median economist's 10th percentile forecast for 2050 in the rapid scenario would indicate tens of millions had left the workforce and reflect an unprecedented shift in the structure of the economy.

This heightened uncertainty in the rapid scenario is also visible in GDP forecasts, where the 90th percentile of the pooled economist distribution under the rapid 2050 scenario reaches 8.43%, suggesting that experts have narrow priors for a world in which AI augments the economy incrementally, but far less confidence about what will happen if the technology proves truly transformative.

Impacts by Sector

Economists' median forecasts for the sizes of different sectors as shares of the labor force are shown in Figure 11. In the unconditional scenario, economists expect the share of business and analytical ("white-collar") roles to continue to rise slowly, reaching 21.0% in 2030 and 22.0% in 2050 compared to a 2025 baseline of 20.4%. The share of care and service workers is forecast to increase more rapidly, reaching 48.0% in 2030 and 52.5% in 2050 in the unconditional scenario, while skilled trade and industrial ("blue-collar") occupations would fall to 12.5% in 2030 and 11.0% in 2050.

In the rapid scenario, the growth in white-collar occupations would stall, with their share remaining flat at around 20.0%–21.0% in 2030 and 2050. Care and service occupations are forecast to see larger increases compared to the unconditional scenario (reaching 57.1% in 2050), while blue-collar occupations would sharply decline, with a median share of 8.0% by 2050—a historical low.

Directionally, other groups largely agree with these aggregate economist forecasts, although there are some areas of disagreement. Under the rapid scenario, by 2050 superforecasters and AI experts expect a decline in white-collar jobs to 16.0% and 18.0%, respectively. AI experts predict a much smaller increase in the share of care and service occupations, growing to only 49.8% by 2050 in the rapid scenario, while the general public is the only group expecting a decline in this sector in the rapid scenario, forecasting a share of 42.0%. The results for other groups are shown in Appendix D.2.

Impacts by Occupation

Each survey participant was randomly shown 10 of the 43 International Standard Classification of Occupations (ISCO-08) sub-major occupation groups and asked to rank them by predicted percent change in employment from 2025 to 2030, indicating whether each would grow or

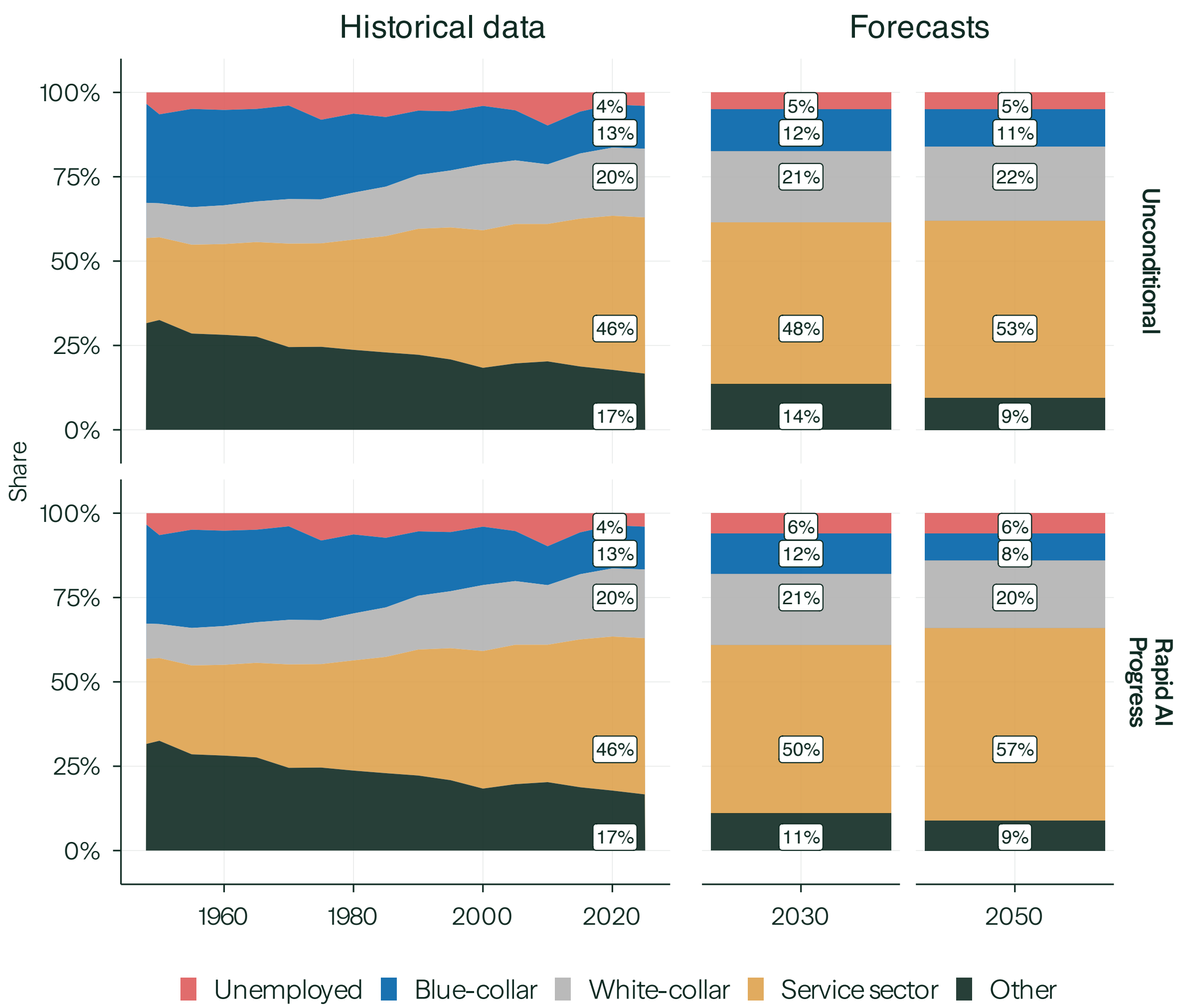


Figure 11: *Economists' forecasts for different groups of occupations as shares of the labor force.* Areas show the median 50th percentile forecast. The 'Other' category is derived by subtracting the sum of the other sectors' median forecasts from 100%. It consists primary of public sector and agricultural workers. Labeled historical values correspond to the beginning of 2025. See Appendix H.4.7 for question details and the source of the historical data.

decline relative to a 0% marker, both unconditionally and conditional on the rapid scenario.[10]

Figure 12 plots the percent of respondents who expect there to be growth in employment in a given occupation between the beginning of 2025 and the beginning of 2030. In the unconditional scenario, occupations economists expect will see the strongest employment growth are personal service workers, personal care workers, health professionals, and military occupations—roles characterized by in-person physical presence, human interaction, or security functions that are difficult to automate. At the bottom of the ranking, economists expect declines in general and keyboard clerks, other clerical support workers, stationary plant and machine operators, and assemblers—routine cognitive and manual roles thought to be particularly vulnerable to technological displacement. Point estimates for blue-collar occupations generally fell below the 50% threshold, indicating that a majority of economists placed these occupations in the job-loss category. This pattern was more pronounced than for white-collar occupations, which clustered closer to or above 50%, and for service occupations, which spanned a wide range but included some of the survey's most optimistic forecasts.

Conditioning on the rapid scenario did not significantly alter these rankings. While most occupation groups shifted modestly leftward—that is, fewer respondents predicted positive growth—the differences between the two scenarios were not statistically distinguishable (also note the relatively small sample size). It is worth noting that the unconditional scenario should not be read as a counterfactual with no LLM exposure; respondents were presumably already incorporating LLM effects into their unconditional predictions.

In Appendix D.2.8, we compare the fraction of economists who predict each occupation will experience growth with the measure of AI exposure from Eloundou et al. (2024).[11][12] We do not observe a relationship between our results and AI exposure. We also compare the AI exposure measure to the difference in the fraction predicting positive growth between the rapid and unconditional scenarios, and again find no relationship.

3.4 Economic Inequality

We measure economic inequality as the fraction of wealth held by the 10% wealthiest households. This metric has had a moderate upward trend since the 1980s, reaching 71.2% in 2023. Like the LFPR, this metric has been relatively stable historically, ranging from 62.7% (in 1985) to 73.2% (in 2013-2014).

[10] There were 10 blocks, each with 10 occupations, and each person was randomly assigned to see one block. Two blocks mistakenly contained the same occupation twice. In these cases, we consider only one job if the respondent answered consistently for the duplicates and do not consider either if they answered inconsistently.

[11] When comparing results, it is important to note that (Eloundou et al., 2024) focus on LLM-exposure, while our survey respondents predicted job growth. While one component of job growth is LLM exposure, there are, of course, many other things that the survey respondent may be considering.

[12] Eloundou et al. (2024) quantify how exposed the occupations are to LLMs by obtaining ratings from humans (and ChatGPT) on how exposed a job's tasks (from O*NET) are. They present several versions of AI exposure; we focus on the version using human raters and Direct Exposure plus 0.5x LLM+ Exposed, where Direct Exposure is defined as "using the described LLM via ChatGPT or the OpenAI playground can decrease the time required to complete the DWA or task by at least half (50%)" and LLM+ Exposed is defined as "access to the described LLM alone would not reduce the time required to complete the activity/task by at least half, but additional software could be developed on top of the LLM that could reduce the time it takes to complete the specific activity/task with quality by at least half. Among these systems, we count access to

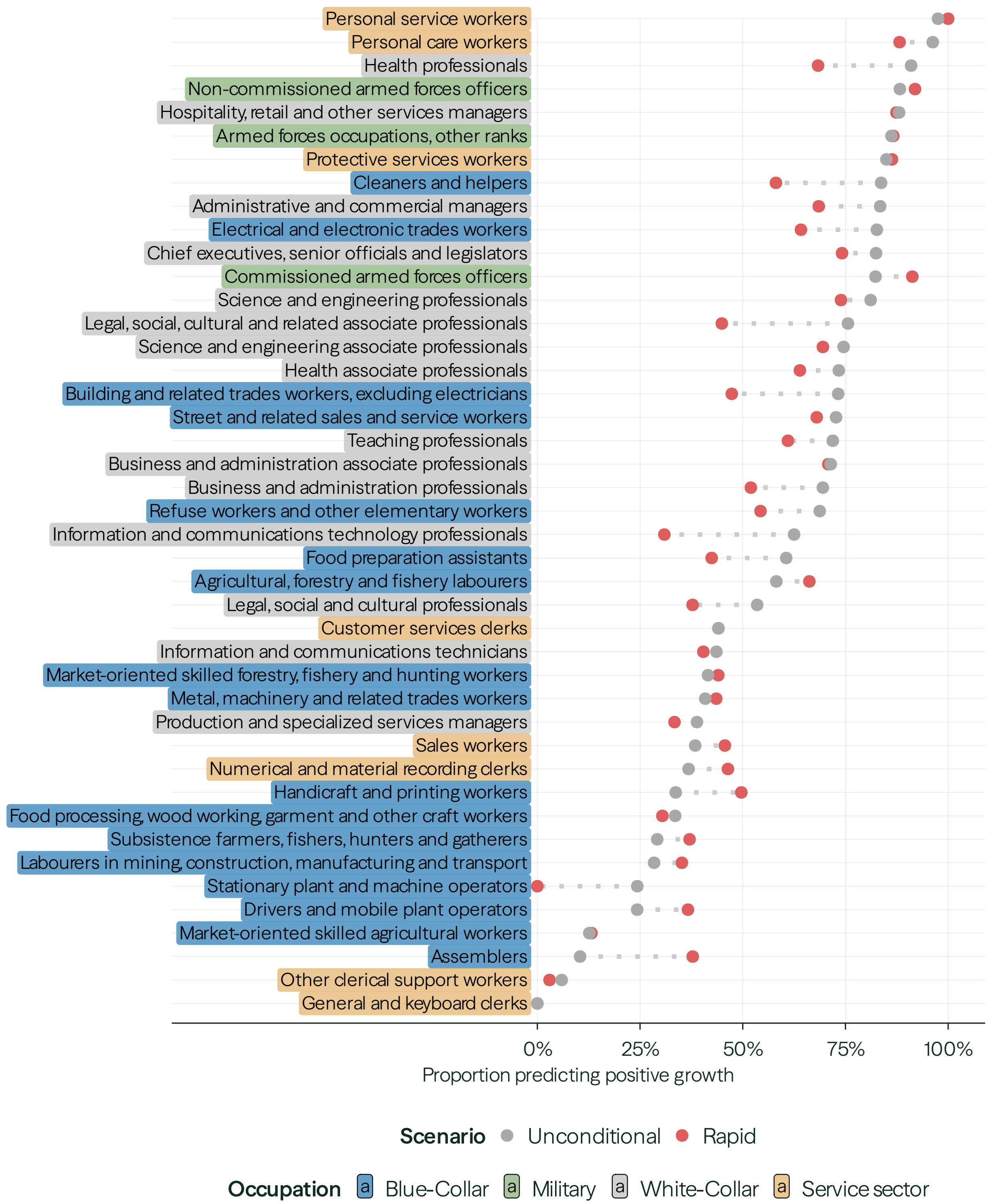


Figure 12: *The fraction of economists predicting a positive change in employment for each occupation between the beginning of 2025 and the beginning of 2030.* Gray points correspond to the unconditional scenario, while red points correspond to the rapid scenario. Dashed lines indicate statistically non-significant results at the 5% level.

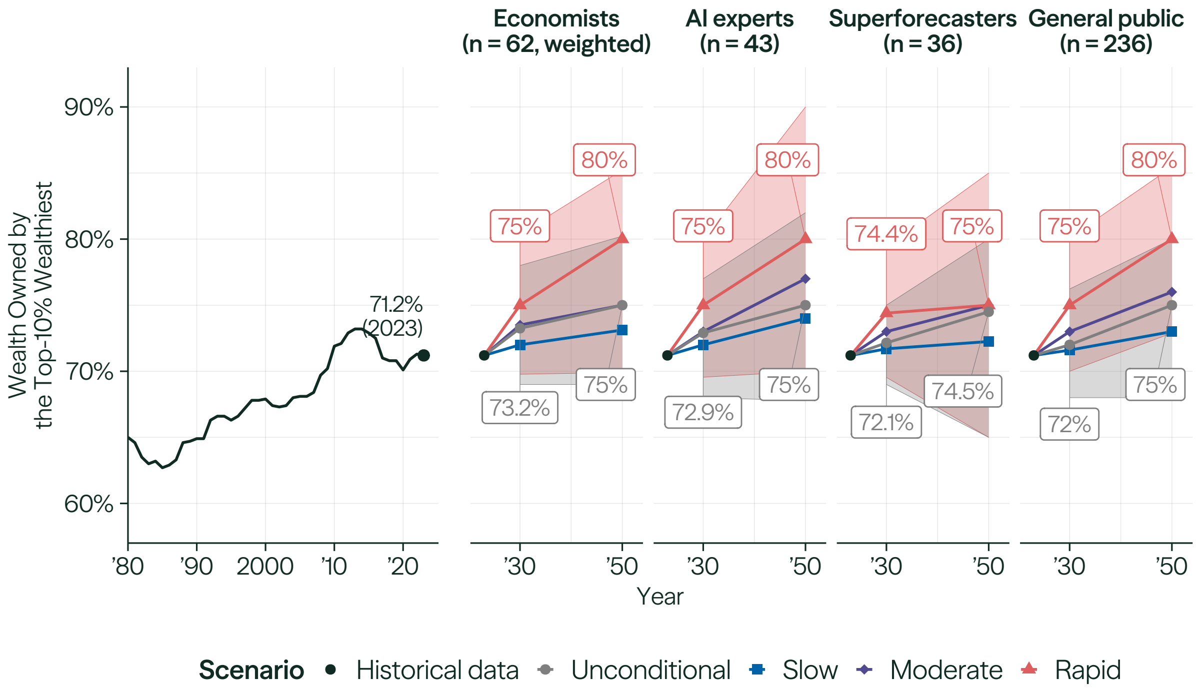


Figure 13: *Forecasts for wealth held by the 10% wealthiest households.* Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3). See Appendix H.4.9 for question details and the source of the historical data.

These historical values, as well as forecasts by different groups, are shown in Figure 13. Economists expect wealth inequality to increase, with a median forecast of 73.2% in 2030 and 75.0% in 2050. In the rapid scenario, the increase is faster: 75.0% in 2030 and 80.0% in 2050. Our secondary measure of inequality, the labor share of income, leads to similar conclusions: inequality is increasing, and faster AI progress is predicted to lead to greater increases in inequality. These results appear in Appendix D.2.10.

Other participant groups agree with economists in directional terms. However, superforecasters give notably more conservative forecasts, especially for longer-term outcomes. For 2050, their unconditional forecast is 74.5%, and the forecast conditional on the rapid scenario is 75.0%.

Although these forecasts indicate inequality is set to increase, economists also predict that median household income will continue to increase (see Appendix Figure 52). Since we are measuring median household income in real terms (adjusted for inflation), this reflects an increase in the purchasing power of the median household. In addition, according to these forecasts, faster AI progress will lead to larger increases. Setting aside that we are measuring different concepts with these two measures (income vs. wealth), a possible interpretation of

image generation systems."

these results is that while both the top-10% of households and the median household will see gains as a result of faster AI progress, these gains may tend to disproportionately accumulate to the top-10%.

In the written rationales economists offered to explain their wealth inequality forecasts, the most frequently mentioned themes were the shift from labor to capital, historical wealth inequality trends, redistribution and tax policy, ownership of AI infrastructure and IP, and uncertainty around 2050 outcomes. A deeper analysis of these rationales can be found in Appendix D.2.9.

Key finding: If the rapid scenario materializes, economists expect significant economic shifts, but not the transformative acceleration some have predicted.

The wealth inequality forecasts under the rapid scenario describe a U.S. economy that would be substantially more unequal than today—but not unrecognizably so. The median economist forecast of 80.0% of national wealth held by the top 10% in 2050 would represent the highest concentration since the late 1930s, and yet that is a level the U.S. has reached before, albeit under very different technological and institutional conditions. This result fits a broader pattern we observe under the rapid scenario in which economists forecast large shifts—GDP growth of 3.5%, LFPR falling to 55.0%, wealth inequality at 80.0%—but shifts that still have historical parallels, such as GDP growth post-WWII, or the LFPR before women entered the workforce en masse, or pre-WWII inequality.

These forecasted impacts stand in marked contrast to the "transformative" economic impacts proposed by some technologists (Amodei, 2024) and highlighted as possible by some economists (Brynjolfsson, Korinek, and Agrawal, 2025). Even in this rapid scenario where AI models can surpass humans at most cognitive tasks and robots can surpass humans at most physical tasks, economists do not forecast—and no other group forecasts—anything like the tenfold increase in economic growth to around 30% discussed in the literature (Davidson, 2021).

3.5 Other Outcomes

In addition to the main survey questions we report on above, we elicited forecasts on eleven additional measures, the results of which are summarized below. The full results can be found in Appendix D.2.

Overall, economists project that unemployment will remain remarkably stable and that real median household incomes will continue to grow, but that the nature of work will change due to increasing use of AI. Labor's share of economic output is expected to drop.

Key Results

Labor Productivity. Economists forecast only modest increases in the annualized change in labor productivity. For 2030, their median forecasts are 2.0% for the unconditional scenario, 2.0% for the slow, 2.5% for the moderate, and 3.2% for the rapid scenario—this compared to a 2025 baseline of 1.94%. For 2050, these expectations shift slightly to 2.5% (unconditional), 2.0% (slow), 3.0% (moderate), and 4.0% (rapid). AI experts, however, are significantly more optimistic about the rapid scenario in 2050, forecasting a 5.0% annualized change in 2050.

Unemployment Rate. Economists expect the overall unemployment rate to remain relatively stable, even under the rapid scenario. For 2030, they forecast 5.0% for the unconditional, 5.0% for the slow, 5.0% for the moderate, and 6.0% for the rapid. For 2050, their estimates are 5.0% (unconditional), 5.0% (slow), 6.0% (moderate), and 6.0% (rapid). AI policy and industry professionals, however, project higher long-term unemployment under the rapid scenario: for 2050, they forecast 8.0%.

Youth Unemployment Rate. Even for 20-to-24-year-old workers, economists expect the unemployment rate to remain relatively stable. They forecast 2030 youth unemployment rates of 9.5% for the unconditional scenario, 9.0% for the slow, 10.0% for the moderate, and 11.0% for the rapid—predictions that fall well within the historical range. By 2050, their forecasts drop slightly across the board to 9.0% (unconditional), 8.2% (slow), 9.8% (moderate), and 10.0% (rapid). As with the overall employment rate, AI policy and industry professionals were more pessimistic under the rapid scenario, predicting 11.4% for 2050.

Labor Share. Economists project a slight downward trend in the share of economic output going to workers, particularly if AI advances quickly. For 2030, they forecast 54.3% for unconditional scenario, 55.0% for the slow, 54.0% for the moderate, and 52.0% for the rapid, compared to a 2025 baseline of 55.48%. For 2050, this drops to 50.0% (unconditional), 52.0% (slow), 50.0% (moderate), and 45.0% (rapid). AI experts, however, expect a drastic collapse in the labor share under the rapid 2050 scenario, forecasting just 40.0%.

Median Household Income. Economists forecast steady real income growth. For 2030, their median estimates are $83,967 for the unconditional scenario, $83,046 for the slow, $85,000 for the moderate, and $87,000 for the rapid, compared to a 2023 baseline of $80,610. By 2050, their forecasts rise to $93,175 (unconditional), $91,864 (slow), $95,142 (moderate), and $100,000 (rapid). AI experts are markedly more pessimistic than economists in the rapid 2050 scenario, expecting a median household income of $95,000.

Life Satisfaction. Economists do not expect AI progress to drastically alter average life satisfaction in the U.S. For 2030, forecasts on the Cantril ladder (Cantril, 1965) are 6.6 for the unconditional scenario, 6.7 for the slow, 6.6 for the moderate, and 6.5 for the rapid, compared to a 2024 baseline of 6.72. In 2050, forecasts are 6.7 (unconditional), 6.7 (slow), 6.5 (moderate), and 6.5 (rapid). Forecasts across all groups and scenarios are remarkably clustered, generally hovering between 6.4 and 6.8 with very little deviation. Superforecasters are an exception: for 2050, they forecast an average life satisfaction of 7.0, independent of the AI scenario.

Work Hours Assisted by Generative AI. Economists foresee significant adoption of generative AI. In 2030, they estimate the percentage of assisted work hours will be 10.1% for the unconditional scenario, 8.0% for the slow, 12.9% for the moderate, and 24.2% for the rapid, compared to a 2024 estimate of 3.35%. By 2050, they expect this to surge to 40.0%

(unconditional), 25.0% (slow), 44.7% (moderate), and 62.0% (rapid). AI experts also project high utilization in the rapid scenario, hitting 60.0% in 2050. By comparison, superforecasters are much more conservative, predicting just 33.0% in 2050 under the rapid scenario.

AI Electricity Consumption. Economists predict growing energy demands for AI. Their 2030 median forecasts for the share of U.S. electricity consumption used by AI are 4.0% for the unconditional scenario, 2.3% for the slow, 4.9% for the moderate, and 7.4% for the rapid, compared to a 2024 baseline estimate of 1%. For 2050, these jump to 8.0% (unconditional), 5.0% (slow), 8.3% (moderate), and 15.0% (rapid). AI experts and superforecasters anticipate somewhat higher electricity usage in 2050 under the rapid scenario, both forecasting 19.5%.

3.6 Policy Responses

We asked survey participants to predict the marginal impact of six policy proposals on GDP growth and the LFPR, under both the unconditional and rapid scenarios, and for 2030 and 2050. Participants were instructed to estimate the effect of each policy in isolation, setting aside any consideration of conditions, political or otherwise, under which each policy might be adopted. We also asked respondents to indicate their support for implementing each policy without conditioning on any specific AI progress scenario. Finally, we asked respondents to estimate the probability that each policy (or a similar policy, as judged by an economist panel) would be implemented by the U.S. by the end of 2026. We present a summarized version of each policy, along with our key findings, below. Findings reported are for impacts on GDP growth and the LFPR in 2030. The full policy descriptions, results, and rationale analyses can be found in Appendix D.3.

1. Retraining Support: *Offers displaced workers in high-automation-risk industries up to $25,000 per year (for up to two years) in training credits, career counseling, and relocation assistance, funded by a small payroll tax.*

2. Modernized Unemployment Insurance: *Expands unemployment benefits to 75% of prior salary for up to 18 months for automation-displaced workers, with added wage loss insurance and streamlined administration, funded by higher employer payroll taxes.*

3. Universal Basic Income: *Gives every American adult $1,000 per month unconditionally, funded by a 15% VAT on all goods and services.*

4. Manhattan Project for AI: *Deploys 0.4% of U.S. GDP annually*[13] *in federal spending to accelerate AI research and infrastructure development, funded by a 0.7% VAT.*

5. Compute Tax: *Taxes heavy AI electricity users $50 per MWh above a set threshold and redistributes the revenue to consumers as stimulus checks.*

[13]This would have corresponded to approximately 120 billion dollars in 2025. For context, Epoch estimates that the combined capital expenditures at Alphabet, Amazon, Meta, Microsoft, and Oracle in 2025 were 448.2 billion dollars: https://epoch.ai/data-insights/hyperscaler-capex-trend

6. Job Guarantee Program: *Guarantees a federally funded job paying at least $15 per hour (indexed to inflation) with full benefits to any adult who wants one, funded by a 0.5% VAT.*

Key Results

The Manhattan Project for AI had the highest projected GDP impact, and the Job Guarantee Program had the highest projected LFPR impact. A comparison of median marginal impacts across policies is shown in Figure 14 for GDP growth and in Figure 15 for the LFPR. However, economists expressed exceptionally low support for the Job Guarantee Program (13.7%), and only middling support for the Manhattan Project for AI (55.8%), suggesting that broader economic and societal considerations, beyond headline GDP and LFPR projections, are the primary drivers of economists' policy preferences.

Retraining Support was the consensus favorite among economists. It drew 71.8% support and only 19.9% opposition (with the remainder registering as "unsure"), received modestly positive forecasts on both GDP (+0.1 p.p.) and LFPR (+0.5 p.p.) for the unconditional scenario, and attracted little concern about its funding mechanism—a small payroll tax. Retraining support was also broadly popular with AI industry and policy professionals, superforecasters, and the general public. The fraction of participants in each group supporting the implementation of the different policies is shown in Figure 16.

Support for the six policies varied significantly between groups. The Job Guarantee Program produced the survey's largest economist-general public divergence: whereas only 13.7% of economists supported it, 57.1% of the general public did. In general, economists' normative support tilted toward more incremental, targeted policies, while the general public was willing to entertain broader interventions.

Universal Basic Income was predicted to have no impact on GDP across both the unconditional and rapid scenarios, and carried a substantial projected LFPR decline for both scenarios. A plurality of economists (38.2%) opposed it—the second-highest opposition rate for any policy in the survey—citing labor supply disincentives and the drag of a 15% VAT as primary concerns; by contrast, a plurality of the general public (47.9% for versus 30.3% opposed) supported it.

Modernized Unemployment Insurance was forecast to have zero impact on both GDP and LFPR. However, it still drew a robust 62.3% support from economists, with some viewing it as a social stabilizer independent of its predicted macroeconomic effects.

All cohorts assigned low probabilities to real-world implementation of any policy by the end of 2026. Economists' median estimates ranged from sub-1% (UBI, Job Guarantee) to 15.0% (Manhattan Project for AI), reflecting a pervasive view that near-term political obstacles are considerable, regardless of a policy's perceived merit.

Many respondents in all cohorts view rapid AI progress as increasing the likelihood of policy enactment in the long term. This is particularly true for safety-net and redistributive policies like UBI, which some respondents—in their rationales—predicted would become inevitable under the rapid scenario. Others indirectly implied the rapid scenario would trigger stabilizing policy responses by arguing near-term action is unlikely *because* AI has not yet caused enough disruption.

Under the rapid scenario, economists expressed heightened uncertainty about whether labor market policies could keep pace with automation. Several noted that workforce interventions might be overwhelmed by structural displacement, and that policies designed for a normal economy could prove inadequate in a world where AI is advancing faster than humans can retrain.

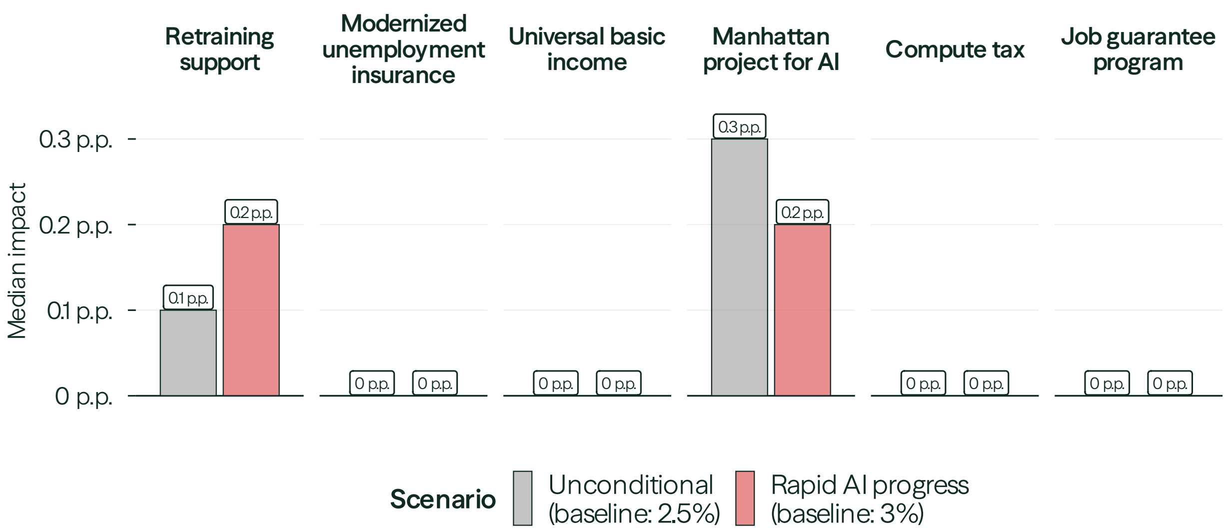


Figure 14: *The median marginal impact of the policies on GDP growth in 2030 (5-year annualized change), according to economists.* Marginal impact is relative to none of the policies being implemented; the legend shows the predicted GDP growth conditional on this baseline. Several policies have zero predicted impact relative to baseline. See Appendix H.5 for question details.

4. Drivers of Disagreement

4.1 Framing the Debate

Debate on the future economic impacts of AI can largely be reduced to two questions:

1. Will AI capabilities progress meaningfully, such that AI systems are capable of completing a large quantity of economically meaningful work?

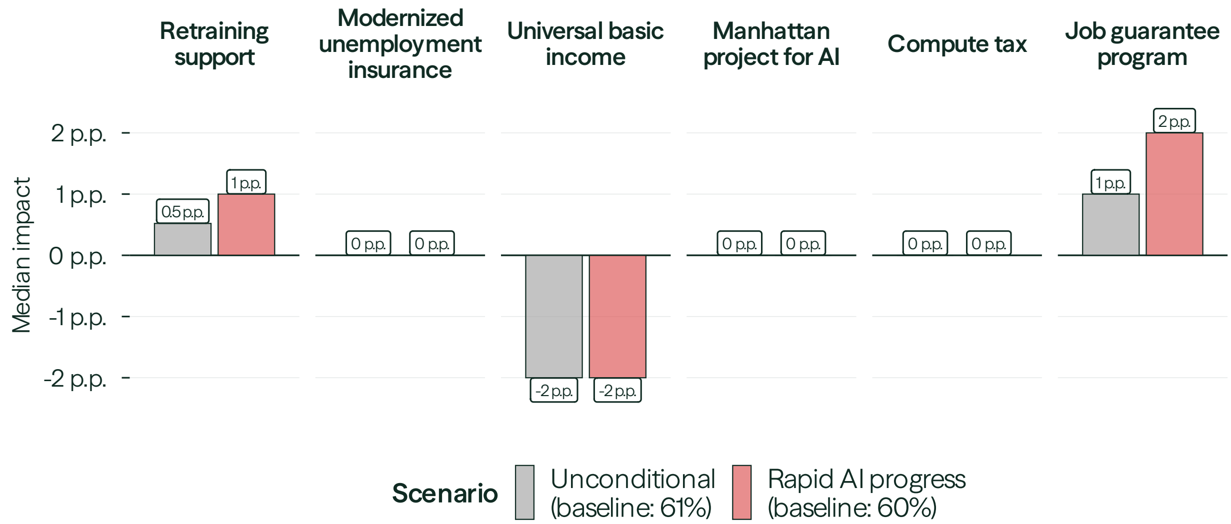


Figure 15: *The median marginal impact of the policies on the LFPR in 2030, according to economists.* Marginal impact is relative to none of the policies being implemented; the legend shows the predicted LFPR conditional on this baseline. Several policies have zero predicted impact relative to baseline. See Appendix H.5 for question details.

2. If this progress in capabilities occurs, what will happen to important economic indicators?

In this section, we emphasize *disagreement* on these two questions. Specifically, we ask: is disagreement about the path for economic indicators driven by disagreement on AI capabilities progress, or disagreement on the effects of capabilities progress on economic indicators? Cunningham (2025) asks this question and concludes:

> The disagreement is about the AI, not about the economics. *The primary reason for the disagreement seems to be about the future rate of AI capabilities progress, not about the more directly economic questions such as (1) the current economic impact of AI; (2) the rate of diffusion & adoption over time; (3) the substitutability between AI-produced and human-produced services.*

Below, we develop a quantitative approach and reach to a different conclusion. When forecasting the future path of key economic indicators, *disagreement centered on the economic impacts of AI capabilities progress*, rather than the degree to which progress will be made. The rationale analyses in Appendix D.2 dovetail with this conclusion. They suggest the factors economists weigh most heavily—historical base rates, adoption lags, demographics, policy responses, macroeconomic headwinds, and structural views on how economies absorb technology—are shaped more by priors about economics and institutions than by the specific AI capability scenario assumed. These rationales also support our assumption that respondents shared a broadly similar understanding of what each scenario entailed, although we discuss the limits of this assumption at the end of this section. We focus our discussion in this section on economists, but we include similar analyses for all other respondent groups in Appendix B.

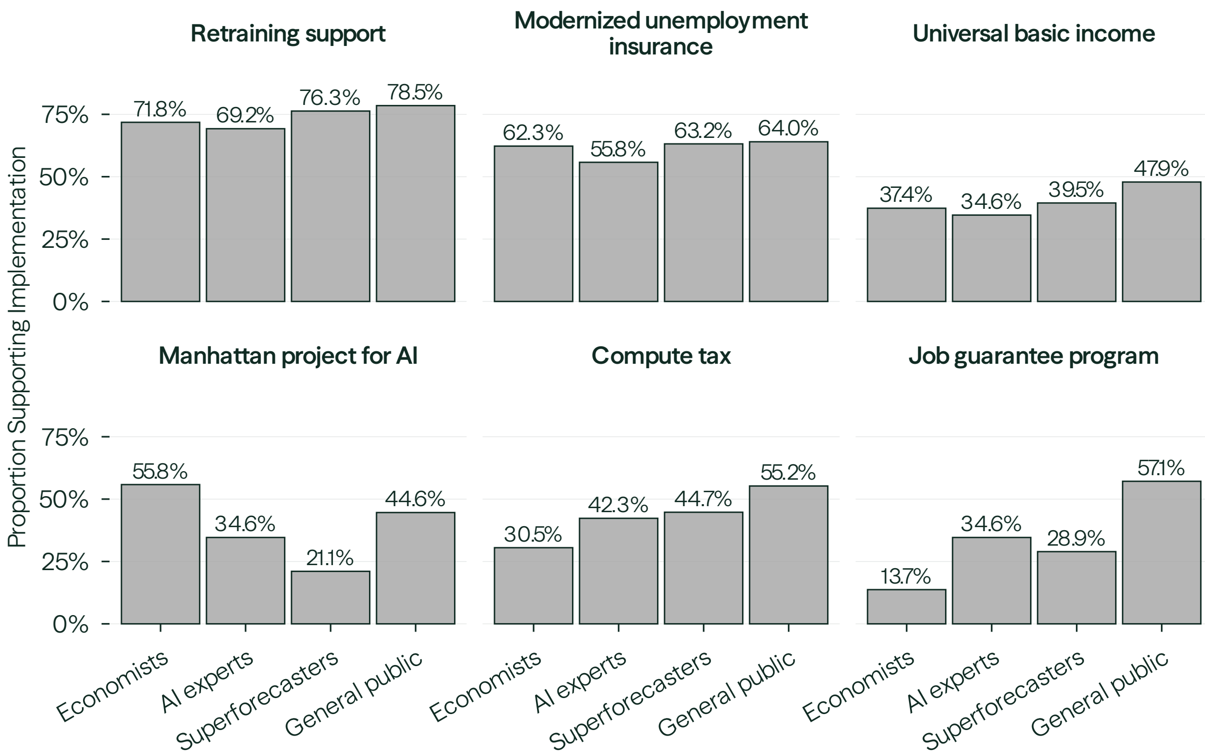


Figure 16: *Proportion of respondents in each group supporting implementation of each policy.* Support reflects responses of 'Yes, with at most minor alterations' to the question 'Do you think [policy] should be implemented?' Respondents could also answer 'No' or 'Unsure.' Policy support was elicited without conditioning on any specific AI progress scenario. See Appendix H.5 for question details.

4.2 Disagreement on Capabilities Progress

First, we ask how much disagreement there is on AI capabilities progress; see Table 1. While the average economist assigns a probability of 14.0% (median 10.0%) to the rapid scenario, the bottom quartile of economists gives the rapid scenario a probability of 6.7% or less, while the top quartile gives forecasts of 20.0% or higher. For the slow scenario, the interquartile range is 16.8% to 60.0%, compared to a mean of 38.6% (median 38.3%). Accordingly, average and median forecasts mask substantial disagreement about the progress of AI capabilities.

Table 1: AI Progress Scenario Probabilities: Economists

Group	Scenario	Mean	25th percentile	50th percentile	75th percentile
Economists	Slow	38.6	16.8	38.3	60.0
Economists	Moderate	47.4	31.5	50.0	64.5
Economists	Rapid	14.0	6.7	10.0	20.0

4.3 Total Variance in Possible Outcomes

Measuring total variance. The disagreement on AI capabilities progress documented in the previous section, while extensive, is not necessarily the primary driver of disagreement between forecasters on their unconditional forecasts of economic outcomes. In order to answer our question—"is disagreement about the path for economic indicators driven by disagreement on AI capabilities progress, or disagreement on the effects of capabilities progress on economic indicators?"—we now assess the *total* variance in possible outcomes.

On select questions, we ask respondents to express their uncertainty in the form of quantile forecasts for the unconditional case and the rapid scenario.[14] We fit a distribution to each respondent's forecasts to fully characterize their beliefs.[15] Given the mean and variance for the unconditional and the rapid scenario distributions, as well as the forecasted probability of the rapid scenario, we can obtain the mean and variance for a bundled slow/moderate scenario.[16] It is possible that the variance of the unconditional outcome distribution is too low—and the probability placed on the rapid scenario too high—to yield a coherent conditional distribution for the bundled slow/moderate scenario.[17] The proportion of incoherent distributions[18] range from 11% to 21% across questions and time horizons for economists. Other groups, notably the

[14]Respondents provide forecasts for the 10^{th}, 50^{th}, and 90^{th} percentiles.

[15]We fit a normal distribution to outcomes with unbounded support (GDP growth, although strictly speaking it is bounded from below by -100%), a gamma distribution to outcomes that are bounded only above or only below (median household income), and a beta distribution to variables that are bounded both above and below (LFPR, unemployment rate, wealth inequality).

[16]We express the unconditional distribution for the outcome as a mixture distribution over the scenarios. The sub-distributions are given by the distribution of the outcome conditional on the rapid or bundled slow/moderate scenario. We use a respondent's scenario probabilities to define the mixture weights.

[17]In this case, the implied variance of the outcome conditional on the slow/moderate scenario will be negative.

[18]Incoherent distributions could reflect incoherence in beliefs or misspecification in the distribution fitting procedure.

general public, tend to have higher proportions of incoherent distributions. Superforecasters, on the other hand, tend to have lower rates of incoherence. We summarize the proportion of incoherent distributions in Table 8. The incoherent distributions were removed from this analysis.

With forecaster-level distributions for the slow/moderate scenario, rapid scenario, and unconditional case, we create 'pooled' distributions by taking a mixture distribution over forecasters, using our derived weights to govern selection probabilities across forecasters in the unconditional case.[19] In effect, we are considering a hierarchical mixture: we first select a scenario according to the aggregated scenario probabilities. Within each scenario, we then select a forecaster. Lastly, we can then draw an outcome from this forecaster-scenario distribution. Accordingly, these distributions represent the full variation in expert views, rather than a distribution created with calibration in mind. Indeed, this pooled distribution is not necessarily the optimal way to aggregate forecasts in terms of forecasting accuracy. For example, Ranjan and Gneiting (2010) show that combining well-calibrated forecasts in this fashion yields forecasts that are miscalibrated. Similar results are reported by Lichtendahl, Grushka-Cockayne, and Winkler (2013). Nevertheless, approaches that aim to generate calibrated aggregate distributions will collapse disagreement between forecasters and are thus ill-suited to the questions posed above. In summary, our approach captures four sources of variation:

1. Within-scenario variance: how much does the outcome vary *within* a given scenario?
2. Between-scenario variance: how much does the *expected* outcome vary *between* scenarios?
3. Within-forecaster uncertainty: how uncertain is a given forecaster about the outcome?
4. Between-forecaster disagreement: how much do *expected* outcomes differ *between* forecasters?

We quantify these four sources of variance with a hierarchical law of total variance decomposition. We first decompose the total variation in the outcome into between- and within-scenario components, corresponding to the first two items above. Next, we further decompose each of these two components into within- and between-forecaster components, yielding the four components of the total variance. Lastly, on the within-scenario variance branch, we can assess how much the rapid and slow/moderate scenarios contribute to each component.[20] See Appendix B for the associated derivations.

Understanding total variance in GDP forecasts: raw data. We now describe in detail a decomposition of 2030 GDP growth forecasts, focusing only on economists. After this discussion, we summarize the results for the other questions. Results for all groups, questions, and time horizons are in Appendix B.

[19]We must accordingly adjust the weights in the rapid and slow/moderate scenarios. For example, a forecaster's weight in the rapid conditional outcome distribution will be proportional to the product of their original weight and their forecasted probability for the rapid scenario.

[20]The within-scenario variance is the probability-weighted sum of the variance in each scenario, so we can calculate directly each scenario's contribution to within-scenario variance.

First, before imposing any assumptions, we can explore the quantile forecasts directly. The median of 50th percentile forecasts in the unconditional scenario is 2.5% (IQR: 2.0, 3.0). We can compare these forecasts to those for the three scenarios: the slow scenario median is 2.0% (IQR: 1.5, 2.2), the moderate scenario median is 2.6% (IQR: 2.2, 3.0), and the rapid scenario median is 3.3% (IQR: 2.9, 4.5)

Next, we can consider the quantile forecasts given in the unconditional and rapid scenarios. For the 10th percentile, the unconditional median is 1.0% (IQR: 0.0, 1.2) and the rapid scenario median is 1.2% (IQR: 0.5, 2.6). For the 90th percentile, the unconditional median is 4.0% (IQR: 3.5, 5.0) and the rapid scenario median is 5.5% (IQR: 4.0, 7.0).

While there are noticeable differences in the central tendencies across scenarios, the 10th and 90th percentile forecasts demonstrate that there remains substantial overlap in outcomes across the scenarios; *within-scenario variance is a critical driver of total variance.*

Nevertheless, the above decomposition does not assess how much of the variance within a scenario owes to forecasters' uncertainty, and how much to disagreement between forecasters. The variance decomposition below addresses this question directly.

Understanding variance in GDP forecasts: fitted distributions. We next assume functional forms for forecaster-level outcome distributions, as described above. We pool these distributions across forecasters to assess total variance in the unconditional and rapid scenarios. The result is shown in Figure 5. In the unconditional pooled distribution, the median growth rate is 2.5%, with an interquartile range of 1.63% to 3.44%. In the rapid scenario, the median growth rate is 3.38%, with an interquartile range of 2.34% to 4.72%. Again, we see notable overlap. The rapid scenario median sits between the 50th and 75th percentile of the unconditional distribution, despite economists assigning the rapid scenario a small 14.0% probability on average.

Understanding variance in GDP forecasts: implied distributions for the slow/ moderate scenario and a decomposition. We next assume that the forecasts for the bundled slow/moderate scenario would be consistent with the forecasts for the rapid and unconditional scenarios. Again, this assumption yields the mean and variance for each forecaster's conditional outcome distribution in the bundled slow/moderate scenario.

Lastly, we explore the variance of these three distributions. The standard deviation of 2030 GDP growth in the unconditional case is 1.49%. Conditioning on the slow/moderate scenario reduces this by 9% to 1.36%. In contrast, conditioning on the rapid scenario increases the standard deviation by 33% to 1.98%. Thus, the rapid scenario not only raises expected GDP growth but also significantly increases uncertainty about this economic outcome. While moving to the slow/moderate scenario reduces the variance of the outcome distribution, substantial within-scenario variance remains.

4.4 Decomposition Results

Before presenting the decomposition results, we note that Appendix B.1 provides a detailed illustrative example using two hypothetical forecasters, demonstrating how the decomposition separates within-scenario from between-scenario variance and how within-forecaster uncertainty can dominate between-forecaster disagreement even when forecasters hold different beliefs about AI progress.

We perform the decomposition, as described in Appendix B.1, and report the results for economists' forecasts of GDP growth, labor force participation rate, and wealth inequality in Figure 17 below. Specifically for forecasts of GDP growth in 2030, within-scenario (WS) variance—comprising 94.9% of total variance—is the dominant driver of total variance, relative to between-scenario (BS) variance (5.1% of the total). On both paths, within-forecaster uncertainty comprises a larger share of the variance: 83% (78.7% / 94.9%) and 96% (4.9% / 5.1%) of the within- and between-scenario variance, respectively. Forecasters are quite uncertain about the future, and this noise is larger than the variance driven by disagreement.

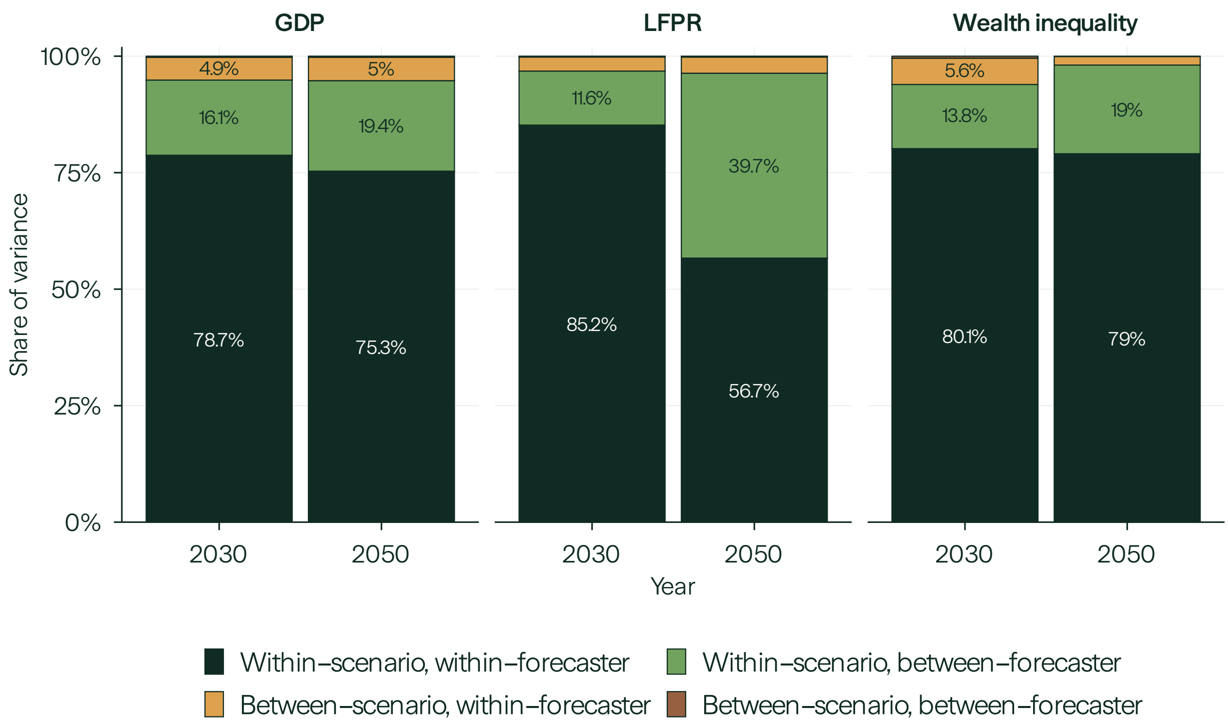


Figure 17: *Decomposition of the variance in economists' forecasts of GDP growth, labor force participation rate, and wealth inequality in 2030 and 2050.*

Lastly, we now consider how this analysis relates to the question of whether forecasters disagree on capabilities progress or outcomes conditional on capabilities progress.

1. If forecasters disagree noticeably on capabilities progress, we expect *between-scenario, between-forecaster* variance to be large.

2. If forecasters disagree noticeably on outcomes conditional on capabilities progress, we expect *within-scenario, between forecaster* variance to be large.

For GDP growth, the first component (0.3%) is small in absolute terms and relative to the second component (16.1%). This suggests that disagreement about outcomes conditional on various levels of progress is a more important driver of total variance in 2030 GDP growth forecasts than disagreement on capabilities progress per se.

This analysis also quantifies the contributions of disagreement versus uncertainty to total variance in outcomes. The *within-forecaster* components all reflect uncertainty, which is outside of this question of *where disagreement* is most prevalent. Hence, we subtract out those components to isolate disagreement. Nevertheless, uncertainty dominates total variance in forecasts, explaining approximately 80% of total variance in Figure 17. Forecasters also highlight uncertainty in their rationales. One forecaster highlights uncertainties around adoption, driving greater variance in the rapid scenario:

> Rapid capability progress creates a genuine upside tail via (i) higher TFP, (ii) faster innovation cycles, and (iii) automation of broader task bundles. But it also widens uncertainty because the same world can feature large transitional frictions and misallocation: costly retooling, brittle deployment in complex domains, and the possibility that measured GDP gains are damped by adjustment costs (even if capabilities are "there").

Table 2: Variance Decomposition: Economists

Outcome	Year	Total Std. Dev.	WS	BS	WS-WF	WS-BF	BS-WF	BS-BF
GDP	2030	1.494	0.949	0.051	0.787	0.161	0.049	0.003
GDP	2050	2.166	0.947	0.053	0.753	0.194	0.050	0.003
LFPR	2030	3.978	0.968	0.032	0.852	0.116	0.030	0.002
LFPR	2050	6.731	0.963	0.037	0.567	0.397	0.035	0.002
Median HH Income	2030	10,568	0.999	0.001	0.928	0.070	0.001	0.000
Median HH Income	2050	16,327	1.000	0.000	0.679	0.321	0.000	0.000
Unemployment Rate	2030	2.534	0.963	0.037	0.810	0.153	0.034	0.002
Unemployment Rate	2050	3.192	0.990	0.010	0.737	0.253	0.009	0.001
Wealth Inequality	2030	3.726	0.939	0.061	0.801	0.138	0.056	0.005
Wealth Inequality	2050	6.424	0.981	0.019	0.790	0.190	0.018	0.001

Note: W = within, B = between, S = scenario, F = forecaster. GDP = Gross Domestic Product, LFPR = Labor Force Participation Rate, HH = household.

We conduct this analysis across all questions, time horizons, and groups. While we report more results in Appendix B, we report results for economists in Table 2. The same patterns hold as above. First, since within-scenario, between forecaster variance dominates between-scenario, between-forecaster variance, we conclude that disagreement on the impacts of AI is primarily driven by disagreement on the conditional impacts of various capability levels, rather than divergence view on AI capabilities progress—although we acknowledge that noise from discretization and scenario ambiguity, as discussed at the end of this section, may account for a small portion of the within-scenario variance. Second, within-forecaster uncertainty dwarfs between-forecaster disagreement. Regardless of realized AI capability progress, forecasters express substantial uncertainty and provide overlapping outcome distributions.

4.5 Limitations of the Decomposition

One caveat is that our scenario descriptions bundled multiple dimensions of AI capability—cognitive tasks such as research and coding alongside physical tasks such as robotics—into single composite scenarios. Respondents were asked to select which scenario, in sum, best represented their views, and were advised that progress might be uneven across domains. Therefore, two respondents who both selected the rapid scenario may have held meaningfully different assumptions about the specific capability profile underlying that label. If respondents interpreted the scenarios differently in this way, some of the within-scenario, between-forecaster variance that our decomposition attributes to disagreement about economic mechanisms could potentially reflect disagreement about the effective capability level assumed within a given scenario. This effect would correspondingly weaken the contrast with Cunningham (2025). In addition to ambiguity, our chosen discretization of progress could introduce some noise in the scenario forecasts. Two respondents might share identical scenario interpretations, but, conditional on rapid progress, one could expect progress to noticeably exceed the threshold between the moderate and rapid scenarios, while another expects progress to fall just above the threshold.

We acknowledge this limitation but believe that its effect was limited. Respondents' written rationales suggest a broadly consistent pattern: forecasters who deviated from the literal scenario descriptions most commonly assumed faster cognitive AI progress and slower robotics progress, rather than adopting wildly divergent capability profiles. This consistency suggests that scenario ambiguity is unlikely to account for much of the within-scenario variance we observe.

5. Discussion

As we documented in our Section 4 variance decomposition, the primary source of disagreement among economists is likely not about whether AI capabilities will advance significantly—majorities assign meaningful probability to the moderate or rapid scenario—but about how quickly the economy can absorb these potentially transformative capabilities, and what absorption will lead to in terms of economic impacts. Specifically, economists who share similar views on the likelihood of rapid AI progress nevertheless diverge on the likely rate of diffusion, the extent to which new job creation will offset displacement, the degree to which lags will occur between adoption and productivity gains, and how institutional and regulatory responses will shape the transition. We also see this in the analysis in Appendix E.1: while economists who assign above-median probabilities to the rapid scenario tend to have slightly higher unconditional forecasts for GDP growth and lower forecasts for the LFPR, the outcome distributions of these above- and below-median participants overlap significantly.

However, despite disagreement on the magnitude of these effects, the majority of experts agree that their net direction will be to attenuate rather than accelerate AI's impact on the economy. Indeed, even under the rapid scenario, where AI systems surpass human performance on most cognitive and physical tasks by 2030, experts do not forecast economic outcomes outside the range of historical experience. Instead, their written rationales point repeatedly to diffusion lags, infrastructure bottlenecks, political instability, and demographic headwinds as mechanisms that will likely prevent even highly capable AI from producing unprecedented economic outcomes in the near term.

This finding stands in marked contrast to warnings, raised by some prominent voices in the AI industry, about rapid economic transformation. Our sample partially captured this view, especially in the AI expert group, which forecast a GDP growth rate of 3.7% in 2030 and 5.3% in 2050 under the rapid scenario. Their 90$^{\text{th}}$ percentile forecast is 6.5% in 2030, meaning that they assign a 10% probability to growth equal to or larger than this. These predictions are higher than the economists' but lower than those of some in the industry (see Cunningham (2025)). One possible explanation is that forecasters in our study over-anchored to historical data, which were prominently displayed in the survey interface (see Figure 80). Additionally, some of the difference (though not all, as described above) could be due to different capability progress beliefs. Our sample and scenario discretization may not capture the most extreme end of rapid progress beliefs, such that even the forecasts conditional on the rapid scenario remain unrepresentative of those in the industry with the most extreme beliefs about capabilities. In Appendix C, we present some early evidence that beliefs about AI timelines may be speeding up across multiple groups: respondents in the Longitudinal Expert AI Panel (LEAP), which ran in February 2026, assigned higher probabilities to the rapid scenario than those in this study (October 2025–February 2026). Even so, we find little difference in economic outcome forecasts between these two samples.

While the aggregate forecasts we find in this study are at the more moderate end of the spectrum of discourse, we note that our survey experts express the most uncertainty under the rapid AI progress scenario where the stakes for policy design are the highest. Experts' unconditional forecasts—the ones that reflect their actual all-things-considered beliefs—cluster around historical baselines, but their uncertainty under the rapid scenario widens significantly for the LFPR, GDP growth, and inequality. While experts only assign the rapid scenario a 14% probability of occurring, given the magnitude of potential consequences, that number is far from negligible. This matters because, if AI progress is slow, existing institutions making incremental adjustments to current policies may prove adequate. But if progress is rapid, the breadth of the outcome distribution implies that policymakers cannot simply plan for the median outcome; they must contend with tail risks, including the potential for a deep contraction in labor force participation.

On the question of which policies might best mitigate negative impacts from AI, our survey revealed a marked divergence between economists and the general public: economists favor targeted, incremental interventions such as retraining support and modernized unemployment insurance, while the general public expressed support for broader interventions such as job guarantees and universal basic income. This gap is disproportionate to the differences in economic forecasts between the two groups—the general public's median unconditional GDP growth and LFPR projections only differ modestly from economists'—and yet the general public is nearly four times as likely as economists to support a job guarantee. If AI progress accelerates and labor market disruption becomes more visible, these underlying disagreements may become the central fault lines of policy debates.

References

Abbott, Ryan and Bret Bogenschneider (2018). "Should Robots Pay Taxes? Tax Policy in the Age of Automation". In: *Harvard Law & Policy Review* 12.1, pp. 145–175. DOI: 10.2139/ssrn.2932483. URL: https://heinonline.org/HOL/P?h=hein.journals/harlpolrv12&i=147.

Acemoglu, Daron (2024). "The Simple Macroeconomics of AI". In: *Economic Policy* 40.121, pp. 13–58. DOI: 10.1093/epolic/eiae042.

Aghion, Philippe and Simon Bunel (2024). *AI and Growth: Where Do We Stand?* Federal Reserve Bank of San Francisco. URL: https://www.frbsf.org/wp-content/uploads/AI-and-Growth-Aghion-Bunel.pdf.

Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones (2019). "Artificial Intelligence and Economic Growth". In: *The Economics of Artificial Intelligence: An Agenda*. Ed. by Ajay Agrawal, Joshua Gans, and Avi Goldfarb. Chicago: University of Chicago Press, pp. 237–290. ISBN: 9780226613338. DOI: 10.7208/chicago/9780226613475.003.0009.

Agrawal, Ajay, Joshua Gans, and Avi Goldfarb (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*. Harvard Business Review Press.

— (2022). *Power and Prediction: The Disruptive Economics of Artificial Intelligence*. Harvard Business Review Press.

Altman, Sam (June 2025). *The Gentle Singularity*. https://blog.samaltman.com/the-gentle-singularity. Blog post, published June 10, 2025. Accessed March 30, 2026.

Amodei, Dario (Oct. 2024). *Machines of Loving Grace: How AI Could Transform the World for the Better*. Essay, darioamodei.com. URL: https://www.darioamodei.com/essay/machines-of-loving-grace.

Anthropic (2025). *Preparing for AI's Economic Impact: Exploring Policy Responses*. URL: https://www.anthropic.com/research/economic-policy-responses.

Arnon, Alexander (Sept. 2025). *The Projected Impact of Generative AI on Future Productivity Growth*. Tech. rep. Penn Wharton Budget Model. URL: https://budgetmodel.wharton.upenn.edu/p/2025-09-08-the-projected-impact-of-generative-ai-on-future-productivity-growth.

Bastani, Spencer and Daniel Waldenström (2024). *AI, Automation and Taxation*. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4811796.

Baumol, William J (2012). *The cost disease: Why computers get cheaper and health care doesn't*. Yale university press.

Beraja, Martin and Nathan Zorzi (2022). *Inefficient Automation*. w30154. National Bureau of Economic Research. DOI: 10.3386/w30154. URL: https://www.nber.org/papers/w30154.

Brynjolfsson, Erik, Bharat Chandar, and Ruyu Chen (2025). *Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence*. Stanford Digital Economy Lab. URL: https://digitaleconomy.stanford.edu/publications/canaries-in-the-coal-mine/.

Brynjolfsson, Erik, Anton Korinek, and Ajay Agrawal (2025). *A Research Agenda for the Economics of Transformative AI*. w34256. National Bureau of Economic Research. DOI: 10.3386/w34256. URL: https://www.nber.org/papers/w34256.

Cantril, Hadley (1965). *The Pattern of Human Concerns*. New Brunswick, NJ: Rutgers University Press.
Clark Center Forum (2025). *AI and Growth*. URL: https://kentclarkcenter.org/surveys/ai-and-growth/.
Comin, Diego and Bart Hobijn (2010). "An Exploration of Technology Diffusion". In: *American Economic Review* 100.5, pp. 2031–2059. DOI: 10.1257/aer.100.5.2031.
Comunale, Mariarosaria and Andrea Manera (2024). *The Economic Impacts and the Regulation of AI: A Review of the Academic Literature and Policy Actions*. DOI: 10.5089/9798400271663.001. URL: https://papers.ssrn.com/abstract=4774326.
Congressional Budget Office (Feb. 2026). *The Long-Term Budget Outlook Data: 2026 to 2056*. Tech. rep. Data available at: https://www.cbo.gov/system/files/2026-02/57054-2026-02-LTBO-econ.xlsx. Accessed: March 19, 2026. URL: https://www.cbo.gov/publication/62044.
Crunchbase (2025). *Crunchbase*. URL: https://www.crunchbase.com/ (visited on 04/08/2025).
Cunningham, Tom (2025). *Forecasts of AI and Economic Growth*. URL: https://tecunningham.github.io/posts/2025-10-19-forecasts-of-AI-growth.html.
Davidson, Tom (2021). *Could Advanced AI Drive Explosive Economic Growth?* https://coefficientgiving.org/research/could-advanced-ai-drive-explosive-economic-growth/. Coefficient, accessed March 31, 2026.
Davis, Scott (Feb. 2026). *AI is Simultaneously Aiding and Replacing Workers, Wage Data Suggest*. Dallas Fed Economics. Accessed: 2026-03-26. Federal Reserve Bank of Dallas. URL: https://www.dallasfed.org/research/economics/2026/0224.
Deloitte (Dec. 2025). *US Economic Forecast 2026-2030*. Tech. rep. Accessed: March 13, 2026. URL: https://www.deloitte.com/us/en/insights/topics/economy/us-economic-forecast/united-states-outlook-analysis.html.
Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock (2024). "GPTs are GPTs: Labor market impact potential of LLMs". In: *Science* 384.6702, pp. 1306–1308.
Epoch AI (2024). *Data on AI Models*. URL: https://epoch.ai/data/ai-models (visited on 11/22/2024).
— (2025). *AI Capabilities and Benchmarking*. Online database. Accessed: 2026-03-30. URL: https://epoch.ai/benchmarks.
Erdil, Ege and Tamay Besiroglu (2024). *Explosive Growth from AI Automation: A Review of the Arguments*. DOI: 10.48550/arXiv.2309.11690. URL: http://arxiv.org/abs/2309.11690.
Federal Reserve (FOMC) (Dec. 2025). *Summary of Economic Projections*. Tech. rep. Accessed: March 13, 2026. URL: https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20251210.pdf.
Filippucci, Francesco, Peter Gal, Karin Laengle, and Matthias Schief (2025). *Macroeconomic Productivity Gains from Artificial Intelligence in G7 Economies*. 41. OECD. DOI: 10.1787/a5319ab5-en. URL: https://doi.org/10.1787/a5319ab5-en.
Filippucci, Francesco, Peter Gal, and Matthias Schief (2024). *Miracle or Myth? Assessing the Macroeconomic Productivity Gains from Artificial Intelligence*. OECD. DOI: 10.1787/b524a072-en. URL: https://www.oecd.org/en/publications/miracle-or-myth-assessing-the-macroeconomic-productivity-gains-from-artificial-intelligence_b524a072-en.html.

Frey, Carl Benedikt and Michael A. Osborne (2017). "The Future of Employment: How Susceptible Are Jobs to Computerisation?" In: *Technological Forecasting and Social Change* 114, pp. 254–280. DOI: 10.1016/j.techfore.2016.08.019.

Gerut, Amanda (2025). *Jamie Dimon on AI: "People Should Stop Sticking Their Head in the Sand"*. URL: https://fortune.com/2025/10/08/jamie-dimon-head-in-the-sand-ai-will-take-jobs-tip-iceberg/.

Gimbel, Martha, Molly Kinder, Joshua Kendall, and Maddie Lee (2025). *Evaluating the Impact of AI on the Labor Market: Current State of Affairs*. URL: https://budgetlab.yale.edu/research/evaluating-impact-ai-labor-market-current-state-affairs.

Goldman Sachs (Oct. 2025). "What Is the US Economy's Potential Growth Rate?" In: Accessed: March 13, 2026. URL: https://www.goldmansachs.com/insights/articles/what-is-the-us-economys-potential-growth-rate.

Grace, Katja, Harlan Stewart, Julia Fabienne Sandkühler, Stephen Thomas, Ben Weinstein-Raun, Jan Brauner, and R. C. Korzekwa (2024). *Thousands of AI Authors on the Future of AI*. DOI: 10.48550/arXiv.2401.02843. URL: https://arxiv.org/abs/2401.02843.

Ham, John C, Julian Wright, and Ziqiu Ye (June 2025). "The Dramatic Rise of the New Society Journals in Economics". In: *The Economic Journal* 136.673, pp. 259–278. ISSN: 0013-0133. DOI: 10.1093/ej/ueaf044. eprint: https://academic.oup.com/ej/article-pdf/136/673/259/63522232/ueaf044.pdf. URL: https://doi.org/10.1093/ej/ueaf044.

Hartman, Rachel, Aaron J. Moss, Shalom N. Jaffe, Cheskie Rosenzweig, Leib Litman, and Jonathan Robinson (2023). "Introducing Connect by CloudResearch: Advancing Online Participant Recruitment in the Digital Age". In: DOI: 10.31234/osf.io/ksgyr. URL: https://doi.org/10.31234/osf.io/ksgyr.

Hendrycks, Dan, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt (2020). "Measuring Massive Multitask Language Understanding". In: *arXiv*. DOI: 10.48550/arxiv.2009.03300.

Humlum, Anders and Emilie Vestergaard (May 2025). *Still Waters, Rapid Currents: Early Labor Market Transformation under Generative AI*. Working Paper 33777. Revised March 2026. National Bureau of Economic Research. DOI: 10.3386/w33777. URL: https://www.nber.org/papers/w33777.

Hyman, Benjamin G., Brian K. Kovak, and Adam Leive (2024). *Wage Insurance for Displaced Workers*. DOI: 10.3386/w32464. URL: https://www.nber.org/papers/w32464.

IARPA (2011). *IARPA Aggregative Contingent Estimation (ACE) Program*. URL: https://www.iarpa.gov/research-programs/ace.

International Monetary Fund (Oct. 2025). *World Economic Outlook*. Accessed: March 13, 2026. October 2025 WEO Entire Dataset in Excel, Countries Tab, Gross domestic product (GDP), Constant prices, Percent change variable for US. URL: https://data.imf.org/en/datasets/IMF.RES:WEO.

Jain, Naman, King Han, Alex Gu, Wen-Ding Li, Fanjia Yan, Tianjun Zhang, Sida Wang, Armando Solar-Lezama, Koushik Sen, and Ion Stoica (2024). "LiveCodeBench: Holistic and Contamination Free Evaluation of Large Language Models for Code". In: *arXiv*. DOI: 10.48550/arxiv.2403.07974.

Jorgenson, Dale W and Kevin J Stiroh (2017). "Raising the speed limit: US economic growth in the information age". In: *Knowledge economy, information technologies and growth*. Routledge, pp. 335–424.

Kits, Remi Sebastian (Feb. 2, 2026). *Weightipy. A modern, high-performance RIM (iterative raking) weighting library for survey data*. Version 0.4.2. Documentation available at https://kaitumisuuringute-keskus.github.io/Weightipy/. URL: https://github.com/kaitumisuuringute-keskus/Weightipy (visited on 03/20/2026).

Korinek, Anton (2024). *Economic Consequences of Frontier AI*. NBER Working Paper No. 32980. Cambridge, MA. DOI: 10.3386/w32980. URL: https://www.nber.org/papers/w32980.

Korinek, Anton and Megan Juelfs (2022). *Preparing for the (Non-Existent?) Future of Work*. w30172. National Bureau of Economic Research. DOI: 10.3386/w30172. URL: https://www.nber.org/papers/w30172.

Korinek, Anton and Joseph E. Stiglitz (2021). *Artificial Intelligence, Globalization, and Strategies for Economic Development*. w28453. National Bureau of Economic Research. DOI: 10.3386/w28453. URL: https://www.nber.org/papers/w28453.

Lichtendahl, Kenneth C., Yael Grushka-Cockayne, and Robert L. Winkler (2013). "Is It Better to Average Probabilities or Quantiles?" In: *Management Science* 59.7, pp. 1594–1611. DOI: 10.1287/mnsc.1120.1667.

LMArena (2024). *Overview Leaderboard*. URL: https://lmarena.ai/leaderboard (visited on 11/21/2024).

McGann, James G. (Jan. 2021). *2020 Global Go To Think Tank Index Report*. Tech. rep. 18. Think Tanks and Civil Societies Program, Lauder Institute, University of Pennsylvania. URL: https://repository.upenn.edu/entities/publication/9f1730fa-da55-40bd-a1f4-1c2b2346b753.

Mellers, Barbara, Eric Stone, Pavel Atanasov, Nick Rohrbaugh, S. Emlen Metz, Lyle Ungar, Michael M. Bishop, Michael Horowitz, Ed Merkle, and Philip E. Tetlock (2015). "Identifying and Cultivating Superforecasters as a Method of Improving Probabilistic Predictions". In: *Perspectives on Psychological Science* 10.3, pp. 267–281. DOI: 10.1177/1745691615577794.

Mellers, Barbara, Lyle Ungar, Jonathan Baron, Jaime Ramos, Burcu Gurcay, Katrina Fincher, Sydney E. Scott, Don Moore, Pavel Atanasov, Samuel A. Swift, Terry Murray, Eric Stone, and Philip E. Tetlock (2014). "Psychological Strategies for Winning a Geopolitical Forecasting Tournament". In: *Psychological Science* 25.5, pp. 1106–1115. DOI: 10.1177/0956797614524255.

Murphy, Connacher, Josh Rosenberg, Jordan Canedy, Zach Jacobs, Nadja Flechner, Rhiannon Britt, Alexa Pan, Charlie Rogers-Smith, Dan Mayland, Cathy Buffington, Simas Kučinskas, Amanda Coston, Hannah Kerner, Emma Pierson, Reihaneh Rabbany, Matthew Salganik, Robert Seamans, Yu Su, Florian Tramèr, Tatsunori Hashimoto, Arvind Narayanan, Philip E. Tetlock, and Ezra Karger (2025). *The Longitudinal Expert AI Panel: Understanding Expert Views on AI Capabilities, Adoption, and Impact*. Working paper 5. Forecasting Research Institute. URL: https://forecastingresearch.org/s/the-longitudinal-expert-ai-panel.pdf (visited on 03/18/2026).

National Center for O*NET Development (Feb. 21, 2024). *European Skills, Competences, Qualifications and Occupations (ESCO) to O*NET-SOC Crosswalk*. Accessed: March 19, 2026. U.S. Department of Labor, Employment and Training Administration. URL: https://www.onetcenter.org/crosswalks.html.

OECD (2023). *OECD Employment Outlook 2023*. Report. Accessed: 2026-03-30. Organisation for Economic Co-operation and Development. URL: https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/07/oecd-employment-outlook-2023_904bcef3/08785bba-en.pdf.

— (Sept. 2025). *OECD global long-run economic scenarios: 2025 update*. Tech. rep. Accessed: March 13, 2026. URL: https://www.oecd.org/en/topics/sub-issues/economic-outlook/long-run-economic-scenarios-2025-update.html.

Office of Management & Budget (OMB) (Sept. 2025). *Mid-Session Review*. Tech. rep. Accessed: March 13, 2026. URL: https://www.whitehouse.gov/wp-content/uploads/2025/09/MSR_2026.pdf.

Ranjan, Roopesh and Tilmann Gneiting (2010). "Combining Probability Forecasts". In: *Journal of the Royal Statistical Society: Series B* 72.1, pp. 71–91.

RePEc (2025). *IDEAS*. URL: https://ideas.repec.org/ (visited on 03/07/2025).

Russakovsky, Olga, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei (2015). "ImageNet Large Scale Visual Recognition Challenge". In: *International Journal of Computer Vision* 115, pp. 211–252. DOI: 10.1007/s11263-015-0816-y.

Survey of Professional Forecasters (Nov. 2025). *Fourth Quarter 2025 Survey of Professional Forecasters*. Tech. rep. Accessed: March 13, 2026. Federal Reserve Bank of Philadelphia. URL: https://www.philadelphiafed.org/-/media/FRBP/Assets/Surveys-And-Data/survey-of-professional-forecasters/2025/spfQ425.pdf.

— (Mar. 2026). *First Quarter 2026 Survey of Professional Forecasters*. Tech. rep. Accessed: March 13, 2026. Federal Reserve Bank of Philadelphia. URL: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/spf-q1-2026.

The Conference Board (Mar. 2026). *Global Forecast Update*. Tech. rep. Accessed: March 13, 2026. URL: https://www.conference-board.org/publications/global-economic-forecast-update.

Trammell, Philip and Anton Korinek (2023). *Economic Growth under Transformative AI*. w31815. National Bureau of Economic Research. DOI: 10.3386/w31815. URL: https://www.nber.org/papers/w31815.

U.S. Bureau of Labor Statistics (Apr. 2024a). *May 2023 National Occupational Employment and Wage Estimates*. National XLSX file. Accessed: March 19, 2026. URL: https://www.bls.gov/oes/tables.htm.

— (Apr. 2024b). *May 2023 OEWS Occupation Definitions [XLSX file]*. Occupational Employment and Wage Statistics (OEWS). Accessed: March 19, 2026. URL: https://www.bls.gov/oes/2023/may/occupation_definitions_m2023.xlsx.

VandeHei, Jim and Mike Allen (May 2025). "Behind the Curtain: A white-collar bloodbath". In: *Axios*. URL: https://www.axios.com/2025/05/28/ai-jobs-white-collar-unemployment-anthropic (visited on 03/30/2026).

Appendix

Table of Contents

A. Participant Recruitment

In this section, we detail our population criteria and sampling frames.

A.1 Economists

We had three sub-populations of interest. In addition to population-specific criteria, individuals in all three had to meet the following criteria:

- **Education criterion**: must have a PhD in economics or related fields
- **Employment criterion**: must be employed as an economist in an OECD member country in either academic, industry, or government positions.
  - Job title includes "economist" OR role primarily involves economic analysis, research, or policy work
    - Example 1: an academic working at the IMF, writing papers about monetary policy
    - Example 2: an economist with a PhD working at a frontier AI model company
  - It was not necessary to reside in an OECD member country; it was sufficient to be affiliated with an organization based in one.
- **Quality criterion**: must have at least 300 (economists working on AI & economists working on growth and technology) / 1,000 (well-known economists) total citations OR be affiliated with a top-100 economics institution/department according to the IDEAS/RePEc ranking (RePEc, 2025)(ranking based on the last 10 years of publications; fetched on October 27, 2025)

A.1.1 Economists Working on AI

Population. The people in this population satisfied the following criteria:

- **Education criterion** (see above)
- **Employment criterion** (see above)
- **Quality criterion** (see above)
- **AI affiliation criterion**: must have (co-)authored at least one published article, academic working paper, or book related to the *economics of AI* (see definition below)
  - *Core definition*: A publication is related to the economics of AI if it analyzes the economic implications of artificial intelligence and machine learning systems. It should address at least one primary focus area, subject to the exclusion criteria.
    - Primary focus areas:
      - Labor markets: Employment, wages, occupational displacement, skill requirements, human-AI complementarity
      - Productivity and growth: AI's contribution to productivity, economic growth, or production functions
      - Firm behavior: AI adoption decisions, returns to AI investment, market competition and concentration
      - Innovation: AI as a tool for innovation, R&D productivity, technological diffusion
      - Inequality: Distributional effects on income, wealth, or labor share
      - Economic policy: Regulation, taxation, labor market policies, competition policy
      - Economic measurement: Measuring AI's impact, valuing AI assets, accounting for AI in national statistics
    - Exclusion Criteria: exclude publications that:
      - Use AI/ML purely as a methodological tool without studying AI itself
      - Focus solely on technical capabilities without economic analysis
      - Address only ethical/legal aspects without economic content
      - Study general technological change without AI-specific analysis
      - Have no explicit link to AI
    - Include Boundary Cases:
      - Automation papers that explicitly discuss AI/ML
      - Historical studies of automation that explicitly connect to AI
      - Economic analysis of AI deployment in specific domains (e.g., algorithmic pricing, credit scoring, hiring algorithms)

Sampling frame. Target sample size: 50.

The sampling frame consisted of three pools: the event, literature, and institution sampling pools. These are described below.

Literature sampling pool.

1. We searched for papers/articles in the field of economics with a JEL code O33 ("Technological Change: Choices and Consequences; Diffusion Processes") and with either "AI" or "artificial intelligence" in the title, keywords, or abstract. We used IDEAS/RePEc for this search and found citation counts on CitEc.

2. We calculated age-adjusted citation counts by dividing the number of citations by the age of the publication.

3. We summed adjusted citation counts by author.

4. Starting from the highest adjusted citation counts, we invited the top-10 and then everyone, skipping every third one (these people were invited to another project sharing the same sampling pool), going down to rank 300.

   (a) For the bottom 50%, we performed a filtering round using an AI-based system* (see note at the end of the section).

Event sampling pool. This pool consisted of the speakers and some participants in events discussing the economics of AI. The basic requirements for the events were as follows:

- Events must have taken place in the U.S. (or online) between the beginning of 2022 and May 2025.
- The event name contains at least one primary keyword and one secondary keyword.
  - Primary keywords: AI, artificial intelligence, automation
  - Secondary keywords: economics (of), economic implications (of), policy implications (of), labor market, work, productivity, growth, technological change, inequality
- The events were manually checked to ensure relevance.

The events were sampled from the five categories described below.

We first invited a random 50% of the people in this pool. We later invited the remaining 50% after using an AI-based system* (see note at the end of the section) to filter the pool to the people who met our population criteria. Before deduplication, this pool consisted of 481 people.

Major academic conferences. These are general economics conferences. We found speakers from sessions within these conferences that fulfilled the event criteria. We used the EconBiz search, filtered to JEL code A1 ("general economics") and event type "conferences". This search included 39 results.

Events organized by policy/research institutions. These were events organized by the policy/research institutions listed in the 2020 Global Go To Think Tank Index Report McGann (2021). We included all speakers and **invited** participants (where available). We took the union of the top-10 think tanks on the "2020 Top International Economics Policy Think Tanks" and "2020 Top Domestic Economic Policy Think Tanks", filtering down to U.S.-based institutions. This resulted in 7 institutions:

- Brookings
- National Bureau of Economic Research (NBER)
- Peterson Institute for International Economics (PIIE)
- Heritage Foundation
- Center for American Progress (CAP)
- Cato Institute
- RAND Corporation

Events organized by public institutions. These were events organized by individual Federal Reserve banks. We included all speakers and **invited** participants (where available).

Events organized by major AI companies. These were events organized by the top-5 AI companies by Epoch Training Compute ranking (see Model Sampling Pool in Appendix A.2). The five companies included:

- xAI (no organized events as of May 2025)
- Google DeepMind (no organized events)
- OpenAI (OpenAI Forum)
- Meta AI (no organized events)
- Anthropic (no organized events)

Institution sampling pool.

1. We found the top-100 economics institutions/departments (using the same ranking used in the quality criterion).
2. We identified the people associated with each institution/department. If there were more than 100 individuals working at the institution, we chose the first/random 100.
3. We filtered the pool using an AI-based system* (see note at the end of the section) to the people who met all of the population criteria.

Before deduplication, this pool consisted of 636 people. We invited all of them.

A.1.2 Economists Working on Growth and Technology

Population. The people in this population satisfied the following criteria:

- **Education criterion** (see above)
- **Employment criterion** (see above)

- **Quality criterion** (see above)
- **Field criterion**: must have (co-)authored at least one published article, academic working paper, or book related to economic growth or technological change (Journal of Economic Literature codes O3 and O4)

Sampling frame. Target sample size: 50.

The sampling frame consisted of two pools: the literature and institution sampling pools. These are described below.

Literature sampling pool.

1. We searched for papers/articles in the field of economics with JEL codes: O32 (Management of Technological Innovation and R&D), O33 (Technological Change: Choices and Consequences; Diffusion Processes), and O4 (Economic Growth and Aggregate Productivity). We used IDEAS/RePEc for this search and found citation counts on CitEc.
2. We calculated age-adjusted citation counts by dividing the number of citations by the age of the publication.
3. We summed adjusted citation counts by author.
4. We invited the top-500 highest-ranked individuals.
   (a) For the bottom 50%, we performed a filtering round using an AI-based system* (see at the end of the section).

Institution sampling pool. The same as the "Economists working on AI" institution sampling pool, except filtered to the people who met the criteria of this population. Before deduplication, this pool consisted of 2203 individuals. However, we only invited a random subset of 1,000 individuals to participate.

A.1.3 Well-Known Economists

Population. This group consisted of well-known, influential economists. A person in this group satisfied at least one of the following criteria:

- Nobel Prize in economics
- In the top 1,000 authors in the RePEc database for publications in the last ten years (link)
- Leadership role in a government or quasi-governmental agency with an economics focus (Federal Reserve, U.S. Treasury, etc.)
- A respondent in the U.S. Economic Experts Panel

Sampling frame. Target sample size: 50.

All people from all pools were invited.

Nobel Prize sampling pool. All winners of the Nobel Prize in economics.

U.S. Economic Experts Panel sampling pool. All panelists (both active and alumni) in the Clark Center U.S. Economic Experts Panel.

RePEc top authors sampling pool. The first 200 individuals from the RePEc ranking (linked above), after filtering to individuals who were affiliated with US-based institutions.

A.2 AI Industry Professionals

Population. This population consisted of individuals satisfying the following criterion:

- **Employment criterion**: must have been working (in 2025 or 2026) in industry, either developing frontier AI models or creating tools that apply them. Only U.S.-based companies and companies with a significant presence in the U.S. were included.

Sampling frame. Target sample size: 50.

The sampling consisted of two pools: the language model pool (by amount of training compute and benchmark performance) and the fundraising sampling pool.

Language model pool. This pool targeted people who develop LLMs at the top AI companies.

1. We determined the top AI companies by looking at two sources:
   (a) Epoch AI's data on notable AI models (Epoch AI, 2024).
      i. We sorted models by training compute (floating point operations [FLOP]).
      ii. We recorded the top-15 leading, non-academic US-based institutions and, where available, authors.
   (b) Chatbot Arena LLM Leaderboard data (LMArena, 2024).
      i. We filtered to the "Hard Prompts (Overall)" category.
      ii. We sorted models by their leaderboard rating.
      iii. We recorded the top-15 non-academic US-based primary institutions.
2. We determined the number of people to sample from each company according to the two rankings. Note that we were not able to find enough contacts from all companies to fill the quotas described below.
   (a) In the initial round of invitations, we sampled 10 individuals from companies ranked 1–5 (per ranking) and 6 individuals from companies ranked 6–15 (per ranking). In other words, we sampled between 6 and 20 individuals per company.

(b) In an additional round of invitations, we sampled 25 individuals from companies ranked 1–5 (per ranking) and 6 individuals from companies ranked 6–16 (per ranking). In other words, we sampled between 6 and 50 individuals per company.

   i. Due to clerical errors, we sampled too many individuals from some companies. The largest discrepancy was sampling 65 instead of 50 individuals.

3. If we did not identify enough individuals in step 1, we found AI-related engineering and research and development staff from author lists in model-related papers, contributors listed in model cards, LinkedIn, and Crunchbase (2025).

4. Individuals were sampled randomly within each company according to the quotas determined in step 2.

Before deduplication, we invited 454 individuals through this pool.

Fundraising sampling pool. This pool targeted individuals working at AI-related startups and companies.

1. We used Crunchbase (Crunchbase, 2025) to identify AI-related startups.

   (a) We selected all private AI-related companies that had raised $500 million or more in *total* funding, with the most recent fundraising date within 2 years.

   (b) We included the first 30 companies by *total* fundraising.

   (c) We filtered out companies not based in the US or not having a significant presence in the US.

2. We sampled AI-related engineering and research and development staff from the companies with contact information from Crunchbase. Note that we were not able to find enough contacts from all companies to fill the quotas described below.

   (a) In the initial round of invitations, we sampled 50 individuals from each company.

   (b) In an additional round of invitations, we sampled 75 individuals from each company.

3. Individuals were sampled randomly within each company.

Before deduplication, we invited 1,755 individuals through this pool.

A.3 AI Policy Professionals

Population. This group consisted of individuals satisfying the following criteria:

- **Employment criterion**: Must have been a researcher in a think tank or other similar organization. Only U.S.-based organizations were included.

- **Field criterion**: Must have done work related to AI policy.

Sampling frame. Target sample size: 50.

The sampling consisted of the think tank sampling pool.

Think tank sampling pool.

1. We identified relevant think tanks.
   (a) We took the union of "AI policy think tanks" from the Horizon Institute of Public Service and the "2020 Best AI Policy and Strategy Think Tanks" from the 2020 Global Go To Think Tank Index Report (Table 56).
   (b) For general-purpose think tanks, we limited our search to AI-specific initiatives, e.g., the Artificial Intelligence and Emerging Technology Initiative at Brookings. Or, we filtered based on reported staff expertise, if available on the website.
   (c) Each AI-related initiative within a think tank was treated as a separate think tank.
   (d) This resulted in 53 (initiatives within) think tanks.
2. We scraped research staff from staff pages. Where a staff page was not available, we used LinkedIn.
3. We sampled staff members randomly from each think tank.
   (a) Initially, we sampled 10 individuals from each think tank.
   (b) In a second round of invitations, if the response rate from a think tank was less than 10% (inclusive), we sampled additional people until the total number of invitations was 15, or until contacts were exhausted.

Before deduplication, we invited 594 individuals through this pool.

A.4 Superforecasters

Population. This group included people with a track record of high accuracy in past forecasting tournaments.

Sampling frame. Target sample size: 50.
We used our connections from prior work to reach out to superforecasters.

A.5 The General Public

Population. The general public consisted of all Americans.

Sampling frame. Target sample size: 500.
We recruited our sample from CloudResearch Connect (Hartman et al., 2023).

Sample Demographics

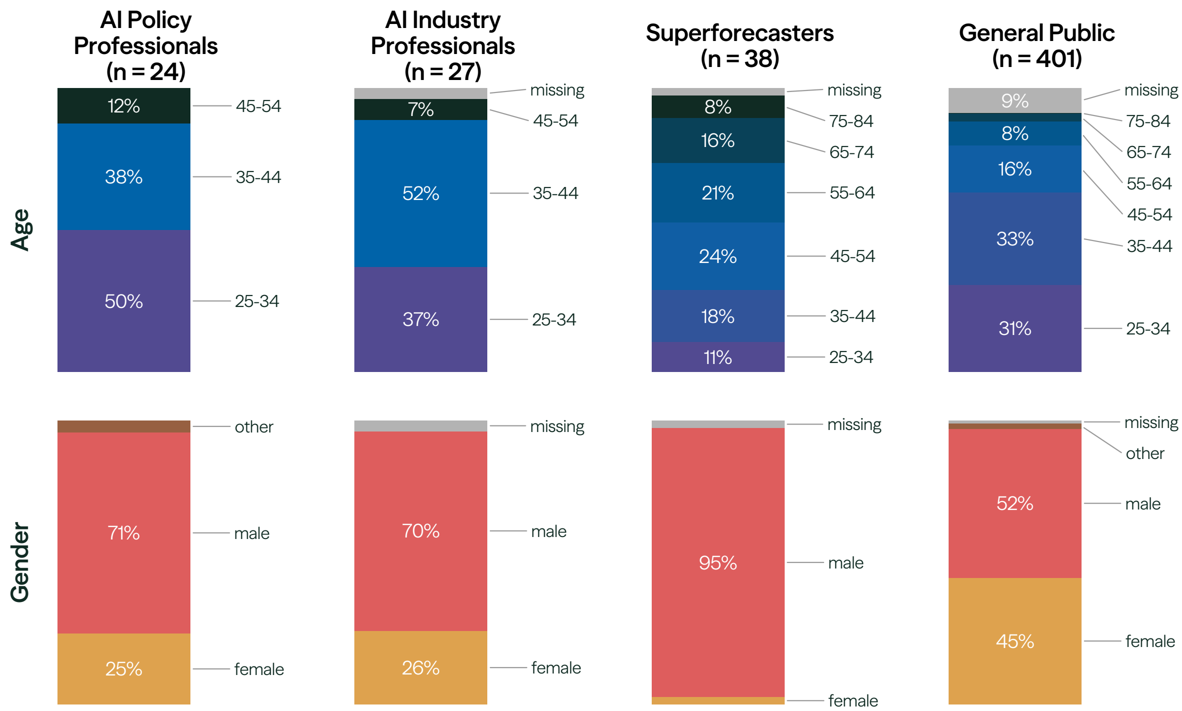


Figure 18: *The age and gender distributions of non-economist populations.*

On the Use of AI-Based Filtering

We used AI-based filtering to ensure a high-quality sample. The system consisted of an AI agent with access to a web search tool. It used publicly available information to determine whether the people we sampled met all of our population criteria. We used two different iterations of the same filtering system. The first iteration was employed prior to sending invitations. This iteration had technical limitations. We used an older model and a suboptimal scaffolding for this iteration, which meant that, while we performed manual spot checks, the system might not have captured exactly the people who met the criteria.

After the survey data collection was complete, we used an improved system to determine the final population assignments and exclusions. We also used human-collected data for this round of filtering.

B. Total Variance Decomposition

B.1 Illustrating the decomposition

To lend more insight to our decomposition results, we consider an illustrative example. Say two forecasters submit 2030 GDP growth forecasts in the form of conditional, normal distributions, given in Table 3.[21]

Table 3: Example forecasts for decomposition

Forecaster	**Scenario**	**Mean**	**Std. Dev.**	**Probability**
A	Rapid	8.0%	0.9%	40%
	Slow/moderate	2.0%	0.6%	60%
B	Rapid	6.0%	0.9%	10%
	Slow/moderate	2.4%	0.6%	90%

In this example, the scenarios are an important driver of total variance. Much of the disagreement in unconditional values owes to the fact that forecaster A and B disagree about the ultimate probability of the rapid scenario (40% vs 10%). Figure 19 demonstrates this feature: while we see a large difference in the unconditional distributions for forecaster A (panel A) and forecaster B (panel B), the conditional distributions are comparatively similar. Forecaster A's unconditional distribution is a more balanced mixture of the two conditional distributions since they give the rapid scenario a probability of 40%. In contrast, forecaster B's unconditional distribution is dominated by their slow/moderate conditional distribution, since they give the rapid scenario a probability of just 10%.

[21] In the analysis below, we fit normal distributions to the rapid and unconditional scenario forecasts, and we then obtain the mean and variance of the bundled slow/moderate scenario by assuming consistency. The implied distribution for the slow/moderate scenario is not necessarily normal.

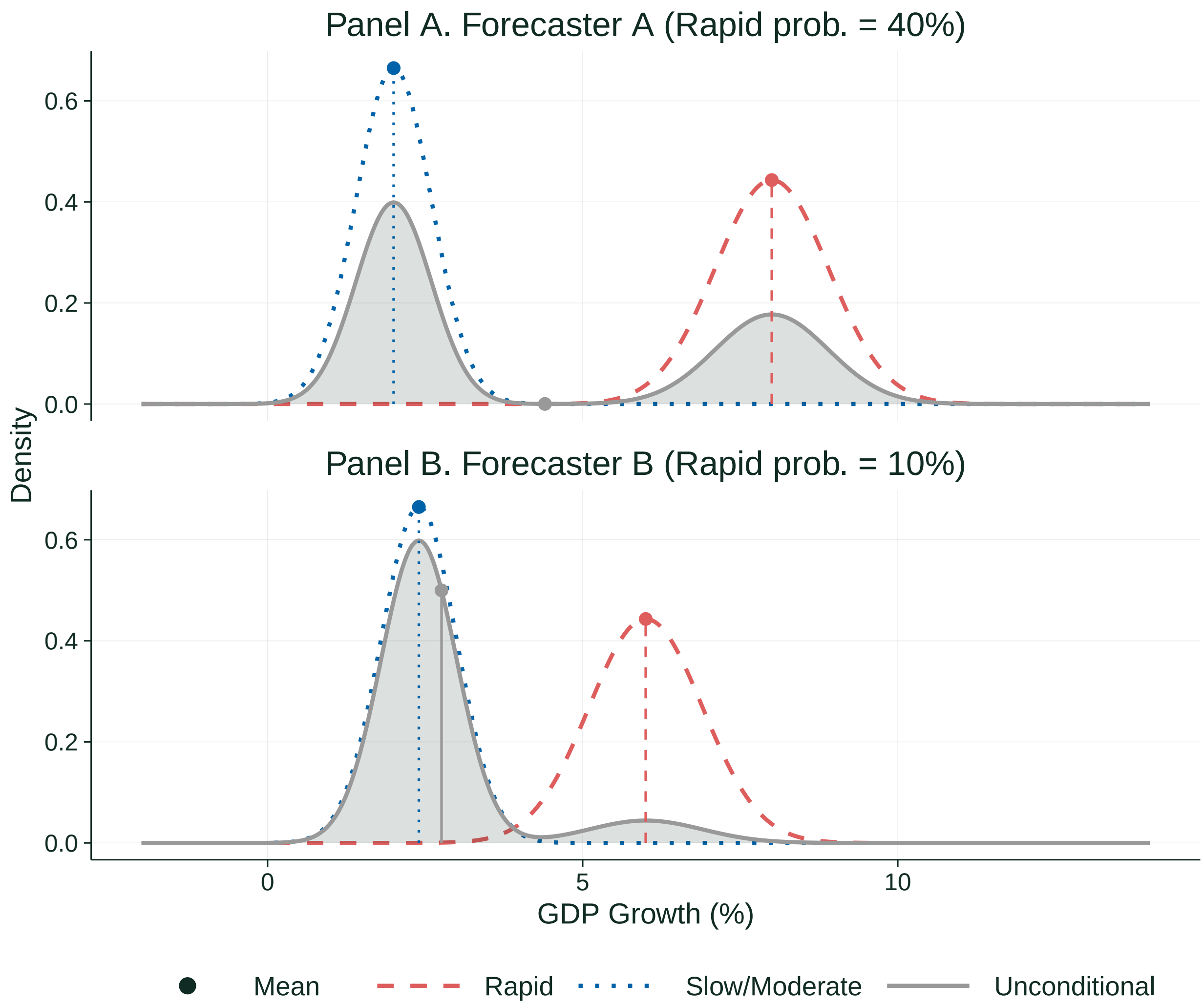


Figure 19: *Example Decomposition, Forecaster-Level Conditional and Unconditional Distributions*

Indeed, we find this balance in the first stage of the decomposition: between-scenario variance accounts for 89% of total variance, while within-scenario variance contributes just 11% of the total variance. We illustrate this first stage of the decomposition in Figure 20. Both conditional distributions depart noticeably from the unconditional mean. In the next stage of the decomposition, detailed in Figure 21, we see less extreme differences between the forecaster-level distributions and the pooled means. While the rapid scenario exhibits a larger gap, its contribution is downweighted by the 25% aggregate probability assigned to the scenario.

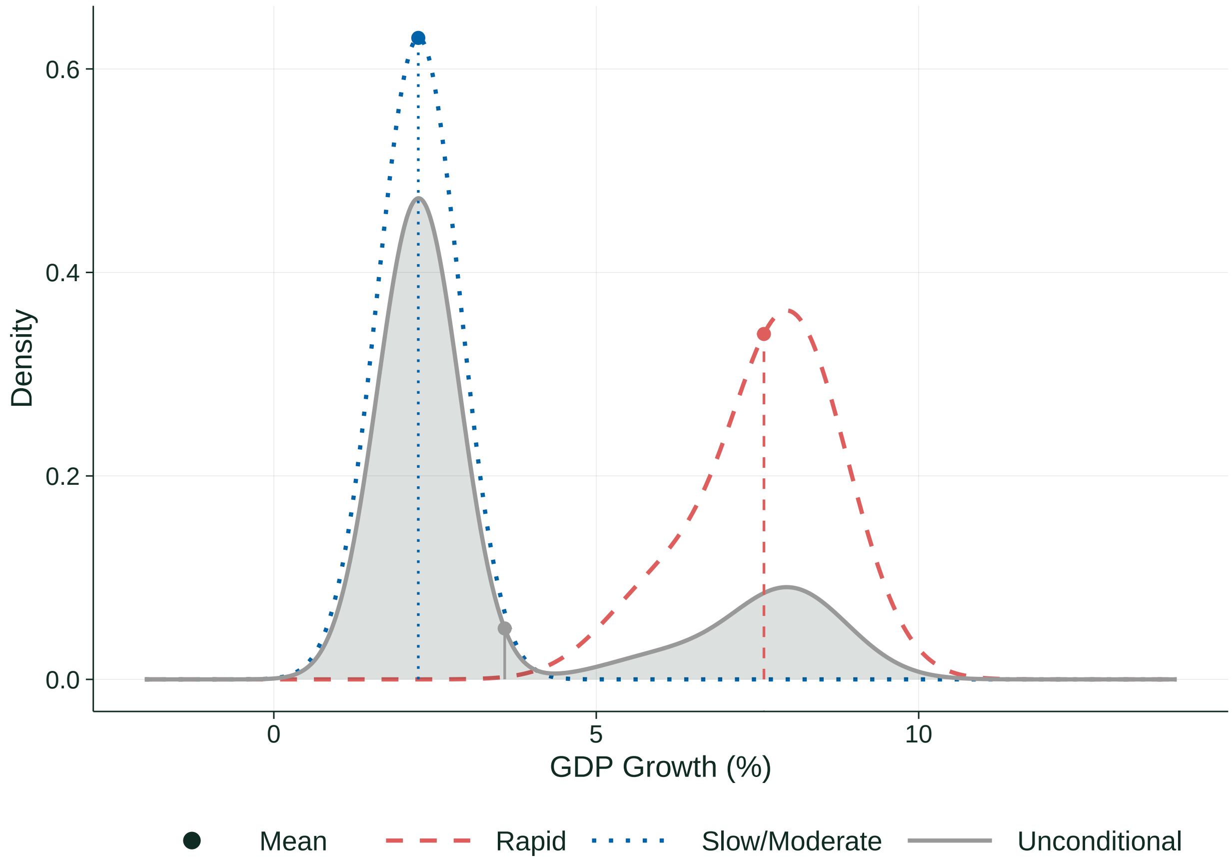


Figure 20: *Example Decomposition, Conditional and Unconditional Distributions*

In both the within- and between-scenario branches of the decomposition, within-forecaster variance dominates between-forecaster variance: 7.8% compared to 3.1% for within-scenario variance, and 78% versus 11% for between-scenario variance. Especially in the slow/moderate bundled scenario, which again makes a larger contribution to the total, the forecasted distributions overlap substantially.

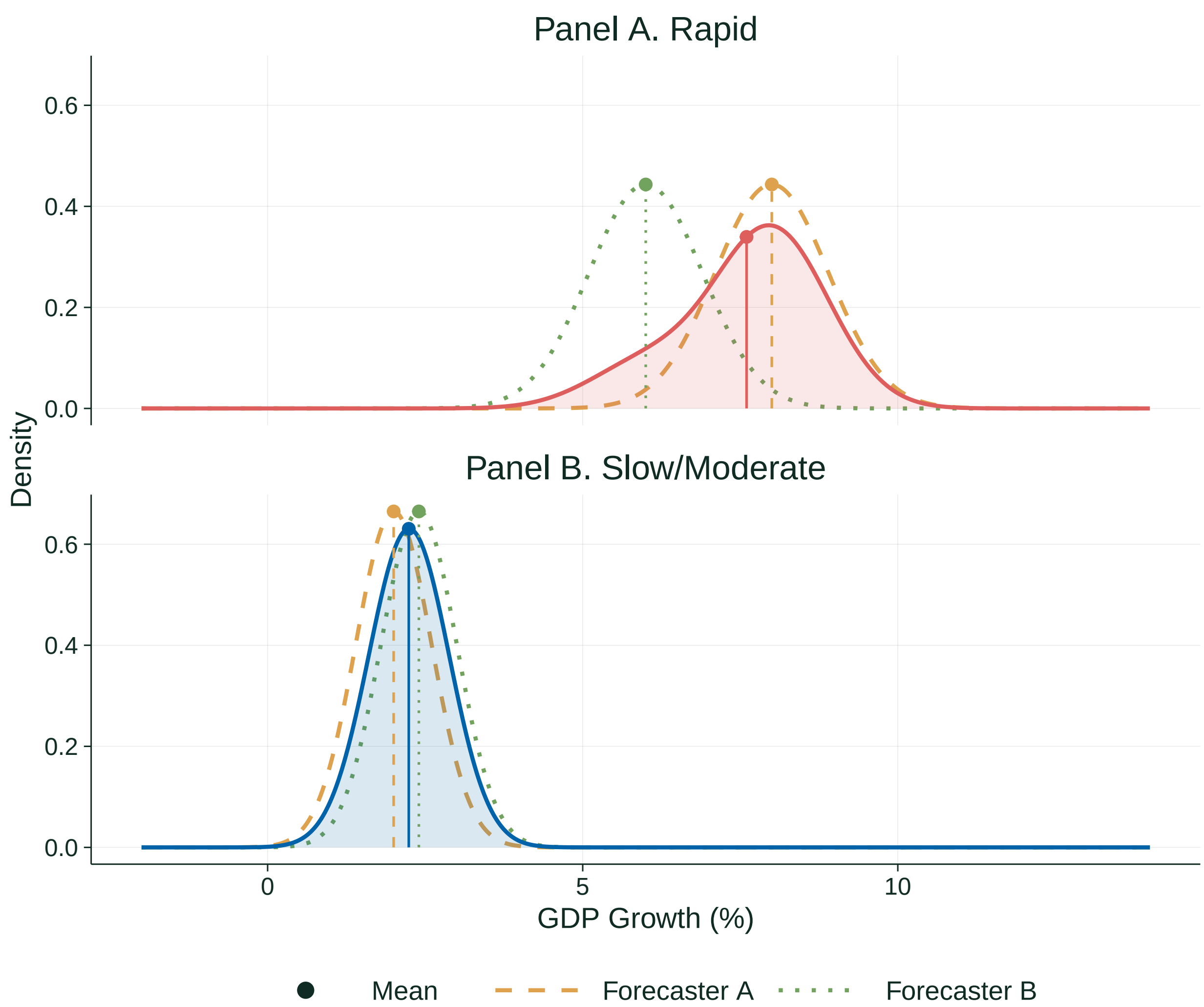


Figure 21: *Example Decomposition, Forecaster-Level Conditional Distributions*

B.2 Decomposition Derivation

We now describe the law of total variance (LTV) decomposition introduced in Section 4. I denotes the randomly selected forecaster, and R denotes a Bernoulli-distributed random variable, equal to 1 in the rapid scenario and 0 in the bundled slow/moderate scenario. Additionally, we use shorthand for the variance components: "WS" denotes within scenario, "WF" within forecaster, "BS" between scenario, "R" rapid scenario, and "SM" slow/moderate bundled scenario. We first decompose the unconditional variance of Y into within-scenario and between-scenario components using a nested LTV decomposition:

$$\mathbb{V}[Y] = \underbrace{\mathbb{E}[\mathbb{V}[Y \mid R, I]]}_{\text{WS, WF}} + \underbrace{\mathbb{E}[\mathbb{V}(\mathbb{E}[Y \mid R, I] \mid R)]}_{\text{WS, BF}} + \underbrace{\mathbb{V}[\mathbb{E}[Y \mid R]]}_{\text{BS}}. \tag{1}$$

We then further decompose into between-forecaster and within-forecaster components using the LTV on the between-scenario term, $\mathbb{V}[\mathbb{E}[Y \mid R]]$:

$$\underbrace{\mathbb{V}[\mathbb{E}[Y \mid R]]}_{\text{BS}} = \underbrace{\mathbb{E}[\mathbb{V}[\mathbb{E}[Y \mid R] \mid I]]}_{\text{BS, WF}} + \underbrace{\mathbb{V}[\mathbb{E}[\mathbb{E}[Y \mid R] \mid I]]}_{\text{BS, BF}}. \tag{2}$$

We then combine to obtain the full decomposition:

$$\mathbb{V}[Y] = \underbrace{\mathbb{E}[\mathbb{V}[Y \mid R, I]]}_{\text{WS, WF}} + \underbrace{\mathbb{E}[\mathbb{V}(\mathbb{E}[Y \mid R, I] \mid S)]}_{\text{WS, BF}} + \underbrace{\mathbb{E}[\mathbb{V}[\mathbb{E}[Y \mid R] \mid I]]}_{\text{BS, WF}} + \underbrace{\mathbb{V}[\mathbb{E}[\mathbb{E}[Y \mid R] \mid I]]}_{\text{BS, BF}}. \tag{3}$$

We can decompose the within-scenario components into contributions from the rapid and bundled slow/moderate scenarios:

$$\begin{aligned} \underbrace{\mathbb{E}[\mathbb{V}[Y \mid R, I]]}_{\text{WS, WF}} &= \underbrace{\mathbb{P}\{R = 1\}\, \mathbb{E}[\mathbb{V}[Y \mid R = 1, I]]}_{\text{Rapid}} \\ &\quad + \underbrace{\mathbb{P}\{R = 0\}\, \mathbb{E}[\mathbb{V}[Y \mid R = 0, I]]}_{\text{Slow/Moderate}} \end{aligned} \tag{4}$$

and

$$\begin{aligned} \underbrace{\mathbb{E}[\mathbb{V}(\mathbb{E}[Y \mid S, I] \mid S)]}_{\text{WS, BF}} &= \underbrace{\mathbb{P}\{R = 1\}\, \mathbb{V}(\mathbb{E}[Y \mid R = 1, I] \mid R = 1)}_{\text{Rapid}} \\ &\quad + \underbrace{\mathbb{P}\{R = 0\}\, \mathbb{V}(\mathbb{E}[Y \mid R = 0, I] \mid R = 0)}_{\text{Slow/Moderate}}. \end{aligned} \tag{5}$$

B.3 Decomposition Results

Table 4: Variance Decomposition: AI Experts

Outcome	Year	Total Std. Dev.	WS	BS	WS-WF	WS-BF	BS-WF	BS-BF
GDP	2030	1.505	0.940	0.060	0.797	0.143	0.055	0.005
GDP	2050	2.286	0.963	0.037	0.651	0.311	0.033	0.004
LFPR	2030	3.946	0.985	0.015	0.830	0.155	0.013	0.002
LFPR	2050	6.866	0.957	0.043	0.340	0.617	0.036	0.007
Median HH Income	2030	9,645	0.995	0.005	0.871	0.124	0.004	0.001
Median HH Income	2050	18,880	0.998	0.002	0.667	0.331	0.002	0.000
Unemployment Rate	2030	2.894	0.968	0.032	0.827	0.140	0.027	0.005
Unemployment Rate	2050	3.622	0.996	0.004	0.691	0.305	0.003	0.001
Wealth Inequality	2030	4.450	0.951	0.049	0.790	0.161	0.043	0.005
Wealth Inequality	2050	6.509	0.977	0.023	0.796	0.181	0.020	0.003

Note: W = within, B = between, S = scenario, F = forecaster. GDP = Gross Domestic Product, LFPR = Labor Force Participation Rate, HH = household.

Table 5: Variance Decomposition: All Experts (Economists & AI Experts)

Outcome	Year	Total Std. Dev.	WS	BS	WS-WF	WS-BF	BS-WF	BS-BF
GDP	2030	1.499	0.946	0.054	0.791	0.155	0.051	0.004
GDP	2050	2.243	0.954	0.046	0.691	0.263	0.042	0.003
LFPR	2030	3.965	0.977	0.023	0.840	0.137	0.021	0.002
LFPR	2050	6.849	0.962	0.038	0.447	0.515	0.034	0.004
Median HH Income	2030	10,136	0.997	0.003	0.903	0.094	0.003	0.000
Median HH Income	2050	17,601	0.999	0.001	0.671	0.328	0.001	0.000
Unemployment Rate	2030	2.686	0.965	0.035	0.818	0.147	0.031	0.004
Unemployment Rate	2050	3.363	0.993	0.007	0.715	0.278	0.007	0.001
Wealth Inequality	2030	4.142	0.948	0.052	0.789	0.159	0.047	0.005
Wealth Inequality	2050	6.457	0.979	0.021	0.792	0.187	0.019	0.002

Note: W = within, B = between, S = scenario, F = forecaster. GDP = Gross Domestic Product, LFPR = Labor Force Participation Rate, HH = household.

Table 6: Variance Decomposition: Superforecasters

Outcome	Year	Total Std. Dev.	WS	BS	WS-WF	WS-BF	BS-WF	BS-BF
GDP	2030	1.249	0.939	0.061	0.831	0.108	0.056	0.005
GDP	2050	2.098	0.966	0.034	0.783	0.182	0.031	0.003
LFPR	2030	3.449	0.964	0.036	0.810	0.154	0.033	0.003
LFPR	2050	4.899	0.973	0.027	0.718	0.254	0.025	0.002
Median HH Income	2030	8,036	0.999	0.001	0.868	0.130	0.001	0.000
Median HH Income	2050	16,027	0.978	0.022	0.716	0.262	0.020	0.002
Unemployment Rate	2030	2.290	0.984	0.016	0.861	0.122	0.015	0.001
Unemployment Rate	2050	2.934	0.998	0.002	0.881	0.117	0.002	0.000
Wealth Inequality	2030	3.622	0.971	0.029	0.787	0.185	0.026	0.002
Wealth Inequality	2050	6.340	0.992	0.008	0.703	0.289	0.007	0.001

Note: W = within, B = between, S = scenario, F = forecaster. GDP = Gross Domestic Product, LFPR = Labor Force Participation Rate, HH = household.

Table 7: Variance Decomposition: General Public

Outcome	Year	Total Std. Dev.	WS	BS	WS-WF	WS-BF	BS-WF	BS-BF
GDP	2030	1.675	0.930	0.070	0.755	0.175	0.063	0.008
GDP	2050	2.287	0.957	0.043	0.664	0.292	0.040	0.003
LFPR	2030	3.082	0.989	0.011	0.767	0.223	0.009	0.001
LFPR	2050	5.429	0.987	0.013	0.578	0.409	0.011	0.002
Median HH Income	2030	9,377	0.984	0.016	0.848	0.136	0.014	0.002
Median HH Income	2050	17,059	0.988	0.012	0.576	0.412	0.010	0.001
Unemployment Rate	2030	2.362	0.972	0.028	0.825	0.148	0.025	0.003
Unemployment Rate	2050	3.083	0.959	0.041	0.657	0.302	0.036	0.005
Wealth Inequality	2030	4.585	0.956	0.044	0.791	0.165	0.039	0.004
Wealth Inequality	2050	5.975	0.946	0.054	0.722	0.224	0.050	0.004

Note: W = within, B = between, S = scenario, F = forecaster. GDP = Gross Domestic Product, LFPR = Labor Force Participation Rate, HH = household.

Table 8: Proportion of Forecaster-Year Pairs Dropped

Outcome	Year	Group	Proportion Dropped
Gross Domestic Product (GDP)	2030	AI Experts	0.222
		Economists	0.070
		General Public	0.379
		Superforecasters	0.174
	2050	AI Experts	0.125
		Economists	0.156
		General Public	0.405
		Superforecasters	0.087
Labor Force Participation Rate	2030	AI Experts	0.176
		Economists	0.103
		General Public	0.271
		Superforecasters	0.143
	2050	AI Experts	0.242
		Economists	0.081
		General Public	0.418
		Superforecasters	0.048
Median Household Income	2030	AI Experts	0.097
		Economists	0.156
		General Public	0.221
		Superforecasters	0.174
	2050	AI Experts	0.258
		Economists	0.146
		General Public	0.231
		Superforecasters	0.000
Unemployment Rate	2030	AI Experts	0.185
		Economists	0.095
		General Public	0.333
		Superforecasters	0.174
	2050	AI Experts	0.300
		Economists	0.057
		General Public	0.307
		Superforecasters	0.053
Wealth Inequality	2030	AI Experts	0.133
		Economists	0.075
		General Public	0.302
		Superforecasters	0.125
	2050	AI Experts	0.208
		Economists	0.114
		General Public	0.231

Table 8: Proportion of Forecaster-Year Pairs Dropped *(continued)*

Outcome	Year	Group	Proportion Dropped
		Superforecasters	0.048

Table 9: Variance Decomposition: Scenario Detail by Outcome, Year, and Group

Outcome	Year	Group	Within Scenario Within Forecaster Rapid	Within Scenario Within Forecaster Slow/Mod.	Within Scenario Between Forecaster Rapid	Within Scenario Between Forecaster Slow/Mod.
Gross Domestic Product (GDP)	2030	AI Experts	0.124	0.673	0.030	0.113
		All Experts	0.149	0.642	0.046	0.109
		Economists	0.166	0.621	0.056	0.105
		General Public	0.170	0.585	0.052	0.122
		Superforecasters	0.150	0.682	0.023	0.085
	2050	AI Experts	0.072	0.580	0.067	0.244
		All Experts	0.085	0.606	0.068	0.195
		Economists	0.100	0.653	0.070	0.124
		General Public	0.115	0.549	0.068	0.224
		Superforecasters	0.130	0.654	0.063	0.119
Labor Force Participation Rate	2030	AI Experts	0.128	0.702	0.070	0.086
		All Experts	0.105	0.734	0.067	0.070
		Economists	0.084	0.768	0.062	0.054
		General Public	0.150	0.617	0.112	0.111
		Superforecasters	0.123	0.688	0.055	0.099
	2050	AI Experts	0.061	0.279	0.102	0.516
		All Experts	0.080	0.367	0.088	0.427
		Economists	0.101	0.466	0.074	0.322
		General Public	0.115	0.463	0.124	0.284
		Superforecasters	0.120	0.598	0.078	0.176
Median Household Income	2030	AI Experts	0.190	0.681	0.034	0.091
		All Experts	0.133	0.770	0.026	0.068
		Economists	0.089	0.839	0.020	0.050
		General Public	0.213	0.635	0.051	0.085
		Superforecasters	0.133	0.735	0.025	0.105
	2050	AI Experts	0.149	0.518	0.091	0.239
		All Experts	0.119	0.552	0.096	0.232
		Economists	0.083	0.595	0.103	0.218
		General Public	0.151	0.425	0.119	0.293
		Superforecasters	0.108	0.608	0.046	0.217
Unemployment Rate	2030	AI Experts	0.175	0.652	0.048	0.092
		All Experts	0.160	0.658	0.043	0.104
		Economists	0.147	0.664	0.037	0.115
		General Public	0.180	0.644	0.047	0.101
		Superforecasters	0.167	0.695	0.048	0.074
	2050	AI Experts	0.117	0.574	0.060	0.245
		All Experts	0.111	0.603	0.051	0.227
		Economists	0.108	0.629	0.046	0.207
		General Public	0.193	0.464	0.131	0.172
		Superforecasters	0.093	0.788	0.053	0.064
Wealth Inequality	2030	AI Experts	0.187	0.603	0.057	0.104
		All Experts	0.176	0.613	0.051	0.108
		Economists	0.161	0.640	0.040	0.098
		General Public	0.141	0.650	0.047	0.118
		Superforecasters	0.111	0.676	0.045	0.139
	2050	AI Experts	0.170	0.625	0.066	0.115
		All Experts	0.137	0.656	0.055	0.132
		Economists	0.116	0.674	0.048	0.143
		General Public	0.187	0.535	0.091	0.133
		Superforecasters	0.131	0.572	0.048	0.241

Table 10: Forecast Standard Deviations by Outcome, Year, and Group

Outcome	Year	Group	Std. Dev.	Std. Dev. (Rapid)	Std. Dev. (Slow/Mod.)
Gross Domestic Product (GDP)	2030	AI Experts	1.505	1.899	1.404
		All Experts	1.499	1.953	1.380
		Economists	1.494	1.977	1.363
		General Public	1.675	1.980	1.537
		Superforecasters	1.249	1.574	1.158
	2050	AI Experts	2.286	2.477	2.209
		All Experts	2.243	2.632	2.129
		Economists	2.166	2.736	2.021
		General Public	2.287	2.630	2.167
		Superforecasters	2.098	2.683	1.964
Labor Force Participation Rate	2030	AI Experts	3.946	5.094	3.730
		All Experts	3.965	4.807	3.785
		Economists	3.978	4.455	3.836
		General Public	3.082	3.769	2.895
		Superforecasters	3.449	4.731	3.214
	2050	AI Experts	6.866	7.650	6.565
		All Experts	6.849	7.955	6.522
		Economists	6.731	8.188	6.364
		General Public	5.429	7.250	5.045
		Superforecasters	4.899	6.309	4.595
Median Household Income	2030	AI Experts	9,645	12,379	9,115
		All Experts	10,136	11,672	9,892
		Economists	10,568	10,747	10,538
		General Public	9,377	11,673	8,737
		Superforecasters	8,036	9,900	7,783
	2050	AI Experts	18,880	24,092	17,799
		All Experts	17,601	22,993	16,670
		Economists	16,327	21,543	15,584
		General Public	17,059	22,291	15,756
		Superforecasters	16,027	18,072	15,519
Unemployment Rate	2030	AI Experts	2.894	3.757	2.681
		All Experts	2.686	3.339	2.517
		Economists	2.534	3.013	2.398
		General Public	2.362	2.802	2.227
		Superforecasters	2.290	3.383	2.115
	2050	AI Experts	3.622	4.246	3.512
		All Experts	3.363	3.972	3.260
		Economists	3.192	3.772	3.094
		General Public	3.083	4.284	2.694
		Superforecasters	2.934	3.289	2.880
Wealth Inequality	2030	AI Experts	4.450	5.876	4.037
		All Experts	4.142	5.479	3.771
		Economists	3.726	4.861	3.409
		General Public	4.585	5.232	4.345
		Superforecasters	3.622	4.682	3.435
	2050	AI Experts	6.509	8.228	6.067
		All Experts	6.457	7.865	6.142
		Economists	6.424	7.577	6.182
		General Public	5.975	7.767	5.341
		Superforecasters	6.340	7.909	6.078

C. Comparison with the Longitudinal Expert AI Panel (LEAP)

The Longitudinal Expert AI Panel (LEAP; Murphy et al., 2025) is an ongoing panel survey of AI experts, composed of computer scientists, economists, AI industry professionals, and AI policy researchers. The project distributes monthly surveys to this expert sample, alongside panels of superforecasters and members of the general public. The researchers distributed an abridged version of this paper's survey in the February 2026 wave of LEAP. The survey included scenario forecasts, as well as forecasts for GDP growth, LFPR, and wealth inequality.

The initial LEAP sample consisted of 68 top AI economists, 54 (79%) of whom are professors; 30 (44%) are from top-50 economics institutions RePEc (2025). These economist respondents have a median of 2,200 citations. Additionally, 76 industry experts completed the first three waves of LEAP. Twenty (26%) of these respondents work for one of five leading AI companies: OpenAI, Anthropic, Google DeepMind, Meta, and Nvidia. Twenty-one of the remaining industry respondents (28% of the total) work for either a top AI company (top-20 model providers, by training compute, as measured by Epoch AI (2024)), were identified as contributors to top-15 LLMs according to training compute or performance on Chatbot Arena in our sampling procedure (Epoch AI (2025); LMArena (2024)), or work for one of the top 30 AI-related companies, as measured by total funds raised (Crunchbase (2025)). The remaining respondents were drawn from literature-based sampling pools, referral sampling, or other categories in the sampling procedure. The industry respondents have a median of 9,100 citations. Murphy et al. (2025) detail the sampling procedure and provide more statistics on the sample composition. The statistics above reflect respondents to the first three surveys and do not account for attrition between those surveys and the February 2026 wave of LEAP. The sampling procedure for LEAP yielded a different composition of expert respondents: while 23% of the expert sample used for comparison below are economists, 57% of our expert respondents are economists.

In Table 11 and Figure 22 below, we compare scenario forecasts between our sample and LEAP. While the general public placed similar weight on the rapid scenario in both surveys, experts in LEAP assigned higher probabilities to the rapid scenario. For example, the median economist in LEAP assigned a probability of 20% to the rapid scenario, compared to 10% in our sample. Superforecasters in LEAP also gave a higher probability to the rapid scenario, but the difference in medians is less stark. While these differences could plausibly owe to differences in the sample composition, differences in timing could also play a role. While the LEAP survey ran from February 9$^{\text{th}}$ to March 2$^{\text{nd}}$, our survey ran from the beginning of October 2025 to the end of February 2026.

Table 11: AI Progress Scenarios, all Forecasts by Survey

		EEAI			LEAP		
Scenario	Group	Median	(IQR)	N	Median	(IQR)	N
Slow	Economists	39.9	(17.4, 60.0)	69	25.0	(15.0, 40.0)	54
	AI experts	30.0	(16.5, 60.0)	52	20.0	(10.0, 30.0)	126
	Computer scientists	NA	NA	NA	25.0	(15.0, 30.9)	51
	All experts	30.0	(18.0, 60.0)	121	23.7	(11.5, 30.9)	231
	Superforecasters	40.5	(30.0, 66.0)	38	26.0	(15.0, 33.8)	55
	General public	30.0	(20.0, 60.0)	401	28.0	(20.0, 35.0)	706
Moderate	Economists	50.0	(30.0, 62.6)	69	50.0	(40.0, 60.0)	54
	AI experts	50.0	(30.0, 60.0)	52	55.0	(45.0, 60.5)	126
	Computer scientists	NA	NA	NA	51.4	(45.0, 64.3)	51
	All experts	50.0	(30.0, 60.0)	121	50.2	(40.0, 60.0)	231
	Superforecasters	46.0	(30.0, 55.0)	38	54.0	(48.0, 61.5)	55
	General public	45.0	(30.0, 55.0)	401	49.0	(40.0, 55.0)	706
Rapid	Economists	10.0	(7.3, 20.0)	69	20.0	(10.0, 30.0)	54
	AI experts	15.0	(5.0, 20.0)	52	23.0	(12.0, 30.0)	126
	Computer scientists	NA	NA	NA	15.0	(10.0, 25.0)	51
	All experts	10.0	(5.0, 20.0)	121	20.0	(10.0, 30.0)	231
	Superforecasters	10.0	(5.0, 15.0)	38	15.0	(10.0, 27.8)	55
	General public	19.0	(5.0, 25.0)	401	20.0	(15.0, 28.6)	706

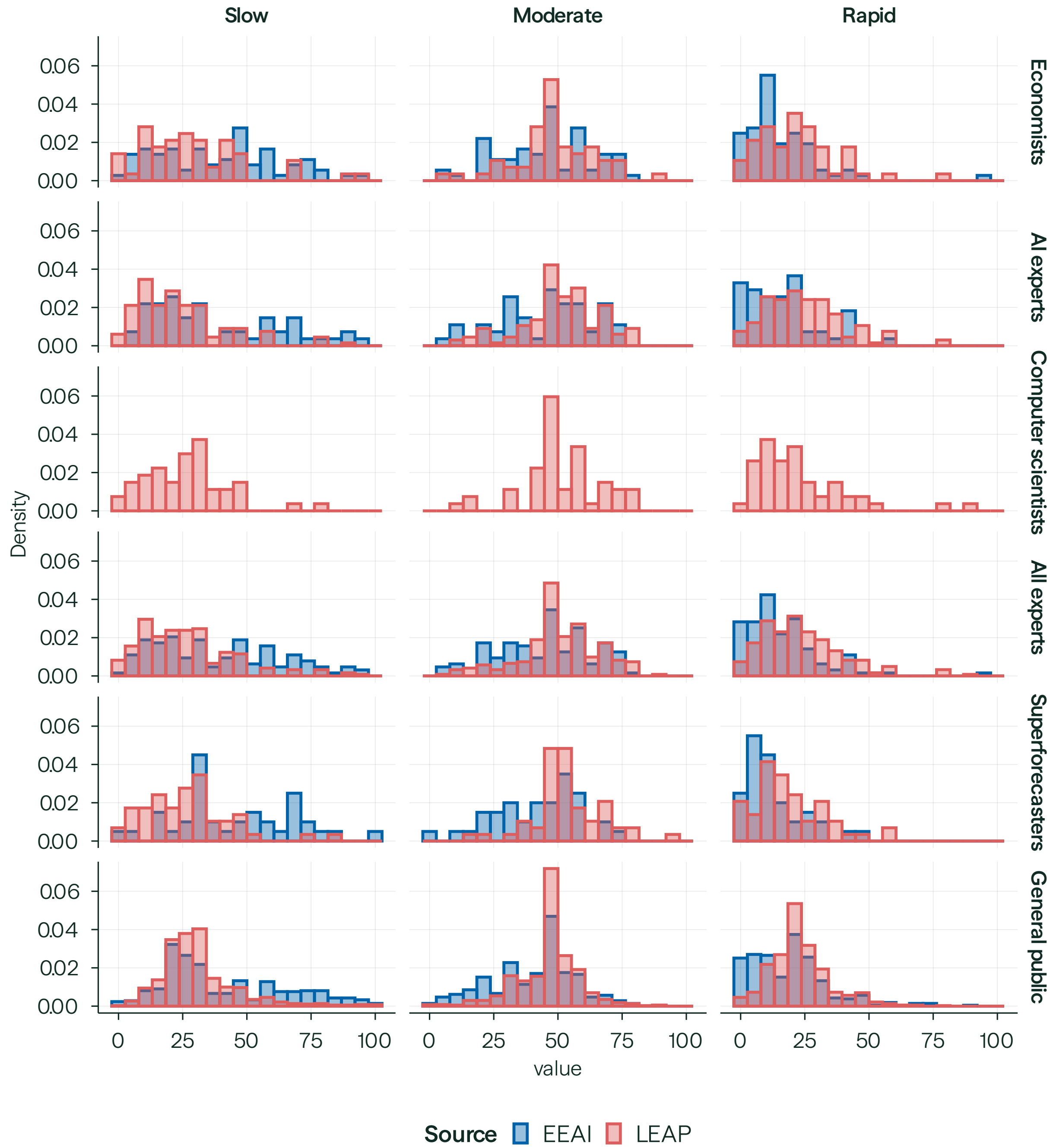


Figure 22: *Comparison of the distribution of forecasts of AI Progress from the sample in this survey (EEAI) and in LEAP.*

Next, we summarize the GDP growth, labor force participation rate, and wealth inequality forecasts for the two samples. We present results for both 2030 and 2050 in Tables 12 to 17. The differences between the two samples on conditional forecasts are less pronounced than in the scenario forecasting. For GDP growth in 2030, the median economist in our sample gives a 50$^{\text{th}}$ percentile forecast in the rapid scenario of 3.3% (IQR: 2.9, 4.5), compared to 3.0%

(2.8, 4.8%) in LEAP. We summarize differences in median 50th percentile forecasts by group for 2030 and 2050 in Figure 23 and Figure 24.

Table 12: Annual GDP growth rate (%) in 2030 by scenario, percentile, group, and survey.

			EEAI			LEAP		
Scenario	Percentile	Group	Median	(IQR)	N	Median	(IQR)	N
Unconditional	10	Economists	1.0	(0.0, 1.2)	66	0.6	(-0.4, 1.3)	54
	10	AI experts	1.2	(0.3, 2.0)	47	0.5	(-0.4, 1.2)	126
	10	Computer scientists	NA	NA	NA	1.0	(-0.6, 2.0)	51
	10	All experts	1.0	(0.0, 1.7)	113	0.6	(-0.4, 1.5)	231
	10	Superforecasters	1.0	(0.7, 1.8)	35	1.0	(0.0, 1.5)	54
	10	General public	1.0	(0.0, 1.8)	295	0.5	(-0.7, 1.5)	706
	50	Economists	2.5	(2.0, 3.0)	66	2.5	(2.3, 3.0)	54
	50	AI experts	2.5	(2.1, 3.2)	47	2.5	(2.1, 3.2)	126
	50	Computer scientists	NA	NA	NA	3.0	(2.4, 4.0)	51
	50	All experts	2.5	(2.0, 3.0)	113	2.7	(2.2, 3.1)	231
	50	Superforecasters	2.5	(2.3, 2.9)	35	2.5	(2.3, 2.8)	54
	50	General public	2.4	(2.0, 3.0)	295	2.5	(2.0, 3.0)	706
	90	Economists	4.0	(3.5, 5.0)	66	5.0	(3.5, 6.0)	54
	90	AI experts	4.4	(3.5, 6.3)	47	5.1	(4.0, 6.1)	126
	90	Computer scientists	NA	NA	NA	5.8	(4.9, 7.1)	51
	90	All experts	4.1	(3.5, 5.1)	113	5.1	(4.0, 6.2)	231
	90	Superforecasters	4.0	(3.5, 5.0)	35	4.4	(3.4, 5.2)	54
	90	General public	3.9	(3.0, 5.6)	295	5.2	(3.6, 6.1)	706
Slow	50	Economists	2.0	(1.5, 2.2)	66	2.3	(2.0, 2.5)	54
	50	AI experts	2.3	(1.9, 2.6)	47	2.3	(1.7, 2.9)	126
	50	Computer scientists	NA	NA	NA	2.5	(2.0, 3.0)	51
	50	All experts	2.0	(1.6, 2.5)	113	2.3	(1.9, 2.8)	231
	50	Superforecasters	2.2	(1.8, 2.5)	35	2.4	(2.1, 2.6)	54
	50	General public	2.0	(1.6, 2.5)	295	2.3	(1.5, 3.0)	706
Moderate	50	Economists	2.6	(2.2, 3.0)	66	2.8	(2.5, 3.5)	54
	50	AI experts	3.0	(2.5, 3.5)	47	3.0	(2.5, 4.0)	126
	50	Computer scientists	NA	NA	NA	3.5	(2.7, 5.0)	51
	50	All experts	2.9	(2.4, 3.2)	113	3.0	(2.5, 4.0)	231
	50	Superforecasters	2.6	(2.4, 3.3)	35	2.7	(2.5, 3.0)	54
	50	General public	2.7	(2.2, 3.5)	295	3.0	(2.4, 4.0)	706
Rapid	10	Economists	1.2	(0.5, 2.6)	66	1.5	(0.5, 2.0)	54
	10	AI experts	2.2	(1.0, 3.0)	47	1.9	(-0.1, 3.0)	126
	10	Computer scientists	NA	NA	NA	2.5	(0.9, 4.9)	51
	10	All experts	1.9	(0.8, 3.0)	113	1.9	(0.4, 3.0)	231
	10	Superforecasters	2.0	(1.0, 3.0)	35	1.2	(0.6, 2.2)	54
	10	General public	2.0	(0.9, 3.0)	295	1.6	(0.3, 2.9)	706
	50	Economists	3.3	(2.9, 4.5)	66	3.0	(2.8, 4.8)	54
	50	AI experts	3.7	(3.0, 6.0)	47	4.0	(3.0, 6.0)	126
	50	Computer scientists	NA	NA	NA	5.0	(3.5, 9.3)	51
	50	All experts	3.5	(3.0, 5.0)	113	4.0	(3.0, 6.0)	231
	50	Superforecasters	3.7	(3.0, 5.0)	35	3.5	(2.6, 4.0)	54
	50	General public	3.5	(3.0, 5.0)	295	3.8	(3.0, 5.3)	706
	90	Economists	5.5	(4.0, 7.0)	66	6.1	(4.1, 7.1)	54
	90	AI experts	6.5	(4.5, 9.8)	47	6.9	(5.7, 10.0)	126
	90	Computer scientists	NA	NA	NA	8.4	(6.1, 13.5)	51
	90	All experts	6.0	(4.5, 8.0)	113	6.9	(5.5, 10.0)	231
	90	Superforecasters	6.0	(4.6, 8.6)	35	6.0	(4.6, 7.5)	54
	90	General public	6.0	(4.3, 8.1)	295	6.6	(5.2, 8.4)	706

Table 13: Annual GDP growth rate (%) in 2050 by scenario, percentile, group, and survey.

			EEAI			LEAP		
Scenario	Percentile	Group	Median	(IQR)	N	Median	(IQR)	N
Unconditional	10	Economists	0.4	(-0.5, 1.0)	64	0.9	(-0.1, 1.5)	54
	10	AI experts	1.2	(0.0, 2.5)	47	0.9	(-0.4, 2.1)	126
	10	Computer scientists	NA	NA	NA	0.8	(-0.5, 1.9)	51
	10	All experts	1.0	(0.0, 1.7)	111	0.9	(-0.3, 1.9)	231
	10	Superforecasters	1.0	(-0.1, 1.3)	35	0.8	(-0.4, 1.0)	54
	10	General public	1.0	(0.0, 2.1)	286	0.7	(-0.2, 2.1)	706
	50	Economists	2.5	(2.0, 3.0)	64	3.0	(2.2, 3.4)	54
	50	AI experts	3.0	(2.1, 5.5)	47	3.0	(2.5, 5.0)	126
	50	Computer scientists	NA	NA	NA	3.0	(2.2, 5.0)	51
	50	All experts	2.9	(2.0, 4.3)	111	3.0	(2.3, 4.8)	231
	50	Superforecasters	2.5	(2.2, 3.1)	35	2.5	(2.1, 3.0)	54
	50	General public	3.0	(2.0, 4.0)	286	3.0	(2.2, 4.2)	706
	90	Economists	5.0	(4.0, 6.9)	64	5.7	(4.1, 6.4)	54
	90	AI experts	5.3	(4.0, 10.0)	47	6.1	(5.0, 9.2)	126
	90	Computer scientists	NA	NA	NA	6.1	(5.0, 8.7)	51
	90	All experts	5.0	(4.0, 7.9)	111	6.0	(4.8, 8.0)	231
	90	Superforecasters	5.0	(3.9, 7.0)	35	5.0	(4.0, 6.1)	54
	90	General public	5.0	(3.4, 8.1)	286	5.9	(4.6, 7.5)	706
Slow	50	Economists	2.0	(1.6, 2.5)	64	2.5	(2.0, 3.0)	54
	50	AI experts	2.6	(1.9, 4.3)	47	2.5	(1.8, 4.0)	126
	50	Computer scientists	NA	NA	NA	2.7	(2.0, 4.0)	51
	50	All experts	2.4	(1.6, 3.0)	111	2.5	(2.0, 3.5)	231
	50	Superforecasters	2.2	(2.0, 2.7)	35	2.4	(2.0, 3.0)	54
	50	General public	2.2	(1.5, 3.4)	286	2.8	(1.6, 4.1)	706
Moderate	50	Economists	2.8	(2.2, 3.3)	64	3.4	(2.5, 4.0)	54
	50	AI experts	4.0	(2.7, 6.0)	47	3.5	(2.8, 7.0)	126
	50	Computer scientists	NA	NA	NA	3.4	(2.5, 5.8)	51
	50	All experts	3.0	(2.3, 5.0)	111	3.5	(2.6, 5.5)	231
	50	Superforecasters	2.6	(2.3, 3.5)	35	2.8	(2.3, 3.5)	54
	50	General public	3.0	(2.3, 4.8)	286	3.6	(2.6, 5.7)	706
Rapid	10	Economists	1.0	(0.0, 2.0)	64	1.9	(0.9, 3.0)	54
	10	AI experts	2.3	(1.0, 4.7)	47	2.0	(0.4, 5.0)	126
	10	Computer scientists	NA	NA	NA	2.4	(0.1, 4.2)	51
	10	All experts	1.5	(0.8, 3.0)	111	2.0	(0.5, 4.0)	231
	10	Superforecasters	1.0	(0.0, 2.1)	35	0.9	(-0.4, 1.5)	54
	10	General public	2.5	(1.2, 4.0)	286	2.4	(0.9, 4.7)	706
	50	Economists	3.5	(3.0, 4.5)	64	4.0	(3.1, 5.6)	54
	50	AI experts	5.3	(3.1, 10.0)	47	6.0	(3.7, 11.1)	126
	50	Computer scientists	NA	NA	NA	5.5	(3.8, 10.0)	51
	50	All experts	4.0	(3.0, 7.0)	111	5.0	(3.5, 10.0)	231
	50	Superforecasters	4.0	(2.6, 5.0)	35	3.4	(2.5, 5.1)	54
	50	General public	4.5	(3.1, 7.0)	286	5.0	(3.5, 7.8)	706
	90	Economists	7.0	(5.0, 10.0)	64	7.1	(5.1, 9.3)	54
	90	AI experts	9.3	(5.2, 15.9)	47	10.1	(6.7, 16.9)	126
	90	Computer scientists	NA	NA	NA	9.8	(7.0, 15.9)	51
	90	All experts	7.0	(5.0, 12.3)	111	8.6	(6.2, 15.0)	231
	90	Superforecasters	7.0	(5.0, 11.9)	35	6.6	(5.0, 11.1)	54
	90	General public	7.1	(5.0, 11.1)	286	8.0	(5.9, 11.1)	706

Table 14: LFPR (%) in 2030 by scenario, percentile, group, and survey.

			EEAI			LEAP		
Scenario	Percentile	Group	Median	(IQR)	N	Median	(IQR)	N
Unconditional	10	Economists	57.3	(55.0, 59.6)	63	57.7	(55.7, 59.0)	54
	10	AI experts	57.9	(53.9, 59.4)	48	57.7	(55.0, 59.9)	126
	10	Computer scientists	NA	NA	NA	56.7	(55.7, 59.0)	51
	10	All experts	57.7	(54.3, 59.6)	111	57.6	(55.7, 59.4)	231
	10	Superforecasters	59.0	(55.0, 60.0)	37	58.0	(57.2, 60.0)	54
	10	General public	59.0	(55.7, 60.5)	268	58.0	(55.7, 59.7)	706
	50	Economists	61.0	(60.0, 62.5)	63	61.4	(60.0, 62.0)	54
	50	AI experts	61.3	(60.0, 62.3)	48	61.8	(60.0, 62.8)	126
	50	Computer scientists	NA	NA	NA	61.4	(60.0, 62.6)	51
	50	All experts	61.1	(60.0, 62.4)	111	61.5	(60.0, 62.5)	231
	50	Superforecasters	62.0	(60.0, 63.0)	37	62.0	(61.0, 62.5)	54
	50	General public	62.0	(61.0, 63.0)	268	62.0	(60.1, 63.0)	706
	90	Economists	65.0	(62.8, 68.0)	63	64.7	(63.4, 66.8)	54
	90	AI experts	65.0	(63.1, 67.5)	48	65.0	(63.1, 67.1)	126
	90	Computer scientists	NA	NA	NA	66.1	(64.2, 66.7)	51
	90	All experts	65.0	(63.0, 67.7)	111	65.0	(63.3, 66.9)	231
	90	Superforecasters	65.0	(63.0, 67.0)	37	65.2	(63.5, 66.3)	54
	90	General public	65.0	(63.0, 67.7)	268	65.6	(63.5, 67.1)	706
Slow	50	Economists	61.5	(60.0, 62.4)	63	62.0	(60.2, 62.7)	54
	50	AI experts	62.0	(61.0, 62.4)	48	62.0	(61.0, 62.5)	126
	50	Computer scientists	NA	NA	NA	62.0	(60.2, 63.0)	51
	50	All experts	62.0	(61.0, 62.4)	111	62.0	(60.6, 62.7)	231
	50	Superforecasters	62.1	(61.0, 63.0)	37	62.0	(61.3, 62.7)	54
	50	General public	62.0	(61.0, 62.9)	268	61.8	(60.0, 63.0)	706
Moderate	50	Economists	60.7	(59.0, 61.7)	63	60.5	(59.9, 62.0)	54
	50	AI experts	61.1	(59.8, 62.5)	48	61.0	(58.0, 62.5)	126
	50	Computer scientists	NA	NA	NA	60.0	(55.1, 62.0)	51
	50	All experts	61.0	(59.0, 62.0)	111	60.5	(58.0, 62.1)	231
	50	Superforecasters	61.0	(60.0, 62.4)	37	61.4	(60.0, 62.2)	54
	50	General public	61.7	(60.0, 63.0)	268	62.0	(60.0, 63.3)	706
Rapid	10	Economists	54.7	(50.0, 59.0)	63	55.0	(49.0, 58.0)	54
	10	AI experts	55.0	(49.1, 58.9)	48	55.0	(45.8, 59.1)	126
	10	Computer scientists	NA	NA	NA	51.0	(39.6, 57.7)	51
	10	All experts	55.0	(50.0, 59.0)	111	54.9	(45.2, 58.3)	231
	10	Superforecasters	54.0	(50.0, 59.0)	37	55.9	(52.5, 58.0)	54
	10	General public	56.7	(50.8, 60.0)	268	58.0	(52.7, 60.7)	706
	50	Economists	59.3	(56.4, 61.0)	63	59.7	(55.0, 61.0)	54
	50	AI experts	60.0	(56.9, 62.1)	48	59.0	(54.7, 62.0)	126
	50	Computer scientists	NA	NA	NA	57.4	(45.0, 61.7)	51
	50	All experts	60.0	(56.7, 61.9)	111	59.0	(51.2, 61.5)	231
	50	Superforecasters	59.0	(55.5, 62.0)	37	60.0	(57.5, 61.3)	54
	50	General public	60.2	(56.9, 63.0)	268	61.9	(57.9, 64.9)	706
	90	Economists	62.3	(60.9, 65.0)	63	63.8	(59.4, 66.0)	54
	90	AI experts	64.2	(62.1, 66.2)	48	63.2	(60.0, 65.8)	126
	90	Computer scientists	NA	NA	NA	61.6	(53.0, 66.1)	51
	90	All experts	63.0	(61.1, 65.9)	111	63.1	(59.4, 65.9)	231
	90	Superforecasters	63.0	(61.0, 65.0)	37	63.4	(62.0, 66.3)	54
	90	General public	63.8	(60.4, 66.4)	268	65.0	(61.6, 68.9)	706

Table 15: LFPR (%) in 2050 by scenario, percentile, group, and survey.

			EEAI			LEAP		
Scenario	Percentile	Group	Median	(IQR)	N	Median	(IQR)	N
Unconditional	10	Economists	50.0	(44.6, 55.7)	60	55.4	(47.7, 58.0)	54
	10	AI experts	53.7	(48.3, 58.9)	49	53.8	(48.0, 58.0)	126
	10	Computer scientists	NA	NA	NA	53.9	(40.4, 58.0)	51
	10	All experts	51.3	(45.0, 58.0)	109	54.7	(45.7, 58.0)	231
	10	Superforecasters	52.0	(45.1, 57.0)	34	55.0	(50.0, 57.8)	54
	10	General public	56.9	(53.3, 59.0)	258	56.7	(53.7, 59.7)	706
	50	Economists	58.3	(55.2, 60.5)	60	60.0	(55.0, 61.5)	54
	50	AI experts	59.7	(54.9, 62.0)	49	59.0	(55.0, 61.5)	126
	50	Computer scientists	NA	NA	NA	59.3	(52.1, 62.5)	51
	50	All experts	59.0	(55.0, 61.5)	109	59.3	(55.0, 61.7)	231
	50	Superforecasters	58.2	(54.0, 61.0)	34	60.0	(57.0, 62.0)	54
	50	General public	60.0	(58.5, 63.0)	258	60.5	(58.5, 63.1)	706
	90	Economists	65.0	(60.7, 69.3)	60	64.3	(60.9, 67.4)	54
	90	AI experts	65.0	(61.0, 68.6)	49	64.3	(61.0, 67.0)	126
	90	Computer scientists	NA	NA	NA	64.2	(61.3, 69.3)	51
	90	All experts	65.0	(61.0, 68.9)	109	64.3	(61.0, 67.5)	231
	90	Superforecasters	64.0	(61.0, 68.0)	34	66.0	(63.0, 67.0)	54
	90	General public	64.0	(62.0, 67.8)	258	64.3	(62.0, 67.3)	706
Slow	50	Economists	59.2	(57.1, 60.6)	60	60.0	(58.0, 63.3)	54
	50	AI experts	59.7	(58.0, 62.0)	49	59.5	(56.0, 62.0)	126
	50	Computer scientists	NA	NA	NA	59.2	(55.0, 62.9)	51
	50	All experts	59.5	(58.0, 61.5)	109	60.0	(56.2, 62.1)	231
	50	Superforecasters	59.1	(57.0, 62.0)	34	60.0	(58.5, 62.4)	54
	50	General public	60.0	(58.5, 62.4)	258	60.0	(57.5, 63.0)	706
Moderate	50	Economists	57.0	(55.0, 60.4)	60	58.0	(54.6, 62.0)	54
	50	AI experts	59.0	(55.0, 61.6)	49	58.0	(50.2, 60.8)	126
	50	Computer scientists	NA	NA	NA	56.2	(42.2, 61.2)	51
	50	All experts	58.1	(55.0, 61.4)	109	57.9	(50.0, 61.0)	231
	50	Superforecasters	58.0	(52.0, 61.3)	34	58.9	(56.0, 60.5)	54
	50	General public	60.0	(57.0, 62.0)	258	60.1	(56.3, 63.9)	706
Rapid	10	Economists	45.5	(40.0, 55.0)	60	48.7	(35.7, 56.0)	54
	10	AI experts	45.7	(34.2, 57.2)	49	45.0	(28.3, 55.0)	126
	10	Computer scientists	NA	NA	NA	40.9	(15.4, 52.4)	51
	10	All experts	45.7	(38.1, 56.0)	109	45.0	(30.0, 55.0)	231
	10	Superforecasters	46.8	(15.0, 54.0)	34	48.5	(35.0, 55.0)	54
	10	General public	53.3	(45.0, 59.0)	258	55.7	(46.3, 60.7)	706
	50	Economists	55.0	(50.0, 60.0)	60	55.0	(47.0, 60.4)	54
	50	AI experts	54.0	(44.1, 61.0)	49	52.0	(44.4, 60.0)	126
	50	Computer scientists	NA	NA	NA	50.0	(30.0, 57.0)	51
	50	All experts	55.0	(47.1, 60.0)	109	52.0	(40.0, 60.0)	231
	50	Superforecasters	54.6	(35.9, 60.0)	34	55.8	(50.0, 60.0)	54
	50	General public	58.0	(50.0, 63.0)	258	60.0	(53.0, 65.0)	706
	90	Economists	61.0	(58.9, 67.0)	60	61.2	(56.9, 67.6)	54
	90	AI experts	61.3	(54.8, 65.8)	49	60.0	(50.0, 66.0)	126
	90	Computer scientists	NA	NA	NA	55.0	(42.7, 65.4)	51
	90	All experts	61.0	(55.0, 65.9)	109	60.0	(50.0, 66.3)	231
	90	Superforecasters	63.0	(58.0, 67.5)	34	64.4	(59.9, 67.5)	54
	90	General public	62.5	(57.3, 67.6)	258	64.3	(57.4, 69.3)	706

Table 16: Wealth inequality (fraction of the national wealth owned by the top 10% wealthiest households) in 2030 by scenario, percentile, group, and survey.

			EEAI			LEAP		
Scenario	Percentile	Group	Median	(IQR)	N	Median	(IQR)	N
Unconditional	10	Economists	69.0	(65.1, 70.0)	64	68.0	(66.3, 70.0)	54
	10	AI experts	68.0	(65.0, 70.0)	45	68.5	(66.7, 70.0)	126
	10	Computer scientists	NA	NA	NA	66.8	(64.9, 68.8)	51
	10	All experts	68.7	(65.0, 70.0)	109	67.8	(66.0, 69.8)	231
	10	Superforecasters	69.0	(67.5, 70.0)	36	68.0	(66.8, 70.0)	54
	10	General public	68.0	(65.0, 70.0)	257	66.8	(64.8, 69.0)	706
	50	Economists	73.2	(72.0, 75.0)	64	73.0	(71.0, 75.0)	54
	50	AI experts	72.9	(70.0, 73.8)	45	73.0	(72.0, 74.6)	126
	50	Computer scientists	NA	NA	NA	72.0	(70.8, 74.0)	51
	50	All experts	73.0	(71.9, 74.5)	109	72.9	(71.6, 74.5)	231
	50	Superforecasters	72.1	(71.3, 73.1)	36	72.0	(71.5, 73.0)	54
	50	General public	72.0	(71.0, 74.0)	257	72.0	(70.0, 73.0)	706
	90	Economists	78.0	(75.0, 80.2)	64	77.2	(75.2, 80.0)	54
	90	AI experts	77.0	(75.0, 80.4)	45	77.4	(75.2, 80.0)	126
	90	Computer scientists	NA	NA	NA	77.2	(75.3, 78.7)	51
	90	All experts	77.2	(75.0, 80.2)	109	77.2	(75.2, 80.0)	231
	90	Superforecasters	75.0	(74.0, 77.5)	36	76.0	(74.0, 78.0)	54
	90	General public	76.5	(75.0, 80.0)	257	76.2	(74.9, 78.2)	706
Slow	50	Economists	72.0	(70.6, 73.0)	64	72.0	(71.0, 73.5)	54
	50	AI experts	72.0	(70.0, 73.0)	45	72.0	(71.5, 74.0)	126
	50	Computer scientists	NA	NA	NA	72.6	(70.5, 74.0)	51
	50	All experts	72.0	(70.2, 73.0)	109	72.0	(71.0, 74.0)	231
	50	Superforecasters	71.7	(71.0, 72.0)	36	72.0	(71.0, 73.0)	54
	50	General public	71.6	(70.0, 73.0)	257	71.5	(70.0, 73.0)	706
Moderate	50	Economists	73.5	(72.0, 75.0)	64	74.0	(72.0, 75.5)	54
	50	AI experts	73.0	(71.0, 74.6)	45	73.5	(72.5, 76.8)	126
	50	Computer scientists	NA	NA	NA	73.5	(72.0, 76.7)	51
	50	All experts	73.5	(72.0, 75.0)	109	74.0	(72.0, 76.7)	231
	50	Superforecasters	73.0	(72.0, 74.0)	36	73.0	(72.0, 73.5)	54
	50	General public	73.0	(71.1, 75.0)	257	73.0	(70.0, 75.0)	705
Rapid	10	Economists	69.8	(67.1, 72.0)	64	70.0	(68.3, 74.8)	54
	10	AI experts	69.6	(66.3, 71.6)	45	70.4	(68.6, 74.8)	126
	10	Computer scientists	NA	NA	NA	71.3	(69.4, 74.5)	51
	10	All experts	69.8	(67.0, 72.0)	109	70.8	(68.6, 74.8)	231
	10	Superforecasters	69.5	(65.8, 72.0)	36	70.0	(68.8, 72.0)	54
	10	General public	70.0	(66.0, 73.0)	257	69.8	(65.9, 73.8)	705
	50	Economists	75.0	(73.3, 79.9)	64	75.4	(72.9, 80.0)	54
	50	AI experts	75.0	(72.0, 77.6)	45	75.1	(74.0, 80.0)	126
	50	Computer scientists	NA	NA	NA	76.5	(75.0, 80.0)	51
	50	All experts	75.0	(72.9, 78.4)	109	76.0	(74.0, 80.0)	231
	50	Superforecasters	74.4	(73.0, 77.5)	36	75.0	(74.0, 76.3)	54
	50	General public	75.0	(72.4, 78.0)	257	75.0	(71.0, 78.0)	705
	90	Economists	80.4	(77.8, 85.2)	64	81.2	(77.9, 85.2)	54
	90	AI experts	80.0	(77.0, 85.3)	45	82.0	(78.4, 90.0)	126
	90	Computer scientists	NA	NA	NA	81.9	(78.7, 85.2)	51
	90	All experts	80.2	(77.3, 85.2)	109	81.6	(78.4, 87.0)	231
	90	Superforecasters	79.4	(76.0, 83.1)	36	79.0	(77.0, 82.0)	54
	90	General public	80.2	(77.2, 85.1)	257	80.0	(75.9, 84.0)	705

Table 17: Wealth inequality (fraction of the national wealth owned by the top 10% wealthiest households) in 2050 by scenario, percentile, group, and survey.

			EEAI			LEAP		
Scenario	Percentile	Group	Median	(IQR)	N	Median	(IQR)	N
Unconditional	10	Economists	69.0	(64.6, 71.0)	62	68.0	(63.5, 71.8)	54
	10	AI experts	67.9	(63.3, 70.0)	44	69.0	(64.8, 73.8)	126
	10	Computer scientists	NA	NA	NA	70.0	(66.1, 72.8)	51
	10	All experts	68.0	(64.6, 70.2)	106	68.8	(64.8, 72.8)	231
	10	Superforecasters	65.0	(60.5, 69.9)	36	66.0	(60.0, 69.0)	54
	10	General public	68.0	(65.0, 72.2)	260	68.3	(64.8, 70.8)	706
	50	Economists	75.0	(74.3, 77.0)	62	75.0	(70.3, 78.0)	54
	50	AI experts	75.0	(72.0, 78.0)	44	75.0	(73.0, 80.0)	126
	50	Computer scientists	NA	NA	NA	76.0	(74.0, 80.0)	51
	50	All experts	75.0	(73.0, 77.9)	106	75.0	(72.3, 80.0)	231
	50	Superforecasters	74.5	(70.3, 76.3)	36	73.0	(70.7, 76.9)	54
	50	General public	75.0	(72.0, 77.8)	260	73.6	(70.2, 76.0)	706
	90	Economists	80.2	(79.0, 85.4)	62	80.2	(76.0, 85.2)	54
	90	AI experts	82.1	(79.5, 85.1)	44	82.0	(79.0, 85.2)	126
	90	Computer scientists	NA	NA	NA	83.2	(79.2, 86.9)	51
	90	All experts	81.0	(79.0, 85.4)	106	82.0	(78.9, 85.2)	231
	90	Superforecasters	80.0	(76.2, 85.0)	36	79.6	(76.0, 85.0)	54
	90	General public	80.0	(76.9, 85.0)	260	78.7	(75.2, 81.3)	706
Slow	50	Economists	73.1	(72.0, 75.0)	62	73.0	(70.0, 76.0)	54
	50	AI experts	74.0	(70.9, 75.9)	44	75.0	(72.0, 76.1)	126
	50	Computer scientists	NA	NA	NA	75.2	(74.5, 78.0)	51
	50	All experts	74.0	(71.0, 75.0)	106	75.0	(71.0, 77.0)	231
	50	Superforecasters	72.2	(70.0, 75.0)	36	72.0	(70.0, 74.0)	54
	50	General public	73.5	(71.0, 75.0)	260	73.0	(70.0, 75.8)	706
Moderate	50	Economists	75.0	(74.0, 79.4)	62	77.0	(71.4, 80.7)	54
	50	AI experts	77.0	(75.0, 80.5)	44	78.0	(73.0, 81.2)	126
	50	Computer scientists	NA	NA	NA	78.5	(75.0, 81.2)	51
	50	All experts	76.0	(74.0, 80.0)	106	77.6	(73.0, 81.0)	231
	50	Superforecasters	75.0	(71.0, 77.5)	36	74.0	(71.5, 77.0)	54
	50	General public	76.0	(73.0, 79.8)	260	75.0	(71.0, 79.0)	705
Rapid	10	Economists	69.9	(64.9, 74.8)	62	70.9	(64.3, 79.8)	54
	10	AI experts	70.0	(65.0, 75.4)	44	71.0	(60.0, 79.8)	126
	10	Computer scientists	NA	NA	NA	74.8	(69.3, 81.9)	51
	10	All experts	70.0	(65.0, 74.9)	106	72.0	(62.8, 79.8)	231
	10	Superforecasters	65.0	(52.1, 70.0)	36	67.0	(59.8, 72.0)	54
	10	General public	73.0	(65.9, 78.0)	260	72.8	(66.5, 78.0)	705
	50	Economists	80.0	(74.2, 82.0)	62	80.0	(71.5, 85.0)	54
	50	AI experts	80.1	(75.0, 85.5)	44	80.2	(75.0, 87.6)	126
	50	Computer scientists	NA	NA	NA	84.7	(78.0, 90.0)	51
	50	All experts	80.0	(75.0, 85.0)	106	81.0	(75.0, 87.1)	231
	50	Superforecasters	75.0	(70.0, 82.3)	36	75.5	(72.0, 80.0)	54
	50	General public	80.0	(75.0, 85.0)	260	78.0	(72.0, 84.3)	705
	90	Economists	85.2	(80.1, 90.6)	62	85.2	(80.0, 92.1)	54
	90	AI experts	90.0	(83.8, 95.1)	44	90.0	(83.2, 95.0)	126
	90	Computer scientists	NA	NA	NA	92.3	(85.2, 95.8)	51
	90	All experts	88.0	(80.3, 93.0)	106	89.6	(83.2, 95.0)	231
	90	Superforecasters	85.0	(80.0, 90.5)	36	84.1	(80.0, 90.0)	54
	90	General public	85.3	(80.0, 92.0)	260	83.2	(77.2, 90.0)	705

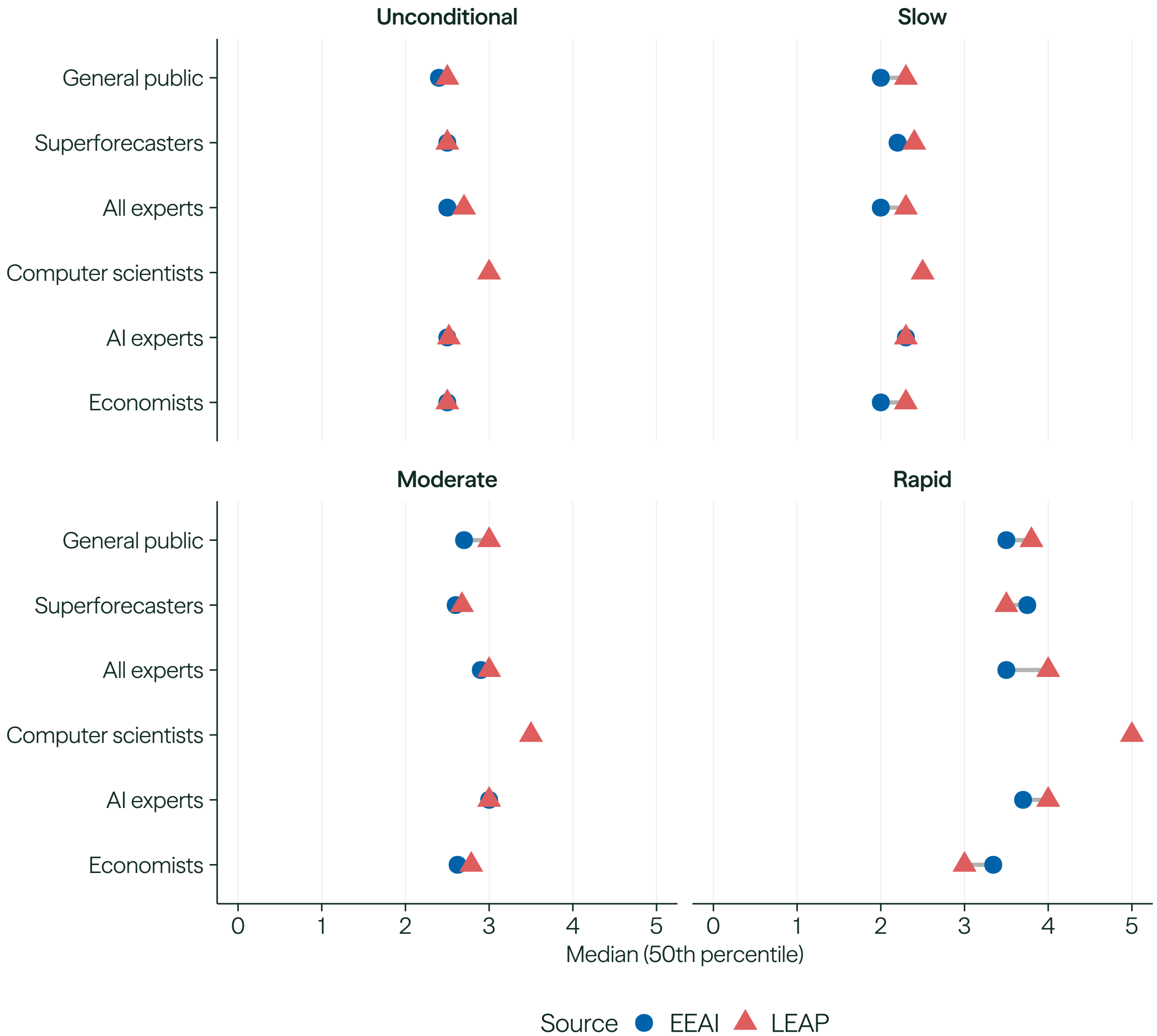


Figure 23: *Comparison of the medians of forecasts of annual GDP growth in 2030 from the sample in this survey (EEAI) and in LEAP.*

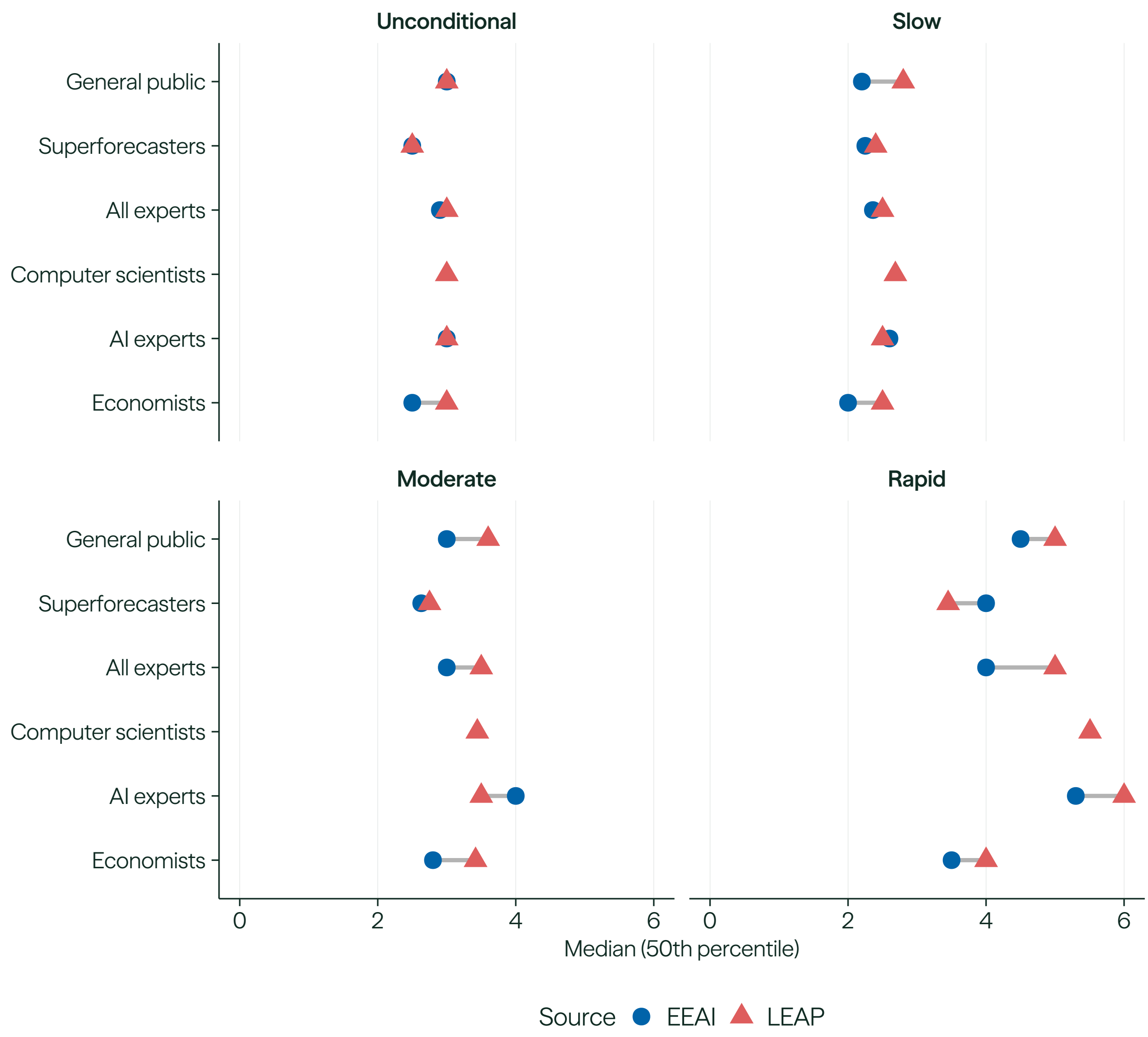


Figure 24: *Comparison of the medians of forecasts of annual GDP growth in 2050 from the sample in this survey (EEAI) and in LEAP.*

D. Additional results

D.1 AI Progress

Table 18: AI Progress Scenario Probabilities by Forecaster Group

Group	Scenario	Mean	25th percentile	50th percentile	75th percentile
AI experts	Slow	38.1	16.5	30.0	60.0
AI experts	Moderate	45.9	30.0	50.0	60.0
AI experts	Rapid	16.1	5.0	15.0	20.0
Economists	Slow	38.6	16.8	38.3	60.0
Economists	Moderate	47.4	31.5	50.0	64.5
Economists	Rapid	14.0	6.7	10.0	20.0
General public	Slow	40.8	20.0	30.0	60.0
General public	Moderate	41.0	30.0	45.0	55.0
General public	Rapid	18.1	5.0	19.0	25.0
Superforecasters	Slow	45.0	30.0	40.5	66.0
Superforecasters	Moderate	42.4	30.0	46.0	55.0
Superforecasters	Rapid	12.6	5.0	10.0	15.0

D.2 Main Outcomes: additional results, rationale analyses

D.2.1 Change in Gross Domestic Product

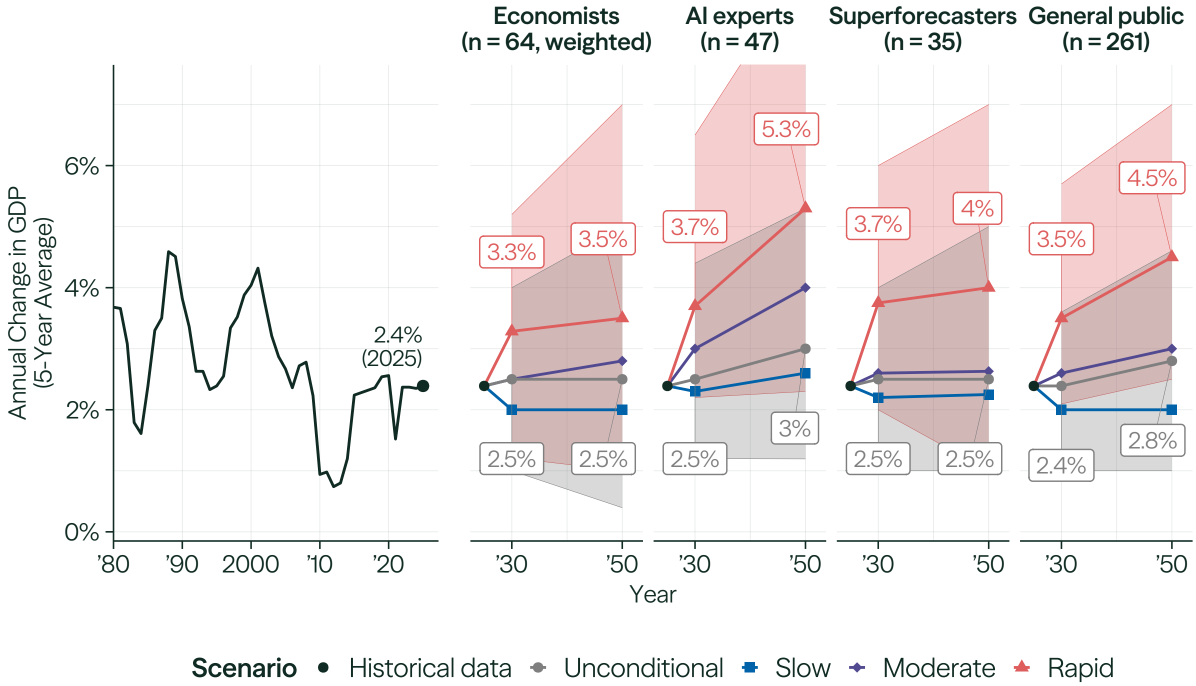


Figure 25: *Forecasts for five-year annualized change in the Gross Domestic Product (GDP).* Lines show medians of 50th percentile forecasts across participants. The most recent historical value for the outcome is shown in each panel as a black point. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3). See Appendix H.4.1 for question details and the source of the historical data.

Figure 26: *Distribution of forecasts for five-year annualized change in Gross Domestic Product (GDP).* Distribution is pooled across participants to summarize the full distribution of participant beliefs. Tail mass outside of figure bounds shown as ball-and-stick at 0% and 10%, with numbers in boxes indicating the proportion of the pooled distribution lies below 0% or above 10%. Interior points show $10^{\text{th}}/50^{\text{th}}/90^{\text{th}}$ percentiles of the distribution. See Appendix H.4.1 for question details and the source of the historical data.

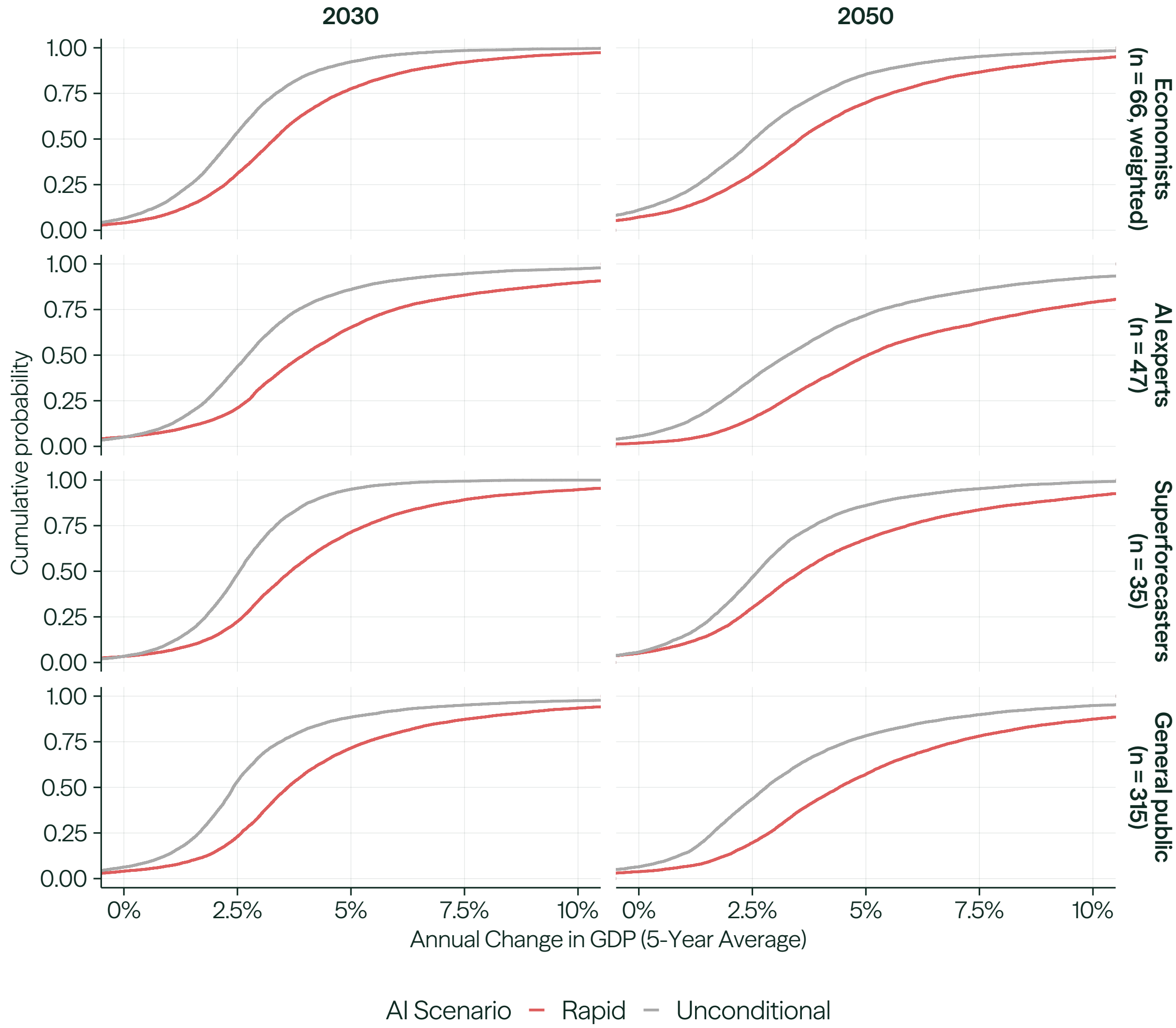


Figure 27: *Cumulative distribution of forecasts for five-year annualized change in Gross Domestic Product (GDP).*

Table 19: Annualized Change in GDP over 5 Years (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	1.0 CI: (0.3, 1.0) IQR: [0.0, 1.2] $n = 66$	1.2 CI: (0.7, 1.5) IQR: [0.3, 2.0] $n = 47$	1.0 CI: (0.9, 1.5) IQR: [0.7, 1.8] $n = 35$	1.0 CI: (1.0, 1.2) IQR: [0.0, 1.8] $n = 295$	1.0 CI: (1.0, 1.1) IQR: [0.5, 1.8] $n = 443$
Unconditional	50	2.5 CI: (2.0, 2.8) IQR: [2.0, 3.0] $n = 66$	2.5 CI: (2.4, 3.0) IQR: [2.1, 3.2] $n = 47$	2.5 CI: (2.4, 2.6) IQR: [2.3, 2.9] $n = 35$	2.4 CI: (2.3, 2.5) IQR: [2.0, 3.0] $n = 295$	2.5 CI: (2.4, 2.5) IQR: [2.0, 3.0] $n = 443$
Unconditional	90	4.0 CI: (4.0, 5.0) IQR: [3.5, 5.0] $n = 66$	4.4 CI: (3.7, 5.0) IQR: [3.5, 6.3] $n = 47$	4.0 CI: (3.5, 4.5) IQR: [3.5, 5.0] $n = 35$	3.9 CI: (3.5, 4.0) IQR: [3.0, 5.6] $n = 295$	4.0 CI: (4.0, 4.4) IQR: [3.3, 5.1] $n = 443$
Slow	50	2.0 CI: (1.7, 2.0) IQR: [1.5, 2.2] $n = 66$	2.3 CI: (2.0, 2.5) IQR: [1.9, 2.6] $n = 47$	2.2 CI: (2.0, 2.5) IQR: [1.8, 2.5] $n = 35$	2.0 CI: (2.0, 2.2) IQR: [1.6, 2.5] $n = 295$	2.0 CI: (2.0, 2.2) IQR: [1.7, 2.5] $n = 443$
Moderate	50	2.6 CI: (2.4, 3.0) IQR: [2.2, 3.0] $n = 66$	3.0 CI: (2.5, 3.1) IQR: [2.5, 3.5] $n = 47$	2.6 CI: (2.5, 2.9) IQR: [2.4, 3.3] $n = 35$	2.7 CI: (2.5, 2.8) IQR: [2.2, 3.5] $n = 295$	2.7 CI: (2.5, 3.0) IQR: [2.4, 3.3] $n = 443$
Rapid	10	1.2 CI: (1.0, 2.0) IQR: [0.5, 2.6] $n = 66$	2.2 CI: (1.5, 2.5) IQR: [1.0, 3.0] $n = 47$	2.0 CI: (1.5, 2.5) IQR: [1.0, 3.0] $n = 35$	2.0 CI: (2.0, 2.3) IQR: [0.9, 3.0] $n = 295$	2.0 CI: (1.8, 2.1) IQR: [0.9, 3.0] $n = 443$
Rapid	50	3.3 CI: (3.0, 3.9) IQR: [2.9, 4.5] $n = 66$	3.7 CI: (3.2, 5.0) IQR: [3.0, 6.0] $n = 47$	3.7 CI: (3.2, 4.0) IQR: [3.0, 5.0] $n = 35$	3.5 CI: (3.4, 3.8) IQR: [3.0, 5.0] $n = 295$	3.5 CI: (3.4, 4.0) IQR: [3.0, 5.0] $n = 443$
Rapid	90	5.5 CI: (4.8, 6.5) IQR: [4.0, 7.0] $n = 66$	6.5 CI: (5.0, 8.0) IQR: [4.5, 9.8] $n = 47$	6.0 CI: (5.1, 7.0) IQR: [4.6, 8.6] $n = 35$	6.0 CI: (5.5, 6.0) IQR: [4.3, 8.1] $n = 295$	6.0 CI: (5.5, 6.2) IQR: [4.5, 8.1] $n = 443$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 20: Annualized Change in GDP over 5 Years (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	0.4	1.2	1.0	1.0	1.0
		CI: (0.0, 1.0)	CI: (0.8, 1.9)	CI: (0.5, 1.0)	CI: (1.0, 1.2)	CI: (0.7, 1.0)
		IQR: [-0.5, 1.0]	IQR: [0.0, 2.5]	IQR: [-0.1, 1.3]	IQR: [0.0, 2.1]	IQR: [0.0, 1.5]
		$n = 64$	$n = 47$	$n = 35$	$n = 286$	$n = 432$
Unconditional	50	2.5	3.0	2.5	3.0	2.8
		CI: (2.1, 3.0)	CI: (2.5, 4.5)	CI: (2.4, 3.0)	CI: (2.5, 3.0)	CI: (2.5, 3.0)
		IQR: [2.0, 3.0]	IQR: [2.1, 5.5]	IQR: [2.2, 3.1]	IQR: [2.0, 4.0]	IQR: [2.1, 4.0]
		$n = 64$	$n = 47$	$n = 35$	$n = 286$	$n = 432$
Unconditional	90	5.0	5.3	5.0	5.0	5.0
		CI: (4.5, 5.5)	CI: (4.8, 7.5)	CI: (4.0, 6.0)	CI: (4.5, 5.0)	CI: (4.9, 5.1)
		IQR: [4.0, 6.9]	IQR: [4.0, 10.0]	IQR: [3.9, 7.0]	IQR: [3.4, 8.1]	IQR: [4.0, 7.5]
		$n = 64$	$n = 47$	$n = 35$	$n = 286$	$n = 432$
Slow	50	2.0	2.6	2.2	2.2	2.2
		CI: (2.0, 2.1)	CI: (2.5, 3.0)	CI: (2.0, 2.5)	CI: (2.0, 2.4)	CI: (2.0, 2.5)
		IQR: [1.6, 2.5]	IQR: [1.9, 4.3]	IQR: [2.0, 2.6]	IQR: [1.5, 3.4]	IQR: [1.7, 3.0]
		$n = 64$	$n = 47$	$n = 35$	$n = 286$	$n = 432$
Moderate	50	2.8	4.0	2.6	3.0	3.0
		CI: (2.5, 3.0)	CI: (3.0, 5.1)	CI: (2.5, 3.0)	CI: (3.0, 3.4)	CI: (2.8, 3.0)
		IQR: [2.2, 3.3]	IQR: [2.7, 6.0]	IQR: [2.3, 3.5]	IQR: [2.3, 4.8]	IQR: [2.3, 4.0]
		$n = 64$	$n = 47$	$n = 35$	$n = 286$	$n = 432$
Rapid	10	1.0	2.3	1.0	2.5	1.6
		CI: (1.0, 1.4)	CI: (1.6, 3.1)	CI: (0.5, 1.8)	CI: (2.2, 2.8)	CI: (1.2, 2.0)
		IQR: [0.0, 2.0]	IQR: [1.0, 4.7]	IQR: [0.0, 2.1]	IQR: [1.2, 4.0]	IQR: [0.5, 3.0]
		$n = 64$	$n = 47$	$n = 35$	$n = 286$	$n = 432$
Rapid	50	3.5	5.3	4.0	4.5	4.0
		CI: (3.0, 4.0)	CI: (3.5, 7.0)	CI: (2.8, 5.0)	CI: (4.1, 5.0)	CI: (3.6, 4.5)
		IQR: [3.0, 4.5]	IQR: [3.1, 10.0]	IQR: [2.6, 5.0]	IQR: [3.1, 7.0]	IQR: [3.0, 7.0]
		$n = 64$	$n = 47$	$n = 35$	$n = 286$	$n = 432$
Rapid	90	7.0	9.3	7.0	7.1	7.0
		CI: (5.0, 8.0)	CI: (6.4, 12.0)	CI: (5.5, 10.0)	CI: (6.7, 8.0)	CI: (6.3, 8.0)
		IQR: [5.0, 10.0]	IQR: [5.2, 15.9]	IQR: [5.0, 11.9]	IQR: [5.0, 11.1]	IQR: [5.0, 12.0]
		$n = 64$	$n = 47$	$n = 35$	$n = 286$	$n = 432$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Rationale Analysis: GDP In the written rationales economists offered to explain their GDP forecasts, the most frequently mentioned themes were: AI-driven productivity and automation; the importance of historical growth trends; adoption and reorganization lags; macroeconomic and political headwinds; extreme outcomes in the rapid scenario; and demographic and labor-force constraints.

Economists frequently mentioned that AI's potential to raise productivity across all sectors may be a major contributor to GDP growth, particularly with the prospect of AI-enabled research and development breakthroughs in the rapid scenario.[22] Many respondents wrote that slow diffusion of AI technology, particularly in robotics and through 2030, would initially limit GDP growth although they expected that in the long run broad adoption of AI would boost GDP.[23] Participants highlighted their deep uncertainty about 2050 outcomes, particularly in the rapid scenario, mentioning that rapid AI progress may bring existential risk, extreme political change and socioeconomic unrest.[24]

Across expertise groups, the leading drivers were broadly similar, though distinct emphases emerged. AI policy professionals cited AI investment bubble dynamics more frequently than any other group.[25] Superforecasters anchored on historical growth trends as their primary driver, which did not appear as a top driver for any other group. Respondents who gave lower unconditional forecasts tended to refer less to rapid scenario tail risks than high forecasters, but were more likely to reference macroeconomic and political headwinds in their rationales.

In addition to the rationale examples provided in the footnotes here, more rationale examples can be found in Appendix I.

[22] "The main channel through which AI will affect GDP growth is productivity growth. There is a high uncertainty on the impact of AI in labor productivity growth. My best forecast is that the impact will be moderate and will not change that much across scenarios, except for the impact on innovation and scientific discoveries. In this case, acceleration of AI progress would be a game changer," wrote one economist respondent.

[23] "Unconditionally [by 2030] I think GDP won't change much, due to ramp up times. Power plants and robots need to be built first. Regulatory hurdles will slow progress down, so I think GDP will stay stable," wrote one economist respondent.

[24] "I see a risk under the rapid progress scenario that AI capabilities could advance faster than control and governance mechanisms. In that case, humanity could lose control—either of AI systems themselves or of global stability—potentially leading to catastrophic outcomes such as large-scale conflict, bioweapon misuse, or other AI-related existential threats—potentially destroying most of human civilization and thus reducing GDP growth to 0," wrote one economist respondent.

[25] "For the unconditional scenario, I reflected my personal views around the impact of AI and the current situation (as seen in the stock market) that presents a high risk / high stakes situation if AI does not deliver on expectations. With AI falling short of expectations, this would severely limit (and delay) the ability of firms to raise further capital," wrote one AI policy expert respondent.

D.2.2 Change in Labor Productivity

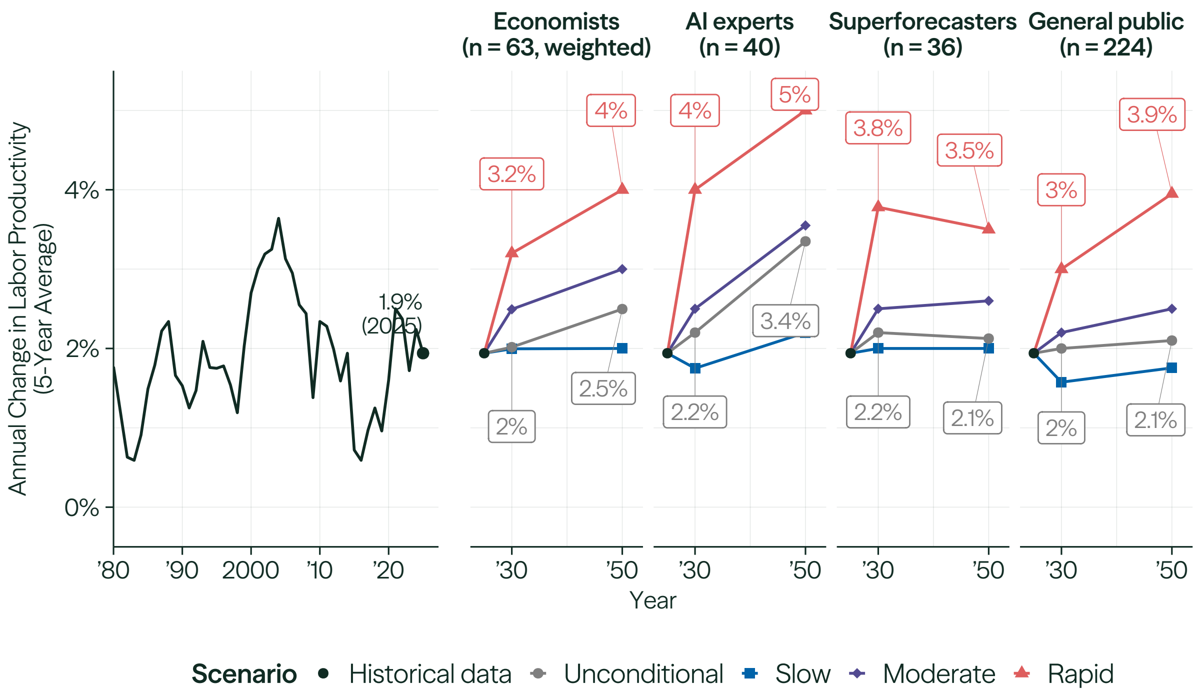


Figure 28: *Forecasts for annualized change in labor productivity (five-year average).* The most recent historical value for the outcome is shown in each panel as a black point. Lines show medians of 50th percentile forecasts across participants. Because we elicited only 50th percentile predictions for labor productivity, this figure does not show uncertainty. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 21: Annualized Change in Labor Productivity over 5 Years (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	2.0 CI: (2.0, 2.5) IQR: [2.0, 2.7] $n = 64$	2.2 CI: (2.0, 2.6) IQR: [2.0, 3.0] $n = 43$	2.2 CI: (2.0, 2.5) IQR: [2.0, 2.7] $n = 37$	2.0 CI: (1.9, 2.0) IQR: [1.5, 2.3] $n = 254$	2.1 CI: (2.0, 2.3) IQR: [1.9, 2.7] $n = 398$
Slow	50	2.0 CI: (1.5, 2.0) IQR: [1.4, 2.0] $n = 64$	2.0 CI: (1.5, 2.0) IQR: [1.4, 2.5] $n = 43$	2.0 CI: (1.9, 2.1) IQR: [1.5, 2.3] $n = 37$	1.6 CI: (1.5, 1.7) IQR: [1.2, 2.0] $n = 254$	2.0 CI: (1.8, 2.0) IQR: [1.5, 2.1] $n = 398$
Moderate	50	2.5 CI: (2.0, 3.0) IQR: [2.0, 3.0] $n = 64$	2.5 CI: (2.5, 3.0) IQR: [2.0, 4.0] $n = 43$	2.5 CI: (2.4, 2.8) IQR: [2.2, 3.3] $n = 37$	2.2 CI: (2.0, 2.3) IQR: [1.8, 3.0] $n = 254$	2.5 CI: (2.4, 2.5) IQR: [2.0, 3.1] $n = 398$
Rapid	50	3.2 CI: (2.6, 4.0) IQR: [2.4, 4.1] $n = 64$	4.0 CI: (3.5, 4.2) IQR: [3.0, 5.9] $n = 43$	3.6 CI: (3.0, 4.5) IQR: [2.7, 5.2] $n = 37$	3.0 CI: (2.8, 3.0) IQR: [2.3, 4.0] $n = 254$	3.5 CI: (3.1, 4.0) IQR: [2.5, 4.7] $n = 398$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 22: Annualized Change in Labor Productivity over 5 Years (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	2.5 CI: (2.2, 3.0) IQR: [2.0, 3.2] $n = 63$	3.1 CI: (2.5, 4.0) IQR: [2.1, 4.2] $n = 42$	2.1 CI: (2.0, 2.5) IQR: [2.0, 3.0] $n = 36$	2.2 CI: (2.0, 2.5) IQR: [1.7, 3.0] $n = 249$	2.4 CI: (2.2, 2.6) IQR: [2.0, 3.5] $n = 390$
Slow	50	2.0 CI: (2.0, 2.1) IQR: [1.7, 2.2] $n = 63$	2.2 CI: (1.9, 2.8) IQR: [1.5, 3.2] $n = 42$	2.0 CI: (2.0, 2.2) IQR: [1.8, 2.5] $n = 36$	1.9 CI: (1.6, 2.0) IQR: [1.2, 2.5] $n = 249$	2.0 CI: (2.0, 2.0) IQR: [1.5, 2.5] $n = 390$
Moderate	50	3.0 CI: (2.4, 3.1) IQR: [2.2, 3.7] $n = 63$	3.5 CI: (2.9, 4.2) IQR: [2.5, 5.0] $n = 42$	2.6 CI: (2.3, 3.0) IQR: [2.1, 3.6] $n = 36$	2.6 CI: (2.5, 2.8) IQR: [2.0, 4.0] $n = 249$	2.9 CI: (2.6, 3.0) IQR: [2.1, 4.0] $n = 390$
Rapid	50	4.0 CI: (3.0, 5.0) IQR: [3.0, 5.0] $n = 63$	5.0 CI: (4.1, 6.0) IQR: [3.2, 8.0] $n = 42$	3.5 CI: (2.5, 5.0) IQR: [2.2, 6.2] $n = 36$	4.0 CI: (3.5, 4.0) IQR: [2.8, 5.1] $n = 249$	4.0 CI: (3.5, 4.5) IQR: [2.6, 6.0] $n = 390$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.2.3 Change in Total Factor Productivity

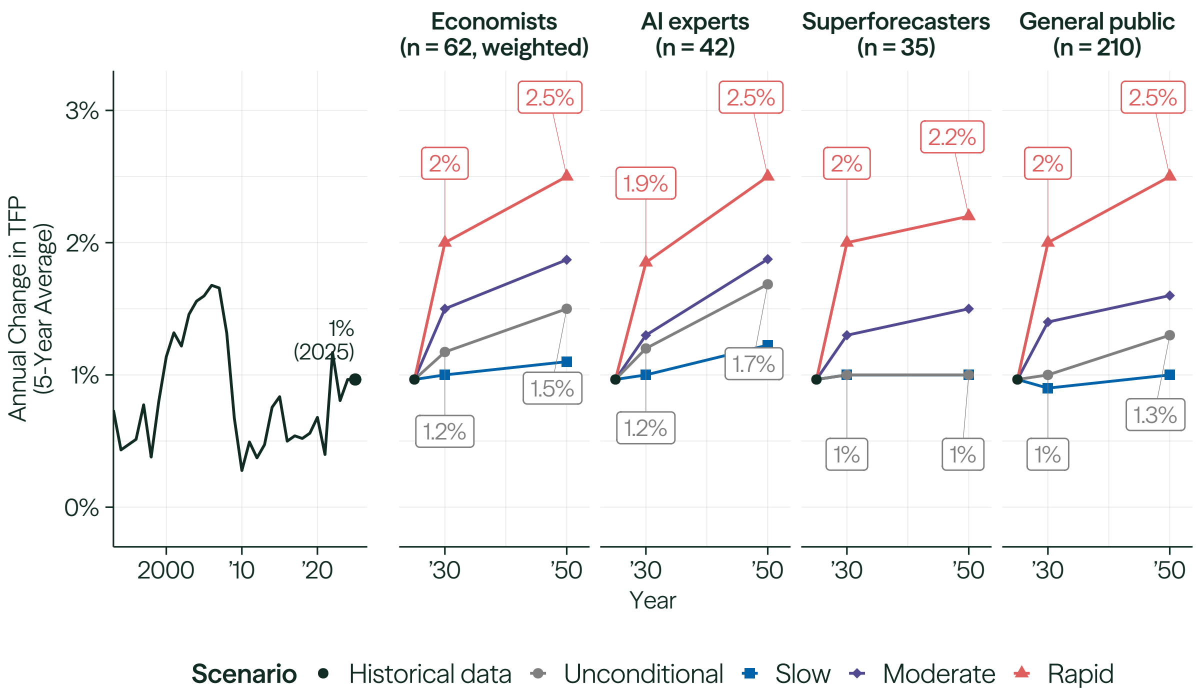


Figure 29: *Forecasts for annual change in total factor productivity (TFP).* The most recent historical value for the outcome is shown in each panel as a black point. Lines show medians of 50th percentile forecasts across participants. Because we elicited only 50th percentile predictions for TFP growth, this figure does not show uncertainty. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 23: Annualized Change in Total Factor Productivity over 5 Years (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	1.2 CI: (1.0, 1.5) IQR: [1.0, 1.5] $n = 62$	1.2 CI: (1.0, 1.4) IQR: [1.0, 1.5] $n = 43$	1.0 CI: (1.0, 1.2) IQR: [0.9, 1.4] $n = 36$	1.0 CI: (1.0, 1.1) IQR: [1.0, 1.4] $n = 234$	1.1 CI: (1.0, 1.2) IQR: [1.0, 1.5] $n = 375$
Slow	50	1.0 CI: (0.9, 1.0) IQR: [0.7, 1.1] $n = 62$	1.0 CI: (0.8, 1.1) IQR: [0.7, 1.2] $n = 43$	1.0 CI: (0.9, 1.0) IQR: [0.8, 1.1] $n = 36$	1.0 CI: (0.9, 1.0) IQR: [0.7, 1.1] $n = 234$	1.0 CI: (1.0, 1.0) IQR: [0.8, 1.1] $n = 375$
Moderate	50	1.5 CI: (1.2, 1.7) IQR: [1.0, 2.0] $n = 62$	1.3 CI: (1.2, 1.5) IQR: [1.0, 1.6] $n = 43$	1.3 CI: (1.1, 1.6) IQR: [1.0, 2.0] $n = 36$	1.3 CI: (1.3, 1.5) IQR: [1.1, 1.8] $n = 234$	1.3 CI: (1.2, 1.5) IQR: [1.0, 2.0] $n = 375$
Rapid	50	2.0 CI: (1.7, 2.5) IQR: [1.5, 2.5] $n = 62$	1.9 CI: (1.7, 2.0) IQR: [1.5, 2.7] $n = 43$	2.0 CI: (1.5, 2.6) IQR: [1.4, 3.0] $n = 36$	2.0 CI: (1.8, 2.0) IQR: [1.4, 2.5] $n = 234$	2.0 CI: (1.8, 2.0) IQR: [1.5, 2.7] $n = 375$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 24: Annualized Change in Total Factor Productivity over 5 Years (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	1.5 CI: (1.2, 1.7) IQR: [1.1, 2.0] $n = 64$	1.7 CI: (1.3, 2.0) IQR: [1.0, 2.5] $n = 43$	1.0 CI: (1.0, 1.3) IQR: [0.9, 1.7] $n = 35$	1.3 CI: (1.2, 1.5) IQR: [1.0, 1.9] $n = 228$	1.4 CI: (1.2, 1.5) IQR: [1.0, 2.0] $n = 370$
Slow	50	1.1 CI: (1.0, 1.2) IQR: [1.0, 1.3] $n = 64$	1.2 CI: (0.9, 1.5) IQR: [0.6, 1.8] $n = 43$	1.0 CI: (0.9, 1.1) IQR: [0.8, 1.5] $n = 35$	1.0 CI: (1.0, 1.0) IQR: [0.8, 1.5] $n = 228$	1.0 CI: (1.0, 1.2) IQR: [0.8, 1.5] $n = 370$
Moderate	50	1.8 CI: (1.6, 2.0) IQR: [1.5, 2.0] $n = 64$	1.9 CI: (1.5, 2.0) IQR: [1.1, 2.7] $n = 43$	1.5 CI: (1.1, 1.8) IQR: [1.0, 2.0] $n = 35$	1.6 CI: (1.5, 1.8) IQR: [1.3, 2.2] $n = 228$	1.7 CI: (1.5, 1.8) IQR: [1.2, 2.1] $n = 370$
Rapid	50	2.5 CI: (2.0, 3.0) IQR: [2.0, 3.0] $n = 64$	2.5 CI: (2.0, 4.5) IQR: [1.7, 5.0] $n = 43$	2.2 CI: (1.6, 3.5) IQR: [1.4, 4.0] $n = 35$	2.5 CI: (2.1, 2.6) IQR: [1.8, 4.0] $n = 228$	2.5 CI: (2.2, 3.0) IQR: [1.6, 4.0] $n = 370$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Rationale Analysis: TFP In the written rationales economists offered to explain their TFP forecasts, the most frequently mentioned themes were historical TFP trends, the link with labor productivity, capital deepening and AI infrastructure, adoption and diffusion frictions, and the breadth of automation across sectors.

A distinctive feature of the TFP rationales was extensive engagement with how TFP relates to labor productivity: many forecasters noted that AI requires heavy capital investment (data centers, energy, compute), so a large share of productivity gains shows up as capital deepening rather than TFP.[26] Economists tended to anchor their TFP forecasts on the historical baseline, particularly in the slow scenario. Some forecasters compared AI's impact on TFP to the IT boom in the late 1990s, arguing that we may see a temporary boost in TFP before a return to historical baselines.[27] Many economists focused on capital deepening, arguing that TFP growth from AI may only materialize after a period of intense capital expenditure on AI infrastructure. Economists also cited lags in adoption and diffusion, and J-curve dynamics as reasons why TFP increase may be small in the near-term but become more apparent by 2050, even in the moderate and rapid scenarios.[28]

Different respondent groups cited broadly similar reasons for their rationales, although AI industry professionals and superforecasters cited diminishing returns from AI more frequently than economists or AI policy professionals. Superforecasters were the only group to cite historical TFP baselines as their top driver, with AI policy professionals placing less emphasis on historical trends relative to other factors than other groups.

In addition to the rationale examples provided in the footnotes here, more rationale examples can be found in Appendix I.

[26] "I think the main additional factor that applies here is that there has been an incredibly sharp accumulation of capital investment in AI infrastructure. This capital deepening will account for a larger share of labor productivity gains than in the past, leading to lower estimates of TFP growth relative to labor productivity growth," wrote one economist respondent.

[27] "1.8% for slow progress and 2030 mirrors the TFP boom of the late 1990s (the internet era), where TFP temporarily spiked due to IT adoption. As the boom fades and AI remains merely an "assisting tool," TFP growth reverts to the historical US average," wrote one economist respondent.

[28] "When firms shift to AI, they accumulate intangible capital (new business processes, re-training) which is not counted as an asset in GDP accounts. This makes TFP look low initially (inputs rise, output stays flat). By 2050, this hidden capital is activated, leading to a delayed TFP boom (1.5%) as the slow progress world finally converges to the frontier," wrote one economist respondent.

D.2.4 Labor Force Participation Rate

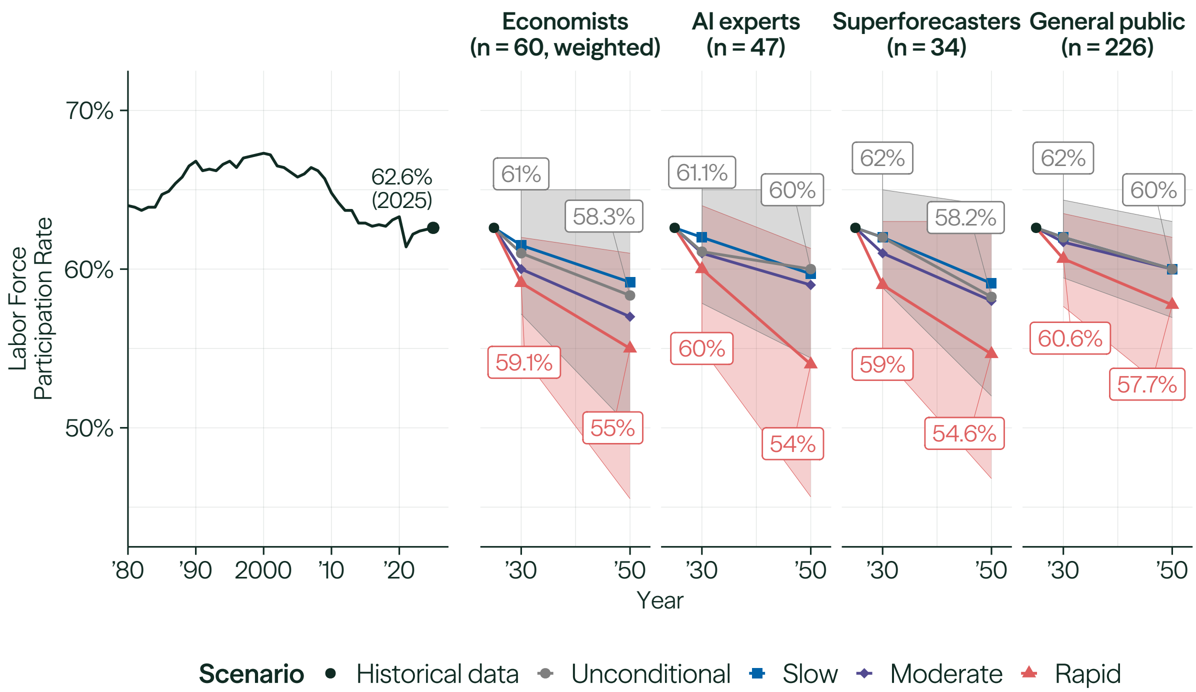


Figure 30: *Forecasts for the labor force participation rate (LFPR).* Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

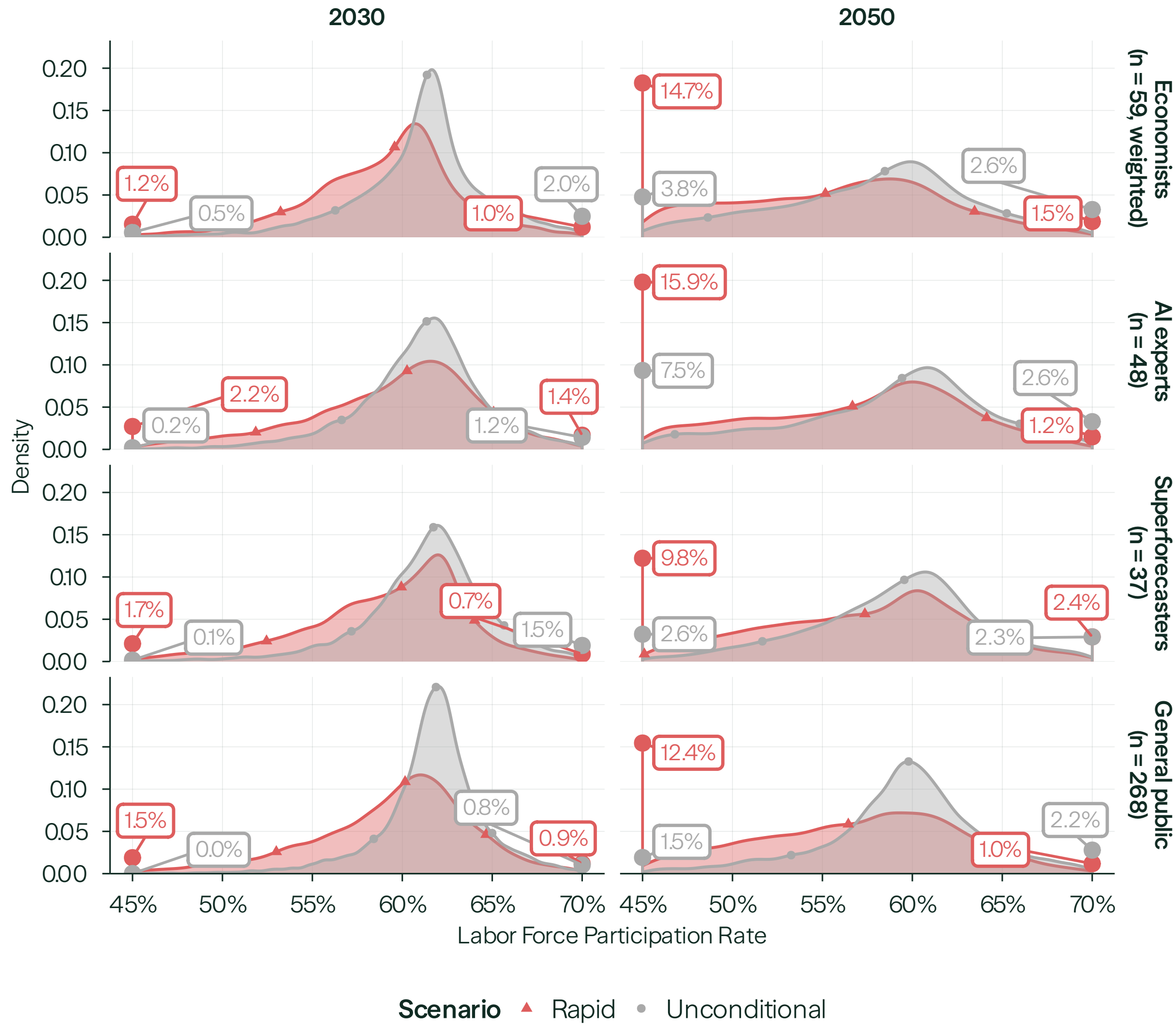


Figure 31: *Distribution of forecasts for labor force participation rate (LFPR).* Distribution is pooled across participants to summarize the full distribution of participant beliefs. Tail mass outside of figure bounds shown as ball-and-stick at 45% and 70%, with numbers in boxes indicating the proportion of the pooled distribution that lies below 45% or above 70%. Interior points show 10th/50th/90th percentiles of the distribution.

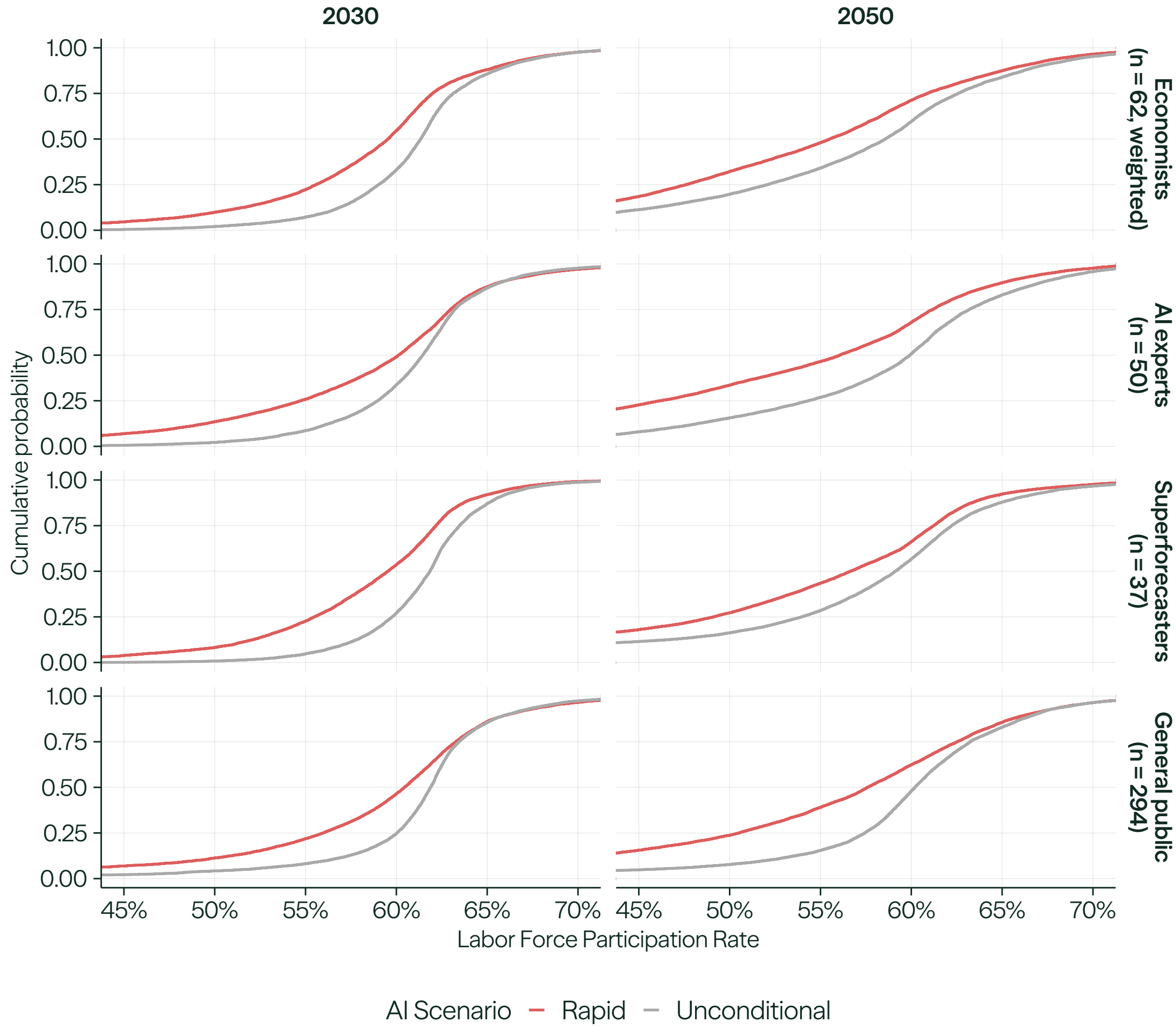


Figure 32: *Cumulative distribution of forecasts for the labor force participation rate (LFPR).*

Table 25: Labor Force Participation Rate (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	57.3 CI: (55.7, 58.7) IQR: [55.0, 59.6] $n = 63$	57.9 CI: (55.0, 58.7) IQR: [53.9, 59.4] $n = 48$	59.0 CI: (57.0, 60.0) IQR: [55.0, 60.0] $n = 37$	59.0 CI: (58.6, 60.0) IQR: [55.7, 60.5] $n = 268$	58.0 CI: (57.7, 58.7) IQR: [55.0, 60.0] $n = 416$
Unconditional	50	61.0 CI: (60.0, 62.0) IQR: [60.0, 62.5] $n = 63$	61.3 CI: (60.9, 62.0) IQR: [60.0, 62.3] $n = 48$	62.0 CI: (61.0, 62.5) IQR: [60.0, 63.0] $n = 37$	62.0 CI: (62.0, 62.1) IQR: [61.0, 63.0] $n = 268$	61.7 CI: (61.1, 62.0) IQR: [60.0, 62.6] $n = 416$
Unconditional	90	65.0 CI: (64.0, 67.0) IQR: [62.8, 68.0] $n = 63$	65.0 CI: (63.5, 66.3) IQR: [63.1, 67.5] $n = 48$	65.0 CI: (63.5, 66.0) IQR: [63.0, 67.0] $n = 37$	65.0 CI: (64.0, 65.0) IQR: [63.0, 67.7] $n = 268$	65.0 CI: (64.0, 65.3) IQR: [63.0, 67.3] $n = 416$
Slow	50	61.5 CI: (60.8, 62.2) IQR: [60.0, 62.4] $n = 63$	62.0 CI: (61.5, 62.0) IQR: [61.0, 62.4] $n = 48$	62.1 CI: (62.0, 62.8) IQR: [61.0, 63.0] $n = 37$	62.0 CI: (62.0, 62.0) IQR: [61.0, 62.9] $n = 268$	62.0 CI: (62.0, 62.0) IQR: [61.0, 62.8] $n = 416$
Moderate	50	60.7 CI: (59.9, 61.4) IQR: [59.0, 61.7] $n = 63$	61.1 CI: (60.0, 62.0) IQR: [59.8, 62.5] $n = 48$	61.0 CI: (60.0, 62.0) IQR: [60.0, 62.4] $n = 37$	61.7 CI: (61.1, 62.0) IQR: [60.0, 63.0] $n = 268$	61.0 CI: (60.5, 61.5) IQR: [59.8, 62.5] $n = 416$
Rapid	10	54.7 CI: (52.3, 56.3) IQR: [50.0, 59.0] $n = 63$	55.0 CI: (52.8, 57.3) IQR: [49.1, 58.9] $n = 48$	54.0 CI: (52.0, 58.0) IQR: [50.0, 59.0] $n = 37$	56.7 CI: (55.6, 58.0) IQR: [50.8, 60.0] $n = 268$	55.0 CI: (54.0, 56.1) IQR: [50.0, 59.0] $n = 416$
Rapid	50	59.3 CI: (58.0, 60.4) IQR: [56.4, 61.0] $n = 63$	60.0 CI: (58.0, 61.0) IQR: [56.9, 62.1] $n = 48$	59.0 CI: (57.0, 61.0) IQR: [55.5, 62.0] $n = 37$	60.2 CI: (60.0, 61.0) IQR: [56.9, 63.0] $n = 268$	59.8 CI: (58.5, 60.0) IQR: [56.0, 62.0] $n = 416$
Rapid	90	62.3 CI: (61.7, 64.7) IQR: [60.9, 65.0] $n = 63$	64.2 CI: (63.0, 65.0) IQR: [62.1, 66.2] $n = 48$	63.0 CI: (62.0, 64.0) IQR: [61.0, 65.0] $n = 37$	63.8 CI: (63.0, 64.0) IQR: [60.4, 66.4] $n = 268$	63.0 CI: (62.6, 64.0) IQR: [61.0, 66.0] $n = 416$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 26: Labor Force Participation Rate (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	50.0 CI: (45.0, 55.0) IQR: [44.6, 55.7] $n = 60$	53.7 CI: (50.3, 57.7) IQR: [48.3, 58.9] $n = 49$	52.0 CI: (48.3, 55.0) IQR: [45.1, 57.0] $n = 34$	56.9 CI: (56.0, 57.2) IQR: [53.3, 59.0] $n = 258$	53.8 CI: (51.1, 55.0) IQR: [47.2, 58.0] $n = 401$
Unconditional	50	58.3 CI: (56.1, 60.0) IQR: [55.2, 60.5] $n = 60$	59.7 CI: (58.0, 60.8) IQR: [54.9, 62.0] $n = 49$	58.2 CI: (56.0, 60.5) IQR: [54.0, 61.0] $n = 34$	60.0 CI: (60.0, 60.5) IQR: [58.5, 63.0] $n = 258$	59.5 CI: (58.1, 60.0) IQR: [55.0, 61.5] $n = 401$
Unconditional	90	65.0 CI: (62.2, 68.0) IQR: [60.7, 69.3] $n = 60$	65.0 CI: (62.0, 66.3) IQR: [61.0, 68.6] $n = 49$	64.0 CI: (62.5, 66.7) IQR: [61.0, 68.0] $n = 34$	64.0 CI: (63.0, 64.7) IQR: [62.0, 67.8] $n = 258$	64.1 CI: (63.0, 65.0) IQR: [61.0, 68.6] $n = 401$
Slow	50	59.2 CI: (58.4, 60.0) IQR: [57.1, 60.6] $n = 60$	59.7 CI: (59.0, 60.6) IQR: [58.0, 62.0] $n = 49$	59.1 CI: (58.1, 60.6) IQR: [57.0, 62.0] $n = 34$	60.0 CI: (60.0, 60.1) IQR: [58.5, 62.4] $n = 258$	59.8 CI: (59.0, 60.0) IQR: [58.0, 62.0] $n = 401$
Moderate	50	57.0 CI: (56.0, 60.0) IQR: [55.0, 60.4] $n = 60$	59.0 CI: (56.0, 60.5) IQR: [55.0, 61.6] $n = 49$	58.0 CI: (55.0, 60.5) IQR: [52.0, 61.3] $n = 34$	60.0 CI: (59.5, 60.0) IQR: [57.0, 62.0] $n = 258$	59.0 CI: (57.0, 60.0) IQR: [55.0, 61.5] $n = 401$
Rapid	10	45.5 CI: (40.0, 50.7) IQR: [40.0, 55.0] $n = 60$	45.7 CI: (41.5, 55.0) IQR: [34.2, 57.2] $n = 49$	46.8 CI: (40.0, 51.0) IQR: [15.0, 54.0] $n = 34$	53.3 CI: (51.0, 55.0) IQR: [45.0, 59.0] $n = 258$	48.0 CI: (45.0, 50.0) IQR: [37.4, 56.3] $n = 401$
Rapid	50	55.0 CI: (50.0, 59.0) IQR: [50.0, 60.0] $n = 60$	54.0 CI: (50.0, 59.0) IQR: [44.1, 61.0] $n = 49$	54.6 CI: (49.9, 59.5) IQR: [35.9, 60.0] $n = 34$	58.0 CI: (57.0, 60.0) IQR: [50.0, 63.0] $n = 258$	55.3 CI: (53.4, 58.0) IQR: [45.7, 61.0] $n = 401$
Rapid	90	61.0 CI: (60.0, 65.0) IQR: [58.9, 67.0] $n = 60$	61.3 CI: (58.7, 64.2) IQR: [54.8, 65.8] $n = 49$	63.0 CI: (60.0, 65.0) IQR: [58.0, 67.5] $n = 34$	62.5 CI: (62.0, 64.0) IQR: [57.3, 67.6] $n = 258$	62.0 CI: (61.0, 63.0) IQR: [55.0, 67.0] $n = 401$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Rationale Analysis: LFPR Economists tended to put most weight on two countervailing factors: AI substituting for human workers, and reallocation of workers across occupations, including the creation of new occupations altogether. Many forecasters expected AI to replace human roles in the short term, but for this effect to be offset by new jobs in the long term, particularly in the slow and moderate scenarios.[29] Other forecasters argued that demographic trends would weigh heavily on LFPR in both directions: with higher participation among

[29]"In a moderate progress scenario labor force participation is likely to decline in the near term as companies replace some jobs, but with aging workforces and declining birth rates there will still be demand for human workers (even in more companion/service focused roles)," wrote one superforecaster respondent.

older workers and women potentially raising LFPR while an aging population and decreased immigration potentially causing LFPR to fall.[30] A small number of forecasters flagged AI-enabled longevity as underrated: if lifespans extend dramatically, retirement as currently conceived may become unsustainable, potentially pushing LFPR up.

Some forecasters gave prominent mentions to income, wealth effects and leisure, with some envisioning a "post-work" economy where fewer people need to work for financial reasons.[31] Economists placed notably more emphasis on discouraged workers and structural unemployment, arguing AI could lead to many people involuntarily dropping out as their skills become obsolete.

In addition to the rationale examples provided in the footnotes here, more rationale examples can be found in Appendix I.

[30] "The labor force participation rate in the U.S. will remain relatively stable through the end of this decade, with a slight downward trend. By 2030, modest declines may result from demographic aging and the continued retirement of the baby-boom generation. On the other hand, new occupations and flexible work arrangements enabled by AI could keep more people (especially older workers and women) in the labor market. Yet demographic pressures, particularly population aging, will likely dominate, pushing overall participation lower," wrote one economist respondent.

[31] "If AI goes very well, with fast progress, it could displace large amounts of labor, and moreover, make us so wealthy that people prefer leisure," wrote one economist respondent.

D.2.5 Unemployment Rate

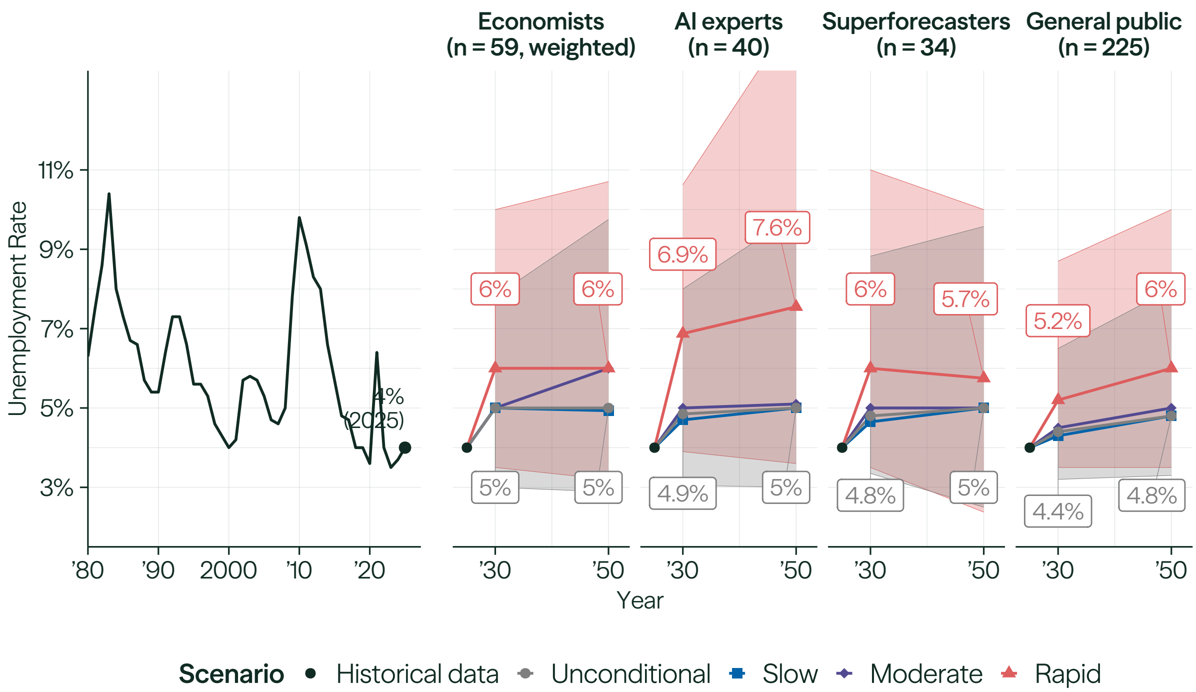


Figure 33: *Forecasts for the unemployment rate.* The most recent historical value for the outcome is shown in each panel as a black point. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

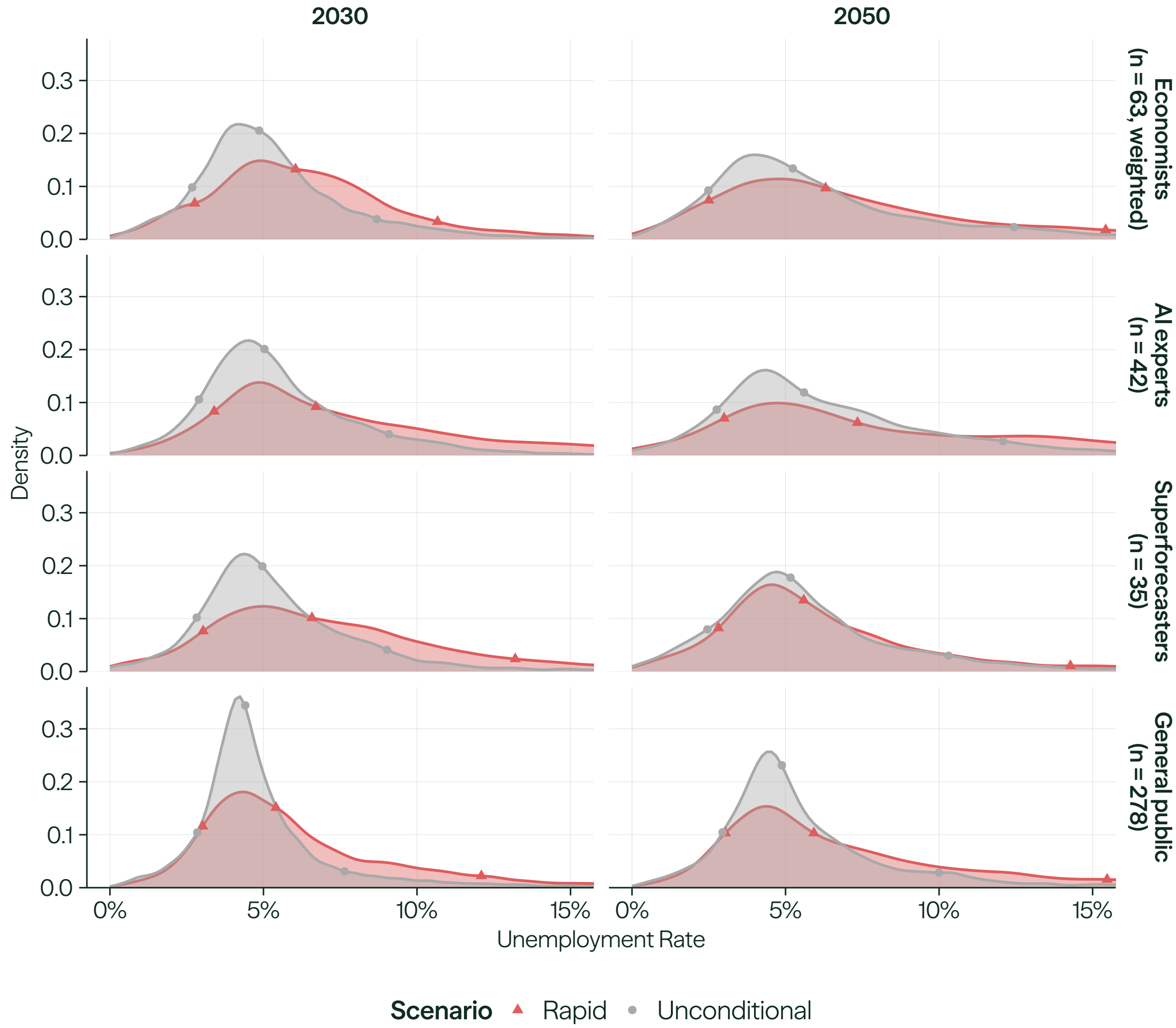


Figure 34: *Distribution of forecasts for the unemployment rate.* Distribution is pooled across participants. Points show 10th/50th/90th percentiles of the distribution.

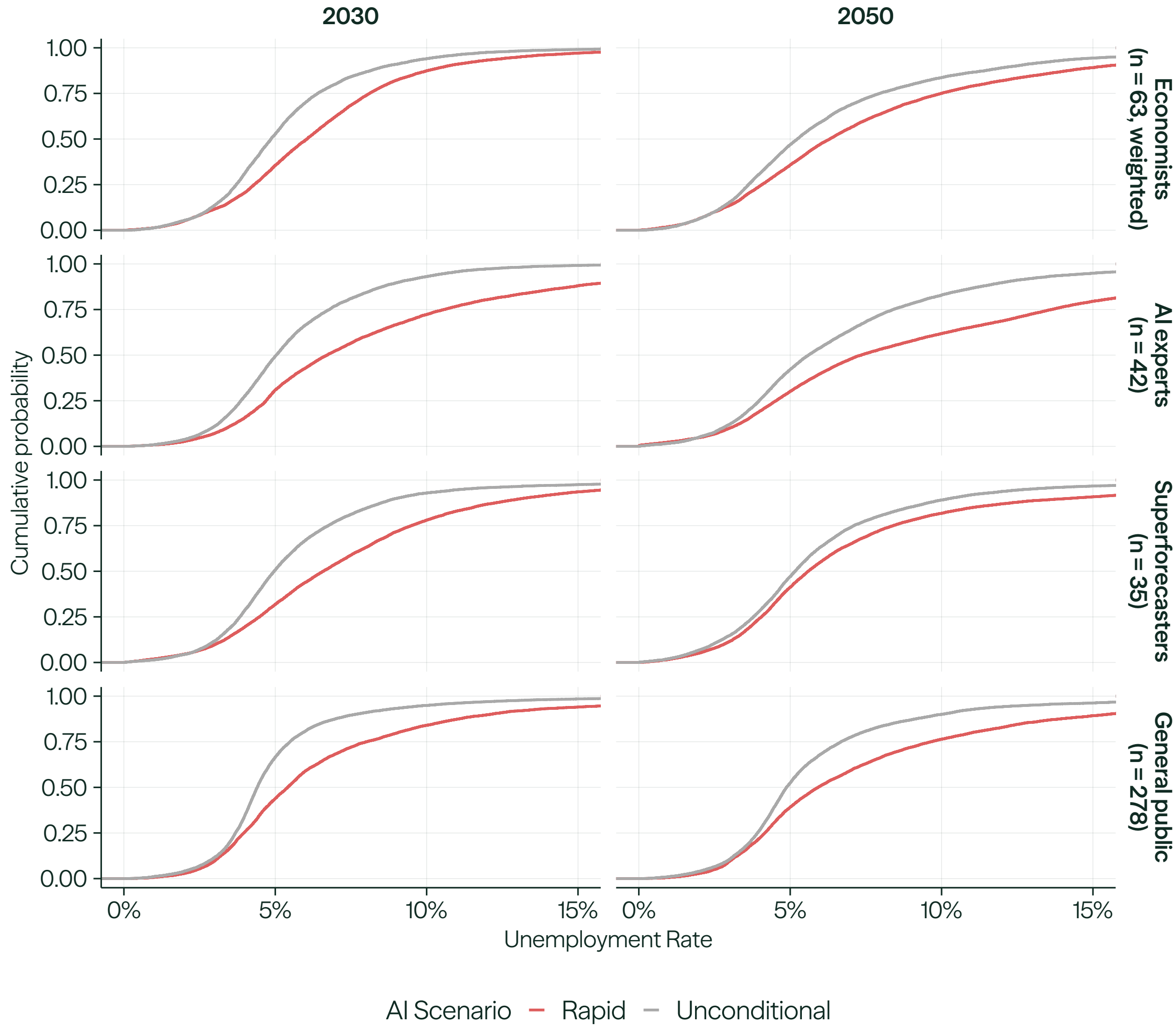


Figure 35: *Cumulative distribution of forecasts for the unemployment rate.*

Table 27: Unemployment Rate (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	3.0 CI: (2.2, 3.7) IQR: [1.6, 4.0] $n = 64$	3.1 CI: (3.0, 3.5) IQR: [2.3, 4.0] $n = 43$	3.5 CI: (3.0, 3.5) IQR: [3.0, 3.8] $n = 35$	3.1 CI: (3.0, 3.2) IQR: [2.0, 3.6] $n = 263$	3.2 CI: (3.0, 3.5) IQR: [2.2, 3.9] $n = 405$
Unconditional	50	5.0 CI: (4.7, 5.4) IQR: [4.3, 5.6] $n = 64$	4.8 CI: (4.4, 5.0) IQR: [4.2, 5.5] $n = 43$	4.6 CI: (4.5, 5.2) IQR: [4.4, 5.5] $n = 35$	4.3 CI: (4.2, 4.5) IQR: [4.0, 5.0] $n = 263$	4.7 CI: (4.5, 5.0) IQR: [4.2, 5.5] $n = 405$
Unconditional	90	7.8 CI: (6.8, 8.8) IQR: [6.5, 9.8] $n = 64$	8.3 CI: (7.5, 10.0) IQR: [6.1, 10.5] $n = 43$	8.7 CI: (7.0, 9.0) IQR: [6.1, 9.9] $n = 35$	6.5 CI: (6.0, 7.0) IQR: [5.2, 9.0] $n = 263$	8.0 CI: (7.1, 8.8) IQR: [6.0, 10.0] $n = 405$
Slow	50	5.0 CI: (4.5, 5.0) IQR: [4.0, 5.2] $n = 64$	4.6 CI: (4.4, 5.0) IQR: [4.1, 5.4] $n = 43$	4.5 CI: (4.3, 5.0) IQR: [4.2, 5.2] $n = 35$	4.2 CI: (4.2, 4.4) IQR: [4.0, 4.6] $n = 263$	4.5 CI: (4.4, 4.8) IQR: [4.0, 5.0] $n = 405$
Moderate	50	5.0 CI: (4.5, 5.8) IQR: [4.3, 6.0] $n = 64$	5.0 CI: (4.8, 6.0) IQR: [4.5, 7.0] $n = 43$	5.0 CI: (4.5, 5.5) IQR: [4.5, 5.7] $n = 35$	4.5 CI: (4.4, 4.8) IQR: [4.0, 5.5] $n = 263$	5.0 CI: (4.8, 5.0) IQR: [4.3, 6.0] $n = 405$
Rapid	10	3.5 CI: (3.0, 4.1) IQR: [2.5, 4.5] $n = 64$	3.9 CI: (3.0, 4.5) IQR: [3.0, 5.0] $n = 43$	3.5 CI: (2.8, 4.2) IQR: [2.1, 5.0] $n = 35$	3.5 CI: (3.2, 4.0) IQR: [2.5, 4.9] $n = 263$	3.6 CI: (3.2, 4.0) IQR: [2.5, 5.0] $n = 405$
Rapid	50	6.0 CI: (5.0, 7.0) IQR: [5.0, 7.5] $n = 64$	7.0 CI: (6.0, 8.0) IQR: [4.9, 9.9] $n = 43$	6.0 CI: (5.0, 8.0) IQR: [4.5, 8.0] $n = 35$	5.4 CI: (5.0, 5.5) IQR: [4.2, 7.0] $n = 263$	6.0 CI: (5.6, 7.0) IQR: [4.8, 8.0] $n = 405$
Rapid	90	9.9 CI: (9.0, 10.8) IQR: [7.9, 12.0] $n = 64$	10.8 CI: (9.4, 14.0) IQR: [8.0, 16.0] $n = 43$	11.0 CI: (9.5, 15.0) IQR: [8.1, 15.4] $n = 35$	8.7 CI: (7.8, 9.3) IQR: [6.0, 12.5] $n = 263$	10.0 CI: (9.5, 11.0) IQR: [7.7, 14.5] $n = 405$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 28: Unemployment Rate (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	2.8 CI: (1.3, 3.0) IQR: [0.4, 3.5] $n = 60$	3.0 CI: (2.5, 3.5) IQR: [1.9, 4.0] $n = 41$	2.5 CI: (2.0, 3.1) IQR: [1.5, 3.5] $n = 34$	3.4 CI: (3.0, 3.5) IQR: [2.1, 4.0] $n = 260$	3.0 CI: (2.5, 3.0) IQR: [1.3, 3.6] $n = 395$
Unconditional	50	5.0 CI: (4.4, 6.0) IQR: [4.0, 7.0] $n = 60$	5.0 CI: (4.5, 6.0) IQR: [4.5, 7.1] $n = 41$	5.0 CI: (5.0, 5.2) IQR: [4.2, 6.0] $n = 34$	4.8 CI: (4.6, 5.0) IQR: [4.3, 6.0] $n = 260$	5.0 CI: (4.9, 5.0) IQR: [4.2, 6.1] $n = 395$
Unconditional	90	9.8 CI: (7.8, 12.0) IQR: [7.0, 13.7] $n = 60$	10.0 CI: (8.0, 12.3) IQR: [7.3, 13.1] $n = 41$	9.6 CI: (8.6, 10.4) IQR: [7.5, 11.0] $n = 34$	8.0 CI: (7.0, 8.6) IQR: [6.0, 11.5] $n = 260$	9.0 CI: (8.8, 10.0) IQR: [7.0, 12.5] $n = 395$
Slow	50	5.0 CI: (4.2, 5.0) IQR: [4.0, 5.8] $n = 60$	5.0 CI: (4.9, 5.6) IQR: [4.4, 7.0] $n = 41$	5.0 CI: (4.5, 5.1) IQR: [4.2, 5.8] $n = 34$	4.7 CI: (4.6, 4.9) IQR: [4.1, 5.2] $n = 260$	5.0 CI: (4.8, 5.0) IQR: [4.2, 5.8] $n = 395$
Moderate	50	6.0 CI: (4.8, 6.6) IQR: [4.3, 7.0] $n = 60$	5.2 CI: (5.0, 6.6) IQR: [4.5, 8.0] $n = 41$	5.0 CI: (4.7, 6.0) IQR: [4.3, 6.2] $n = 34$	5.0 CI: (4.8, 5.0) IQR: [4.2, 6.6] $n = 260$	5.0 CI: (5.0, 6.0) IQR: [4.4, 7.0] $n = 395$
Rapid	10	3.2 CI: (3.0, 4.0) IQR: [2.0, 4.8] $n = 60$	3.5 CI: (2.5, 4.7) IQR: [2.0, 7.1] $n = 41$	2.4 CI: (0.8, 3.5) IQR: [0.1, 3.5] $n = 34$	3.6 CI: (3.1, 4.0) IQR: [2.5, 5.7] $n = 260$	3.1 CI: (3.0, 3.5) IQR: [1.8, 4.5] $n = 395$
Rapid	50	6.0 CI: (5.0, 8.0) IQR: [4.1, 9.5] $n = 60$	8.0 CI: (5.6, 10.0) IQR: [5.0, 13.5] $n = 41$	5.7 CI: (4.5, 6.5) IQR: [4.0, 7.0] $n = 34$	6.0 CI: (5.5, 6.5) IQR: [4.4, 9.9] $n = 260$	6.0 CI: (5.5, 6.5) IQR: [4.3, 10.0] $n = 395$
Rapid	90	10.7 CI: (9.1, 13.5) IQR: [8.0, 16.7] $n = 60$	15.0 CI: (10.0, 18.0) IQR: [9.0, 20.9] $n = 41$	10.0 CI: (8.6, 11.0) IQR: [8.0, 15.0] $n = 34$	10.0 CI: (9.0, 11.0) IQR: [6.1, 14.8] $n = 260$	10.5 CI: (10.0, 11.8) IQR: [8.0, 18.0] $n = 395$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.2.6 Youth Unemployment Rate

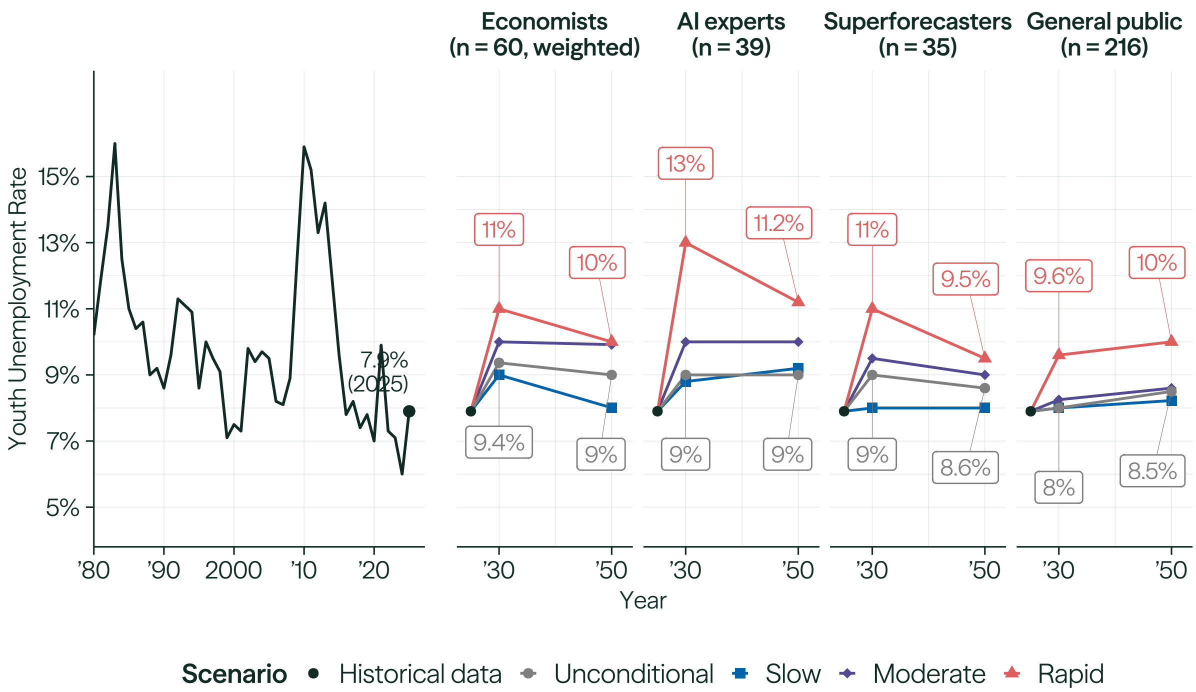


Figure 36: *Forecasts for the unemployment rate for 20–24 year-olds.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Because we elicited only 50th percentile predictions for youth unemployment, this figure does not show uncertainty. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 29: Youth Unemployment Rate (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	9.5 CI: (8.7, 10.0) IQR: [8.0, 10.6] $n = 62$	9.2 CI: (8.5, 10.0) IQR: [8.0, 11.0] $n = 43$	9.0 CI: (8.0, 9.6) IQR: [8.0, 10.0] $n = 35$	8.0 CI: (8.0, 8.1) IQR: [7.2, 9.0] $n = 245$	9.0 CI: (8.5, 9.2) IQR: [8.0, 10.0] $n = 385$
Slow	50	9.0 CI: (8.0, 9.5) IQR: [7.8, 10.0] $n = 62$	8.8 CI: (8.0, 9.0) IQR: [8.0, 10.0] $n = 43$	8.0 CI: (8.0, 9.0) IQR: [7.6, 9.1] $n = 35$	8.0 CI: (8.0, 8.0) IQR: [7.3, 9.0] $n = 245$	8.1 CI: (8.0, 9.0) IQR: [7.6, 9.6] $n = 385$
Moderate	50	10.0 CI: (9.0, 11.0) IQR: [8.5, 11.2] $n = 62$	10.0 CI: (9.4, 11.0) IQR: [8.1, 12.3] $n = 43$	9.5 CI: (8.5, 10.4) IQR: [8.0, 11.8] $n = 35$	8.4 CI: (8.0, 8.5) IQR: [7.2, 10.0] $n = 245$	9.5 CI: (9.0, 10.0) IQR: [8.0, 11.2] $n = 385$
Rapid	50	11.0 CI: (10.0, 14.0) IQR: [9.0, 15.0] $n = 62$	14.0 CI: (10.1, 15.0) IQR: [9.2, 17.9] $n = 43$	11.0 CI: (9.5, 14.0) IQR: [9.0, 17.8] $n = 35$	10.0 CI: (9.0, 10.0) IQR: [7.3, 13.6] $n = 245$	11.0 CI: (10.0, 12.4) IQR: [9.0, 15.0] $n = 385$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 30: Youth Unemployment Rate (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	9.0 CI: (8.0, 10.0) IQR: [8.0, 10.2] $n = 63$	9.2 CI: (8.0, 11.1) IQR: [8.0, 14.0] $n = 40$	8.6 CI: (8.0, 10.0) IQR: [7.6, 10.8] $n = 35$	8.5 CI: (8.0, 9.0) IQR: [7.2, 10.0] $n = 246$	9.0 CI: (8.1, 9.5) IQR: [7.5, 11.0] $n = 384$
Slow	50	8.2 CI: (8.0, 9.3) IQR: [7.6, 10.0] $n = 63$	9.4 CI: (8.0, 10.0) IQR: [7.9, 11.9] $n = 40$	8.0 CI: (8.0, 9.2) IQR: [7.5, 9.9] $n = 35$	8.2 CI: (8.0, 8.6) IQR: [7.0, 10.0] $n = 246$	8.5 CI: (8.0, 9.0) IQR: [7.5, 10.0] $n = 384$
Moderate	50	9.8 CI: (8.0, 10.5) IQR: [8.0, 12.0] $n = 63$	10.0 CI: (8.2, 12.6) IQR: [7.8, 15.0] $n = 40$	9.0 CI: (8.0, 10.0) IQR: [8.0, 11.8] $n = 35$	8.8 CI: (8.3, 9.1) IQR: [7.0, 12.0] $n = 246$	9.1 CI: (8.5, 10.0) IQR: [7.9, 13.0] $n = 384$
Rapid	50	10.0 CI: (8.0, 12.0) IQR: [7.0, 12.6] $n = 63$	11.4 CI: (10.0, 16.2) IQR: [7.6, 22.0] $n = 40$	9.5 CI: (8.0, 12.0) IQR: [8.0, 16.8] $n = 35$	10.0 CI: (9.6, 11.0) IQR: [7.0, 17.0] $n = 246$	10.0 CI: (9.5, 11.5) IQR: [7.6, 17.0] $n = 384$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.2.7 Sector Shares

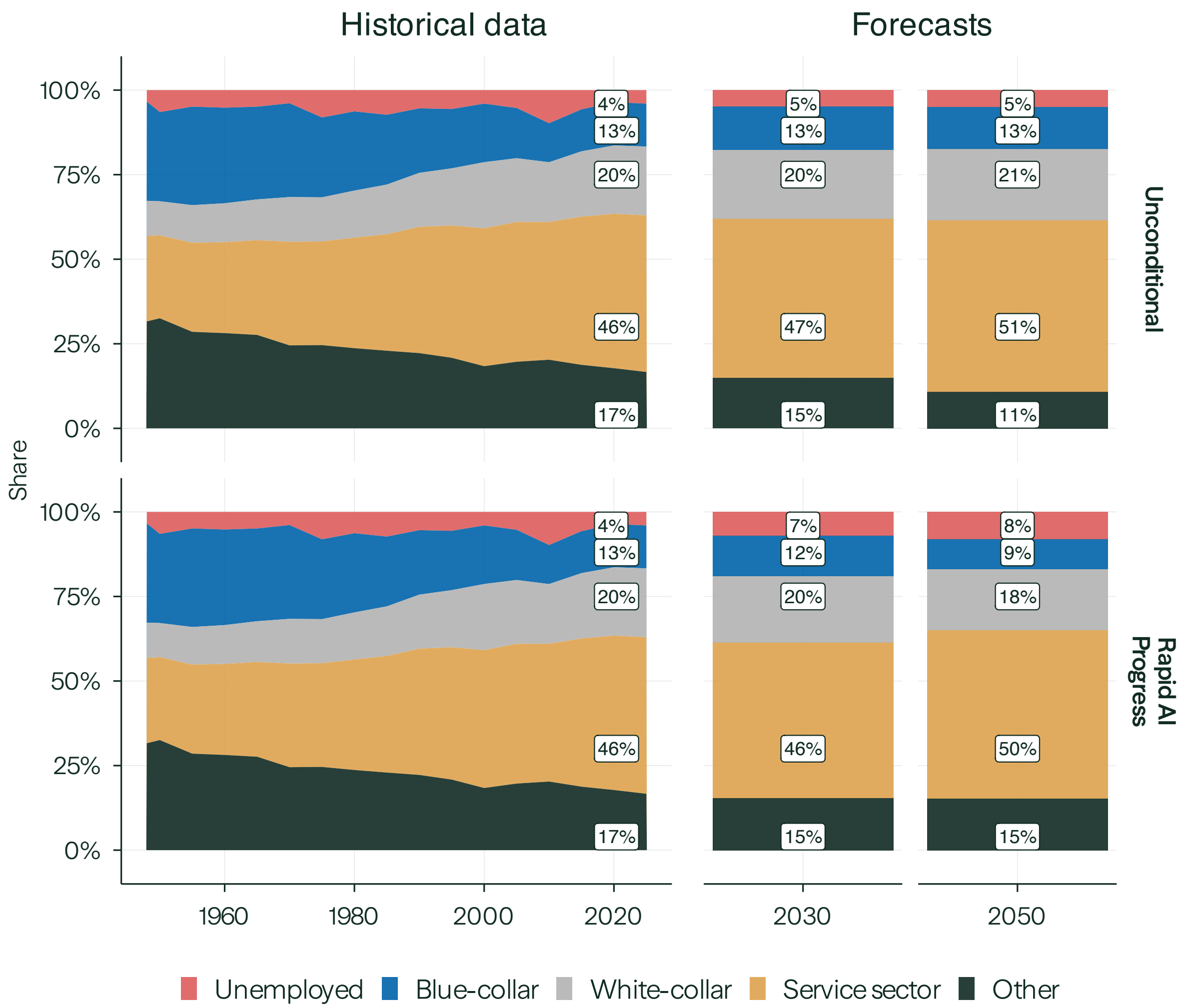


Figure 37: *AI experts' forecasts for different sectors as shares of the labor force.* Areas and labels show the median 50th percentile forecast. Historical shares are shown in the panel on the left. The 'Other' category is derived by subtracting the sum of the other sectors' median forecasts from 100%; it consists primarily of public sector and agricultural workers. Labeled historical values correspond to the beginning of 2025.

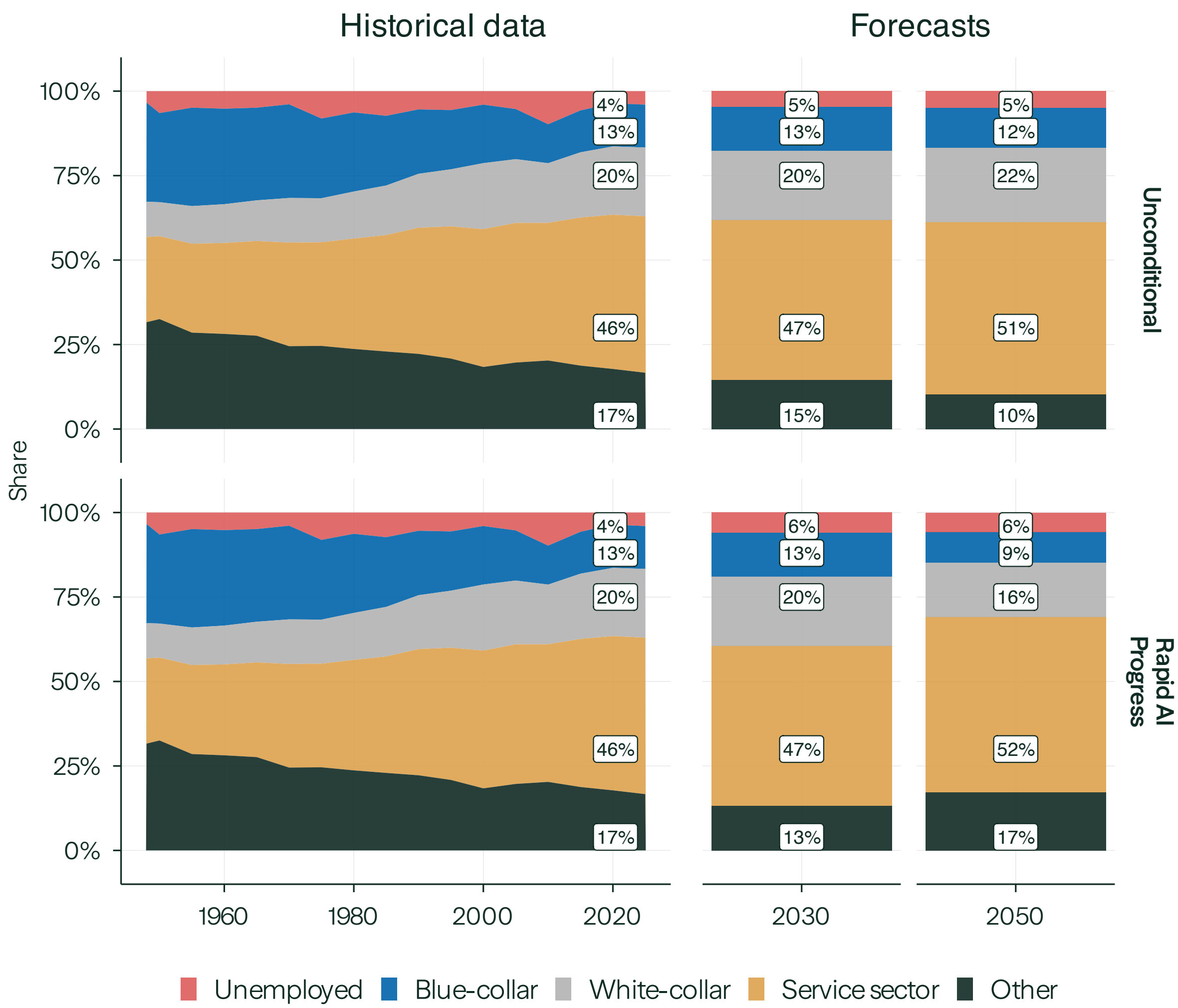


Figure 38: *Superforecasters' forecasts for different sectors as shares of the labor force.* Areas and labels show the median 50th percentile forecast. Historical shares are shown in the panel on the left. The 'Other' category is derived by subtracting the sum of the other sectors' median forecasts from 100%; it consists primarily of public sector and agricultural workers. Labeled historical values correspond to the beginning of 2025.

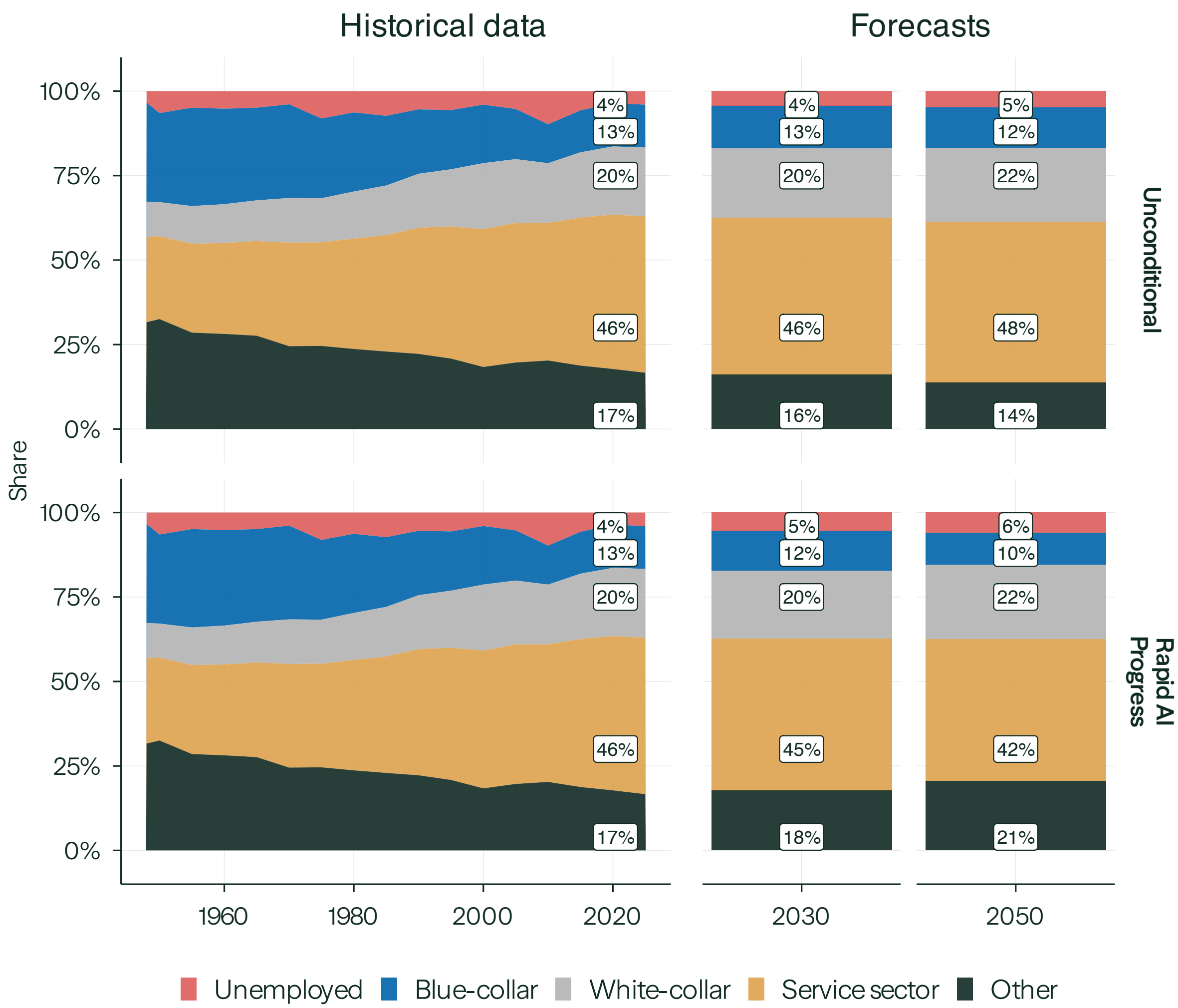


Figure 39: *General public's forecasts for different sectors as shares of the labor force.* Areas and labels show the median 50th percentile forecast. Historical shares are shown in the panel on the left. The 'Other' category is derived by subtracting the sum of the other sectors' median forecasts from 100%; it consists primarily of public sector and agricultural workers. Labeled historical values correspond to the beginning of 2025.

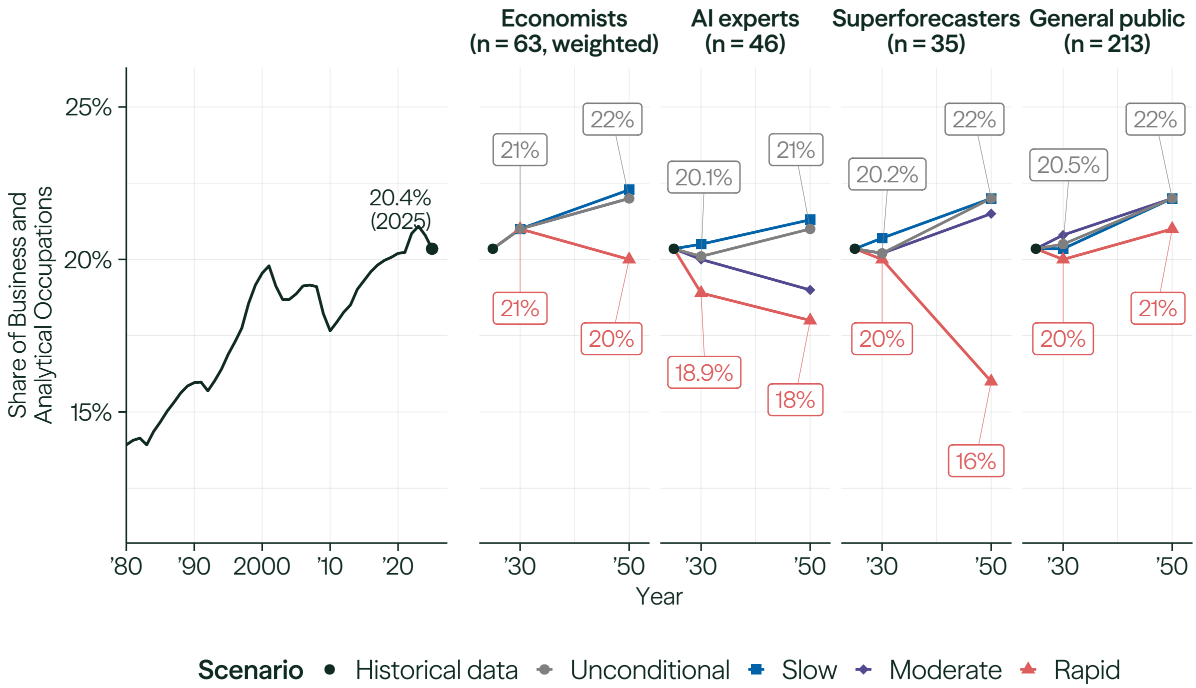


Figure 40: *Forecasts for the share of business and analytical occupations in the labor force.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 31: Business and Analytical Occupations, Share of Labor Force (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	21.0 CI: (20.4, 22.0) IQR: [20.0, 23.6] $n = 64$	20.4 CI: (20.0, 21.9) IQR: [18.8, 22.0] $n = 48$	20.5 CI: (20.0, 21.0) IQR: [19.9, 22.0] $n = 37$	20.5 CI: (20.0, 21.0) IQR: [19.0, 22.0] $n = 243$	21.0 CI: (20.2, 21.0) IQR: [19.8, 22.0] $n = 392$
Slow	50	21.0 CI: (20.0, 22.0) IQR: [20.0, 22.0] $n = 64$	20.6 CI: (20.0, 21.0) IQR: [20.0, 22.0] $n = 48$	20.9 CI: (20.0, 21.0) IQR: [20.0, 21.2] $n = 37$	20.2 CI: (20.0, 20.6) IQR: [19.4, 21.4] $n = 243$	20.9 CI: (20.2, 21.0) IQR: [20.0, 22.0] $n = 392$
Moderate	50	21.0 CI: (20.4, 22.5) IQR: [20.0, 24.6] $n = 64$	20.3 CI: (18.7, 21.4) IQR: [17.6, 23.0] $n = 48$	20.5 CI: (19.0, 21.0) IQR: [19.0, 23.0] $n = 37$	20.5 CI: (20.0, 21.0) IQR: [18.6, 23.0] $n = 243$	20.9 CI: (20.0, 21.0) IQR: [19.0, 23.0] $n = 392$
Rapid	50	21.0 CI: (20.0, 22.0) IQR: [18.5, 25.0] $n = 64$	19.6 CI: (17.0, 20.5) IQR: [15.0, 24.5] $n = 48$	20.4 CI: (18.0, 21.5) IQR: [16.7, 25.0] $n = 37$	20.0 CI: (19.9, 21.0) IQR: [16.5, 24.0] $n = 243$	20.0 CI: (19.9, 21.0) IQR: [17.0, 25.0] $n = 392$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 32: Business and Analytical Occupations, Share of Labor Force (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	22.0 CI: (20.0, 24.0) IQR: [17.1, 25.1] $n = 64$	21.0 CI: (18.0, 23.5) IQR: [15.5, 25.0] $n = 46$	22.0 CI: (19.0, 24.0) IQR: [17.2, 25.0] $n = 35$	22.0 CI: (21.0, 22.5) IQR: [18.0, 24.0] $n = 225$	22.0 CI: (20.1, 23.0) IQR: [17.0, 25.0] $n = 370$
Slow	50	22.0 CI: (20.0, 24.0) IQR: [20.0, 25.0] $n = 64$	21.3 CI: (19.5, 23.5) IQR: [18.0, 25.0] $n = 46$	22.0 CI: (19.0, 23.7) IQR: [18.6, 24.8] $n = 35$	22.0 CI: (21.0, 22.0) IQR: [18.0, 23.5] $n = 225$	22.0 CI: (21.0, 22.5) IQR: [19.0, 25.0] $n = 370$
Moderate	50	22.0 CI: (19.2, 24.0) IQR: [17.4, 25.4] $n = 64$	19.0 CI: (16.0, 24.0) IQR: [15.0, 28.0] $n = 46$	21.5 CI: (17.0, 23.7) IQR: [15.6, 25.0] $n = 35$	22.5 CI: (21.0, 23.5) IQR: [17.0, 25.1] $n = 225$	21.9 CI: (19.0, 23.0) IQR: [16.0, 25.3] $n = 370$
Rapid	50	20.0 CI: (17.3, 23.4) IQR: [16.0, 26.5] $n = 64$	18.0 CI: (13.2, 20.3) IQR: [10.0, 27.3] $n = 46$	16.0 CI: (13.0, 23.7) IQR: [10.0, 25.0] $n = 35$	22.0 CI: (20.0, 24.5) IQR: [13.1, 28.0] $n = 225$	20.0 CI: (17.0, 20.5) IQR: [12.0, 27.0] $n = 370$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

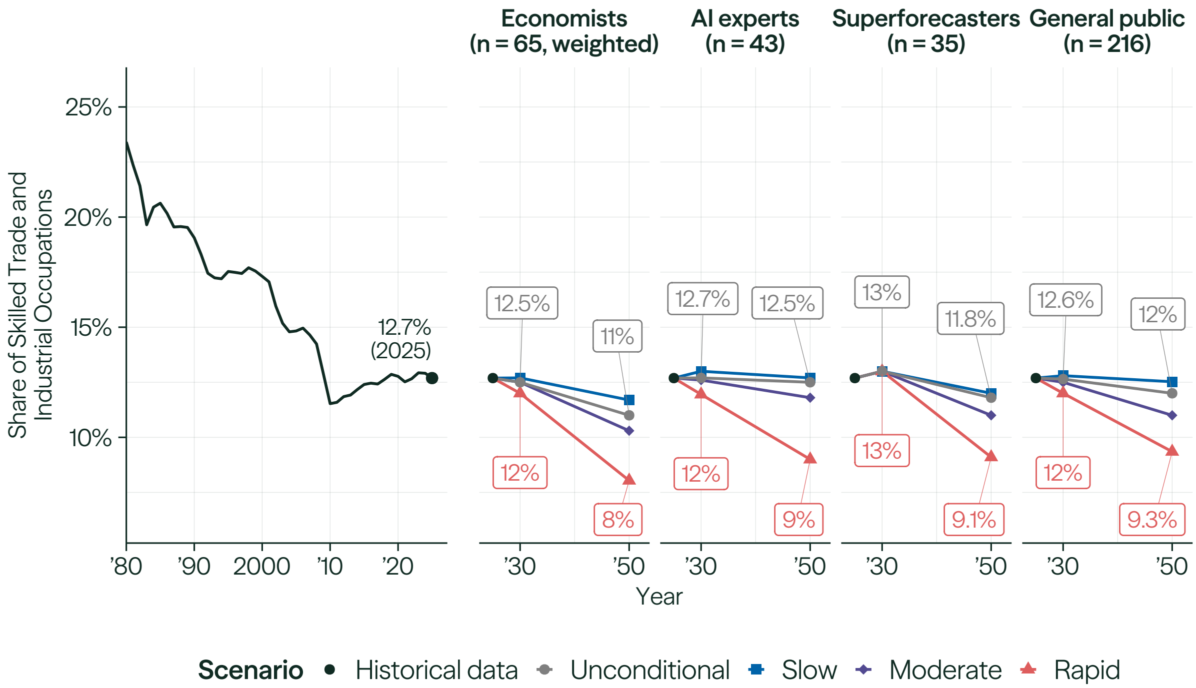


Figure 41: *Forecasts for the share of skilled trade and industrial occupations in the labor force.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 33: Skilled Trade and Industrial Occupations, Share of Labor Force (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	12.5 CI: (12.0, 13.0) IQR: [12.0, 13.4] $n = 65$	12.9 CI: (12.6, 13.4) IQR: [12.0, 14.0] $n = 46$	13.0 CI: (12.5, 13.0) IQR: [12.0, 13.2] $n = 36$	12.6 CI: (12.5, 12.8) IQR: [12.0, 13.7] $n = 248$	12.8 CI: (12.5, 13.0) IQR: [12.0, 13.5] $n = 395$
Slow	50	12.7 CI: (12.0, 13.0) IQR: [12.0, 13.0] $n = 65$	13.0 CI: (12.7, 13.0) IQR: [12.2, 13.5] $n = 46$	13.0 CI: (12.6, 13.0) IQR: [12.0, 13.1] $n = 36$	12.8 CI: (12.6, 12.9) IQR: [12.0, 13.8] $n = 248$	12.9 CI: (12.7, 13.0) IQR: [12.0, 13.2] $n = 395$
Moderate	50	12.5 CI: (11.8, 13.0) IQR: [11.0, 13.4] $n = 65$	12.8 CI: (12.0, 13.5) IQR: [11.7, 14.0] $n = 46$	13.0 CI: (12.2, 13.5) IQR: [12.0, 14.0] $n = 36$	12.5 CI: (12.1, 12.8) IQR: [11.5, 14.0] $n = 248$	12.7 CI: (12.4, 13.0) IQR: [11.7, 14.0] $n = 395$
Rapid	50	12.0 CI: (10.0, 13.0) IQR: [10.0, 13.9] $n = 65$	12.0 CI: (11.3, 14.0) IQR: [10.3, 15.5] $n = 46$	13.0 CI: (12.0, 14.0) IQR: [11.0, 15.0] $n = 36$	11.9 CI: (11.0, 12.0) IQR: [10.0, 15.0] $n = 248$	12.0 CI: (11.6, 13.0) IQR: [10.0, 15.0] $n = 395$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 34: Skilled Trade and Industrial Occupations, Share of Labor Force (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	11.0 CI: (10.0, 13.0) IQR: [8.7, 15.0] $n = 67$	12.5 CI: (11.0, 13.2) IQR: [10.1, 15.0] $n = 43$	11.8 CI: (9.8, 13.0) IQR: [8.6, 13.8] $n = 35$	12.0 CI: (11.5, 12.4) IQR: [10.1, 15.0] $n = 236$	11.8 CI: (11.0, 12.5) IQR: [9.6, 14.8] $n = 381$
Slow	50	11.7 CI: (11.0, 13.0) IQR: [10.0, 13.2] $n = 67$	12.7 CI: (11.5, 14.0) IQR: [11.0, 15.0] $n = 43$	12.0 CI: (10.0, 13.0) IQR: [8.8, 13.1] $n = 35$	12.4 CI: (12.0, 12.9) IQR: [11.0, 15.0] $n = 236$	12.0 CI: (11.8, 12.6) IQR: [10.0, 14.0] $n = 381$
Moderate	50	10.3 CI: (9.1, 13.0) IQR: [8.1, 15.0] $n = 67$	11.8 CI: (10.2, 13.0) IQR: [9.5, 15.0] $n = 43$	11.0 CI: (9.7, 13.0) IQR: [8.7, 13.9] $n = 35$	11.0 CI: (11.0, 12.0) IQR: [9.4, 15.0] $n = 236$	11.0 CI: (10.3, 12.0) IQR: [9.0, 15.0] $n = 381$
Rapid	50	8.0 CI: (8.0, 10.4) IQR: [7.0, 18.0] $n = 67$	9.0 CI: (8.0, 12.0) IQR: [5.3, 14.8] $n = 43$	9.1 CI: (8.0, 13.0) IQR: [6.2, 13.8] $n = 35$	9.5 CI: (9.0, 10.5) IQR: [6.2, 15.0] $n = 236$	9.0 CI: (8.0, 10.0) IQR: [6.0, 15.0] $n = 381$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

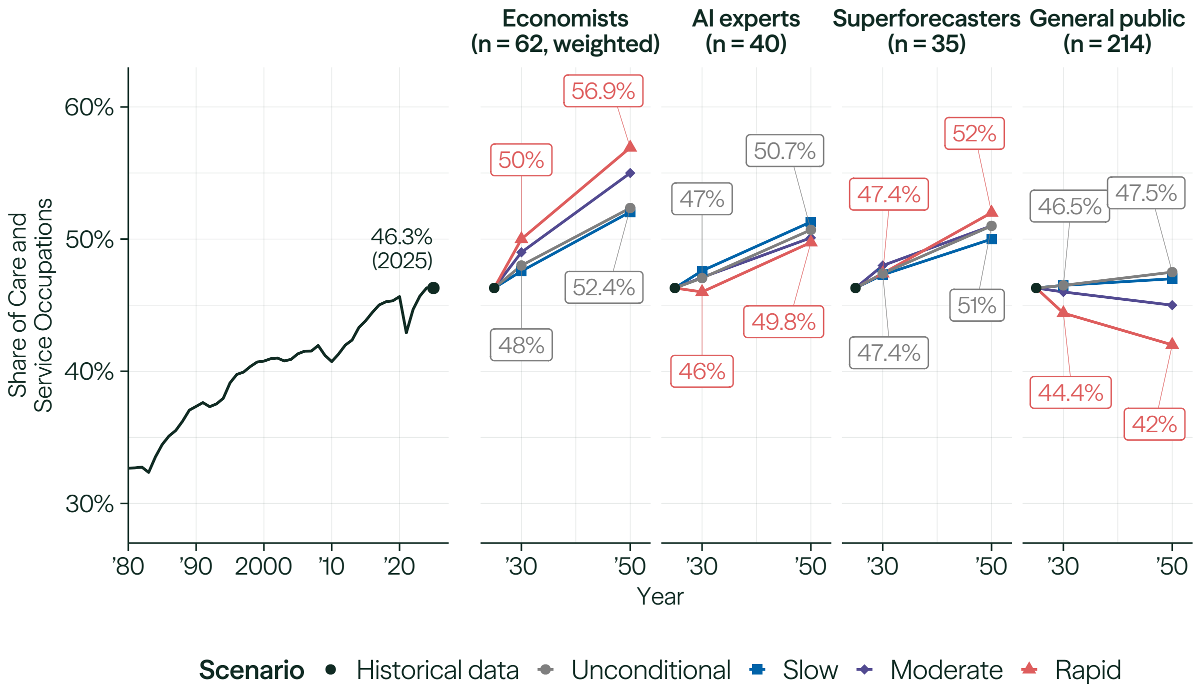


Figure 42: *Forecasts for the share of care and service occupations in the labor force.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. The most recent historical value for the outcome is shown in each panel as a black point. Lines show medians of 50th percentile forecasts across participants. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 35: Care and Service Occupations, Share of Labor Force (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	48.0 CI: (48.0, 49.0) IQR: [47.0, 50.0] $n = 63$	47.1 CI: (47.0, 48.0) IQR: [46.0, 49.5] $n = 44$	47.4 CI: (47.0, 48.0) IQR: [46.6, 48.8] $n = 35$	46.5 CI: (46.2, 47.0) IQR: [45.0, 47.5] $n = 253$	47.5 CI: (47.0, 48.0) IQR: [46.0, 49.2] $n = 395$
Slow	50	47.5 CI: (47.0, 48.2) IQR: [47.0, 50.0] $n = 63$	47.4 CI: (47.0, 48.0) IQR: [46.0, 48.6] $n = 44$	47.3 CI: (47.0, 47.8) IQR: [46.8, 48.0] $n = 35$	46.5 CI: (46.2, 47.0) IQR: [45.0, 48.0] $n = 253$	47.1 CI: (47.0, 47.5) IQR: [46.1, 48.3] $n = 395$
Moderate	50	49.0 CI: (48.0, 50.0) IQR: [48.0, 50.0] $n = 63$	47.1 CI: (46.5, 48.5) IQR: [45.0, 50.0] $n = 44$	48.0 CI: (47.0, 48.2) IQR: [46.8, 49.4] $n = 35$	46.0 CI: (46.0, 46.5) IQR: [44.0, 48.0] $n = 253$	48.0 CI: (47.1, 48.0) IQR: [46.0, 50.0] $n = 395$
Rapid	50	50.0 CI: (49.0, 52.0) IQR: [47.6, 54.5] $n = 63$	46.1 CI: (45.2, 48.9) IQR: [43.3, 51.8] $n = 44$	47.4 CI: (46.0, 49.0) IQR: [45.0, 49.8] $n = 35$	45.0 CI: (44.0, 45.2) IQR: [40.0, 49.0] $n = 253$	47.5 CI: (47.0, 49.0) IQR: [44.5, 52.0] $n = 395$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 36: Care and Service Occupations, Share of Labor Force (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	52.5 CI: (50.0, 55.0) IQR: [48.8, 55.9] $n = 63$	50.7 CI: (48.0, 52.5) IQR: [46.4, 56.0] $n = 42$	51.0 CI: (49.0, 52.0) IQR: [48.0, 54.8] $n = 35$	47.5 CI: (46.0, 48.0) IQR: [40.4, 50.0] $n = 233$	50.0 CI: (50.0, 51.6) IQR: [48.0, 55.0] $n = 373$
Slow	50	52.2 CI: (50.0, 54.0) IQR: [50.0, 55.0] $n = 63$	51.3 CI: (49.5, 53.9) IQR: [48.0, 55.0] $n = 42$	50.0 CI: (49.3, 52.5) IQR: [49.0, 53.4] $n = 35$	47.0 CI: (46.0, 48.0) IQR: [42.6, 50.0] $n = 233$	50.0 CI: (50.0, 52.0) IQR: [48.0, 54.0] $n = 373$
Moderate	50	55.0 CI: (50.0, 56.0) IQR: [50.0, 60.0] $n = 63$	50.1 CI: (48.5, 54.7) IQR: [45.0, 57.3] $n = 42$	51.0 CI: (49.0, 54.0) IQR: [48.1, 55.0] $n = 35$	45.0 CI: (44.0, 47.5) IQR: [38.6, 52.0] $n = 233$	50.8 CI: (50.0, 53.0) IQR: [46.5, 57.0] $n = 373$
Rapid	50	57.1 CI: (52.0, 60.0) IQR: [50.0, 62.8] $n = 63$	49.8 CI: (42.7, 59.8) IQR: [40.0, 65.0] $n = 42$	52.0 CI: (46.0, 56.0) IQR: [40.5, 59.5] $n = 35$	42.0 CI: (40.0, 45.0) IQR: [32.4, 52.0] $n = 233$	51.1 CI: (48.6, 54.0) IQR: [40.0, 60.0] $n = 373$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.2.8 Change in Employment by Occupation

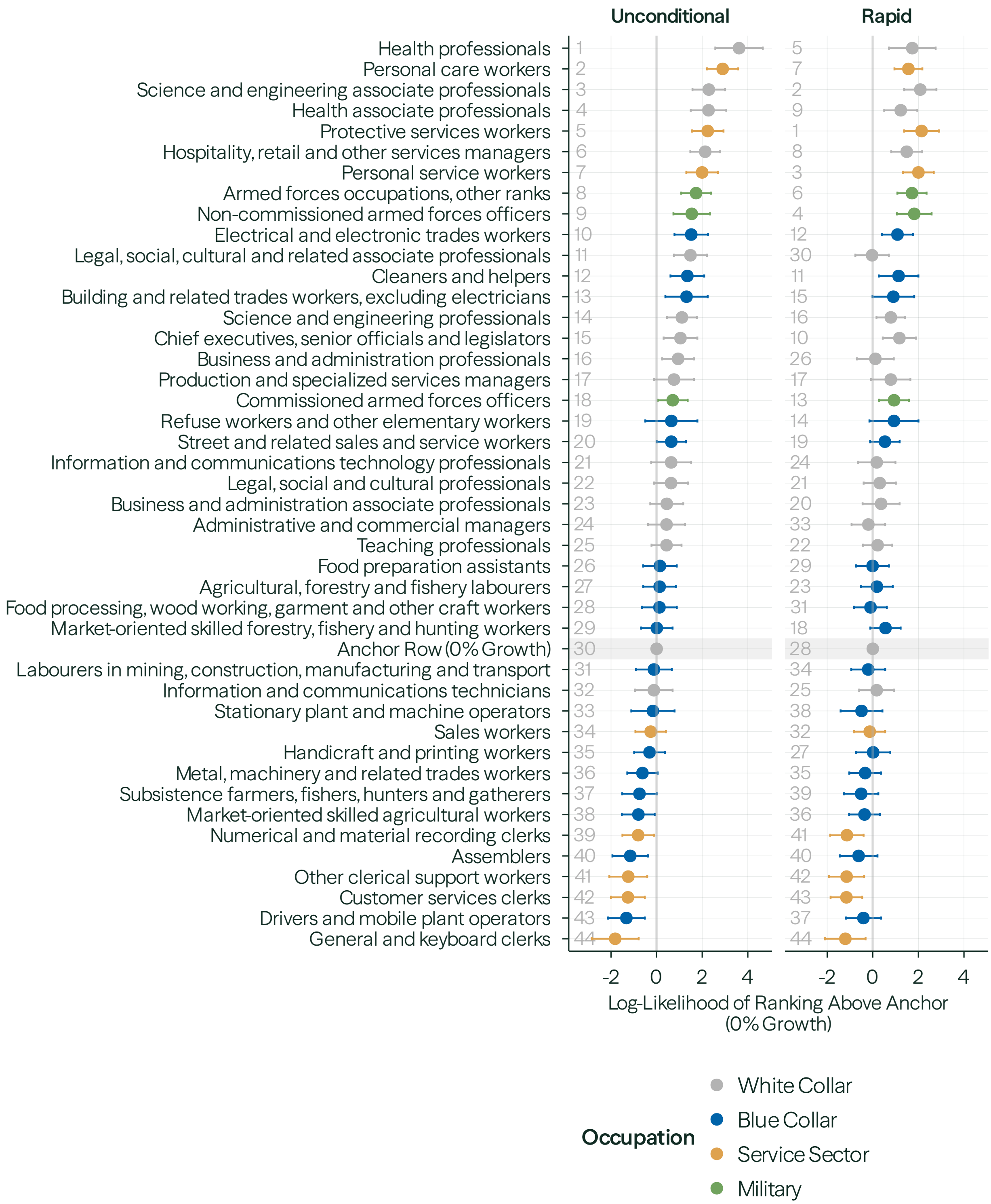


Figure 43: *Log-likelihood of ranking each occupation above 0% growth.* Higher values indicate that respondents more consistently ranked the occupation above the anchor, implying expected positive employment growth between the beginning of 2025 and the beginning of 2030.

We compare the percent of economists who predict each occupation will experience growth with the measure of AI exposure from Eloundou et al. (2024). To do so, we aggregate their 923 occupations into (all but one) of our occupation categories.[32] In Panel (a) of Figure 44, we present the results in a scatterplot, with percent predicting positive growth in the unconditional scenario (from our paper) on the y-axis and AI exposure (from Eloundou et al. (2024)). If the raters in our survey thought that occupation groups with higher AI exposure would experience more job loss, we would expect there to be a negative relationship. However, we do not observe any relationship, with correlations (weighted by total estimated workers) near 0.[33][34] In Panel (b) of Figure 44, we present a similar scatterplot, but on the y-axis, we show the percent predicting positive growth in the *rapid* scenario minus the percent predicting positive growth in the *unconditional* scenario. We again observe little relationship (with weighted correlations around -0.10).

[32]We obtain the AI exposure data from Eloundou et al. (2024) at `https://github.com/openai/GPTs-are-GPTs/blob/main/data/occ_level.csv`. These include the AI exposure for 923 occupations, which are at the eight-digit O*NET-SOC Code level, while our data are at the 2-digit ISCO level. We weight each of the 923 occupations by May 2023 BLS employment (U.S. Bureau of Labor Statistics, 2024a); employment is only available at the 6-digit SOC level, so we divide it equally (as we do not know the true shares) for the 8-digit job(s) within a given 6-digit code. In some cases, we use (U.S. Bureau of Labor Statistics, 2024b) to adjust the 6-digit code to be in accordance with how the employment counts were obtained. 'Fishing and Hunting Workers' was the only occupation without a weight; we exclude this category (this appears to mainly affect the ISCO category of Market-oriented skilled forestry, fishery and hunting workers). Next, we merge in a crosswalk between SOC and ESCO (the European version of ISCO) (National Center for O*NET Development, 2024). ('Dining Room and Cafeteria Attendants and Bartender Helpers' is not in the crosswalk, it is imperfect, but we assign it to 5,132 (bartender), a category within Service and Sales Workers). The SOC codes in the crosswalk are 8-digit, while the ESCO codes are of differing levels (some occupations are split into up to four sub-levels), but all ESCO codes are at least 4 digits long. Thus, though imperfect, we deduplicate the ESCO codes at the 4-digit level. Each 8-digit SOC code can and often does map to multiple 4-digit ESCO codes; as such, within an 8-digit SOC code, we divide the weight equally across ESCO groups. Finally, we aggregate the AI exposure measure to the 2-digit ESCO code level, weighting by employment. The end result is AI exposure aggregated to 42 of our 43 occupation groups (one group, Subsistence farmers, fishers, hunters, and gatherers, did not have any rating).

[33]See Appendix Figure 45 for the version conditioning on the rapid scenerio.

[34]In Figure 46, we show these data in a different way: we sort by AI exposure and show 95% confidence intervals for percent predicting positive growth in the unconditional scenario. Figure 47 shows the same but for the rapid scenario.

(a) *Unconditional Forecast*

(b) *Rapid Forecast Minus Unconditional Forecast*

Figure 44: The y-axis is the fraction of economists predicting a positive change in employment for each occupation between the beginning of 2025 and the beginning of 2030 in the unconditional scenario (Panel a) and the difference between the rapid and unconditional scenarios (Panel b). The x-axis is AI exposure from Eloundou et al. (2024), aggregated to our occupations. Occupation titles are shaded blue for blue-collar, green for military, white for white-collar, and yellow for service. The size of a bubble corresponds to the estimated number of workers for that occupation.

Figure 45: The y-axis is the fraction of economists predicting a positive change in employment for each occupation between the beginning of 2025 and the beginning of 2030 in the rapid scenario. The x-axis is AI exposure from Eloundou et al. (2024), aggregated to our occupations. Occupations titles are shaded blue for blue-collar, green for military, white for white-collar, and yellow for service. The size of a bubble corresponds to estimated number of workers for that occupation.

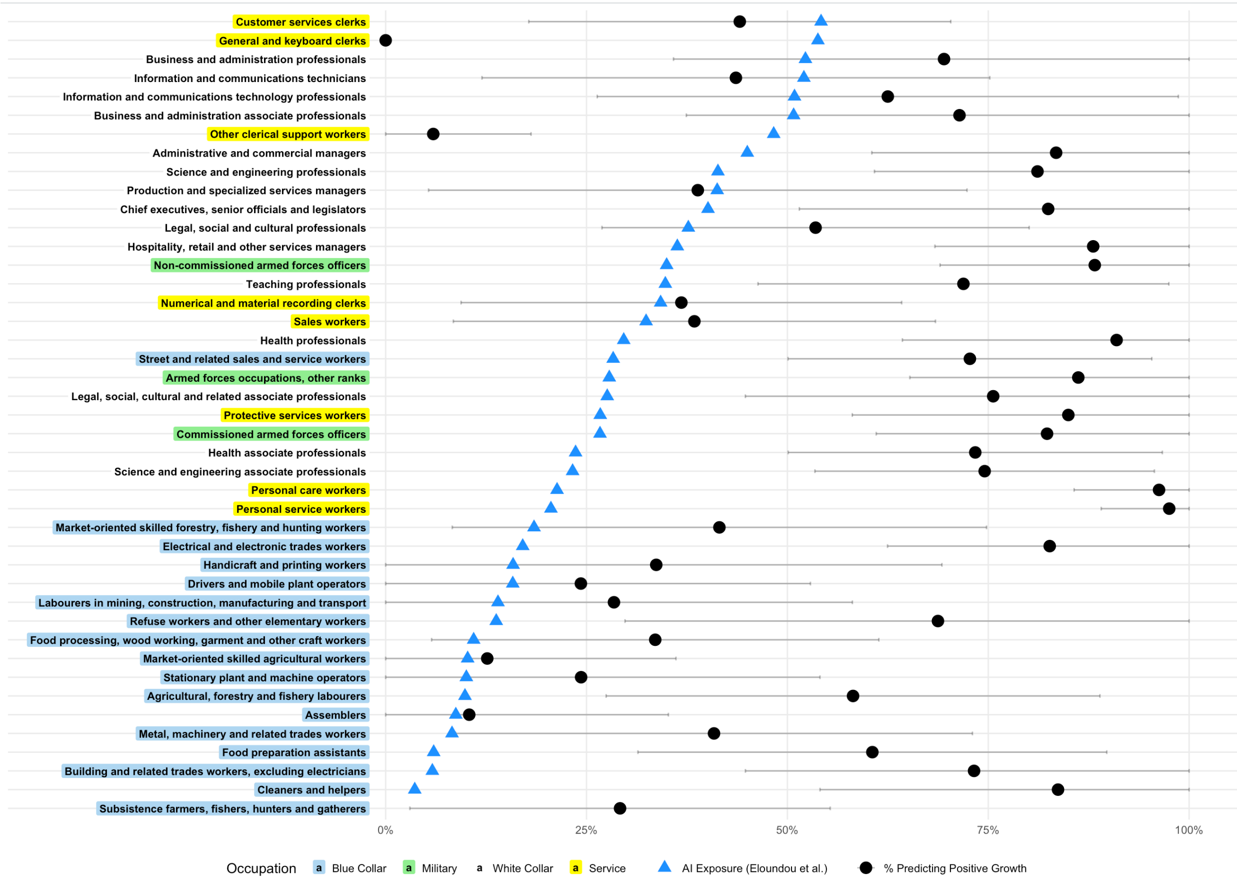


Figure 46: The fraction of economists predicting a positive change in employment for each occupation between the beginning of 2025 and the beginning of 2030 in the unconditional scenario (black dots) and AI exposure from Eloundou et al. (2024) aggregated to our occupations (blue dots). Occupations titles are shaded blue for blue-collar, green for military, white for white-collar, and yellow for service.

Figure 47: The fraction of economists predicting a positive change in employment for each occupation between the beginning of 2025 and the beginning of 2030 in the rapid scenario (black dots) and AI exposure from Eloundou et al. (2024) aggregated to our occupations (blue dots). Occupations titles are shaded blue for blue-collar, green for military, white for white-collar, and yellow for service.

D.2.9 Wealth Inequality

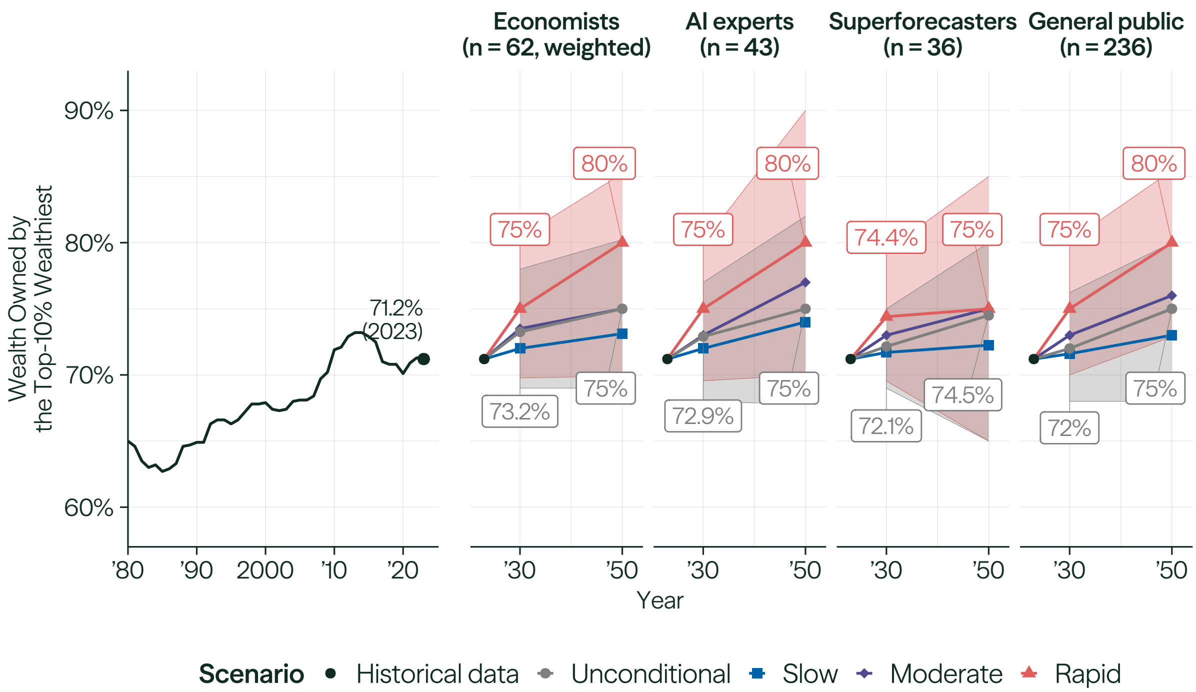


Figure 48: *Forecasts for wealth held by the 10% wealthiest households.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast.

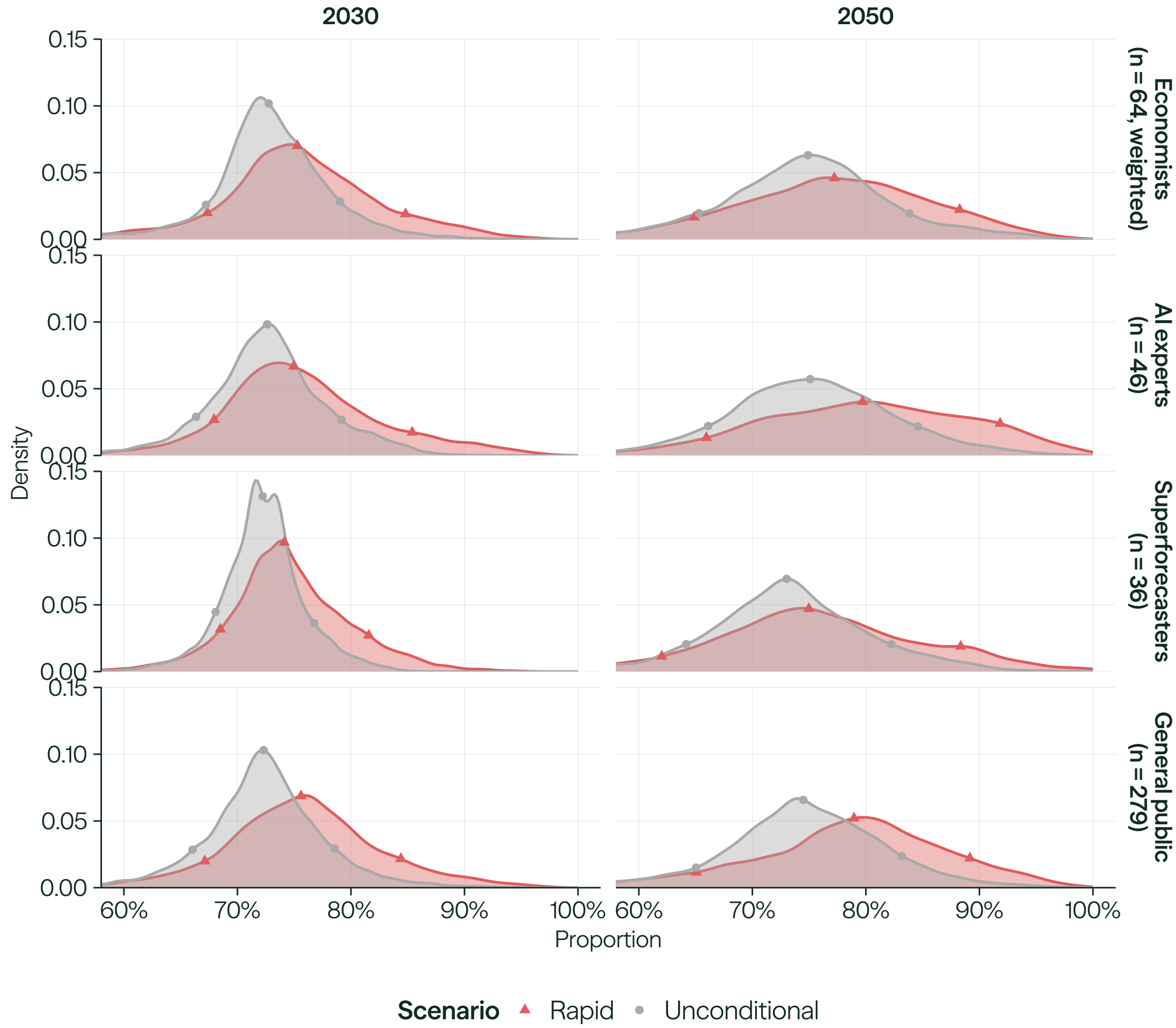


Figure 49: *Distribution of forecasts for wealth held by the 10% wealthiest households.* Distribution is pooled across participants. Points show 10th/50th/90th percentiles of the distribution.

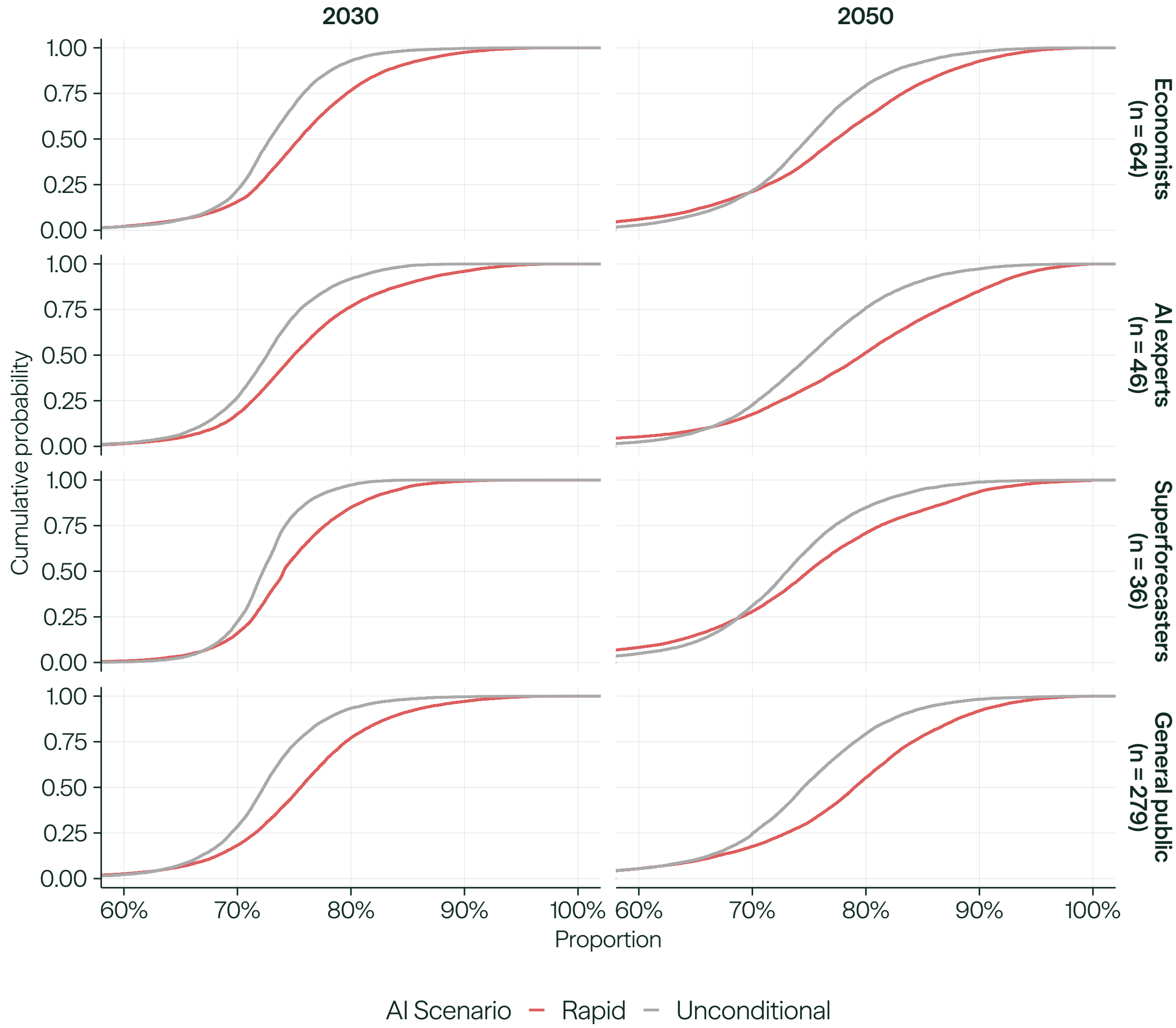


Figure 50: *Cumulative distribution of forecasts for wealth held by the 10% wealthiest households.*

Table 37: Top-10% Wealth Share (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	69.0 CI: (67.1, 70.0) IQR: [65.1, 70.0] $n = 64$	68.0 CI: (66.4, 70.0) IQR: [65.0, 70.0] $n = 45$	69.0 CI: (68.0, 70.0) IQR: [67.5, 70.0] $n = 36$	68.0 CI: (67.0, 68.0) IQR: [65.0, 70.0] $n = 257$	68.6 CI: (68.0, 69.1) IQR: [65.5, 70.0] $n = 402$
Unconditional	50	73.2 CI: (73.0, 75.0) IQR: [72.0, 75.0] $n = 64$	72.9 CI: (72.0, 73.0) IQR: [70.0, 73.8] $n = 45$	72.1 CI: (72.0, 73.0) IQR: [71.3, 73.1] $n = 36$	72.0 CI: (72.0, 72.0) IQR: [71.0, 74.0] $n = 257$	72.9 CI: (72.0, 73.0) IQR: [71.1, 74.0] $n = 402$
Unconditional	90	78.0 CI: (75.2, 80.0) IQR: [75.0, 80.2] $n = 64$	77.0 CI: (76.0, 78.6) IQR: [75.0, 80.4] $n = 45$	75.0 CI: (74.8, 76.0) IQR: [74.0, 77.5] $n = 36$	76.5 CI: (76.0, 77.2) IQR: [75.0, 80.0] $n = 257$	76.5 CI: (75.5, 77.2) IQR: [75.0, 80.0] $n = 402$
Slow	50	72.0 CI: (71.0, 72.0) IQR: [70.6, 73.0] $n = 64$	72.0 CI: (71.0, 72.5) IQR: [70.0, 73.0] $n = 45$	71.7 CI: (71.3, 72.0) IQR: [71.0, 72.0] $n = 36$	71.6 CI: (71.0, 72.0) IQR: [70.0, 73.0] $n = 257$	72.0 CI: (71.5, 72.0) IQR: [70.6, 73.0] $n = 402$
Moderate	50	73.5 CI: (73.0, 74.4) IQR: [72.0, 75.0] $n = 64$	73.0 CI: (72.0, 74.0) IQR: [71.0, 74.6] $n = 45$	73.0 CI: (72.0, 73.8) IQR: [72.0, 74.0] $n = 36$	73.0 CI: (73.0, 73.5) IQR: [71.1, 75.0] $n = 257$	73.0 CI: (73.0, 73.5) IQR: [72.0, 75.0] $n = 402$
Rapid	10	69.8 CI: (69.6, 71.0) IQR: [67.1, 72.0] $n = 64$	69.6 CI: (68.0, 70.7) IQR: [66.3, 71.6] $n = 45$	69.5 CI: (68.0, 71.0) IQR: [65.8, 72.0] $n = 36$	70.0 CI: (69.8, 70.3) IQR: [66.0, 73.0] $n = 257$	69.8 CI: (69.5, 70.0) IQR: [66.8, 72.0] $n = 402$
Rapid	50	75.0 CI: (75.0, 77.0) IQR: [73.3, 79.9] $n = 64$	75.0 CI: (74.0, 76.0) IQR: [72.0, 77.6] $n = 45$	74.4 CI: (73.0, 76.0) IQR: [73.0, 77.5] $n = 36$	75.0 CI: (75.0, 76.0) IQR: [72.4, 78.0] $n = 257$	75.0 CI: (75.0, 76.0) IQR: [73.0, 78.0] $n = 402$
Rapid	90	80.4 CI: (79.2, 83.0) IQR: [77.8, 85.2] $n = 64$	80.0 CI: (79.0, 81.9) IQR: [77.0, 85.3] $n = 45$	79.4 CI: (77.0, 80.5) IQR: [76.0, 83.1] $n = 36$	80.2 CI: (80.0, 82.0) IQR: [77.2, 85.1] $n = 257$	80.0 CI: (79.9, 80.5) IQR: [77.0, 85.0] $n = 402$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 38: Top-10% Wealth Share (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	69.0 CI: (65.0, 69.8) IQR: [64.6, 71.0] $n = 62$	67.9 CI: (65.0, 69.3) IQR: [63.3, 70.0] $n = 44$	65.0 CI: (63.0, 67.5) IQR: [60.5, 69.9] $n = 36$	68.0 CI: (67.8, 69.0) IQR: [65.0, 72.2] $n = 260$	67.5 CI: (65.4, 68.1) IQR: [63.0, 70.0] $n = 402$
Unconditional	50	75.0 CI: (75.0, 75.6) IQR: [74.3, 77.0] $n = 62$	75.0 CI: (74.0, 76.0) IQR: [72.0, 78.0] $n = 44$	74.5 CI: (71.5, 75.0) IQR: [70.3, 76.3] $n = 36$	75.0 CI: (74.0, 75.0) IQR: [72.0, 77.8] $n = 260$	75.0 CI: (75.0, 75.0) IQR: [71.6, 77.0] $n = 402$
Unconditional	90	80.2 CI: (80.0, 85.0) IQR: [79.0, 85.4] $n = 62$	82.1 CI: (80.0, 85.0) IQR: [79.5, 85.1] $n = 44$	80.0 CI: (78.4, 82.0) IQR: [76.2, 85.0] $n = 36$	80.0 CI: (80.0, 81.2) IQR: [76.9, 85.0] $n = 260$	80.3 CI: (80.0, 82.0) IQR: [78.0, 85.0] $n = 402$
Slow	50	73.1 CI: (73.0, 75.0) IQR: [72.0, 75.0] $n = 62$	74.0 CI: (73.2, 75.0) IQR: [70.9, 75.9] $n = 44$	72.2 CI: (71.0, 74.0) IQR: [70.0, 75.0] $n = 36$	73.5 CI: (73.0, 74.0) IQR: [71.0, 75.0] $n = 260$	73.9 CI: (73.0, 74.0) IQR: [70.7, 75.0] $n = 402$
Moderate	50	75.0 CI: (74.4, 76.5) IQR: [74.0, 79.4] $n = 62$	77.0 CI: (75.3, 78.5) IQR: [75.0, 80.5] $n = 44$	75.0 CI: (73.0, 76.0) IQR: [71.0, 77.5] $n = 36$	76.0 CI: (75.0, 77.0) IQR: [73.0, 79.8] $n = 260$	75.0 CI: (75.0, 76.0) IQR: [73.0, 79.0] $n = 402$
Rapid	10	69.9 CI: (67.4, 72.0) IQR: [64.9, 74.8] $n = 62$	70.0 CI: (68.0, 73.4) IQR: [65.0, 75.4] $n = 44$	65.0 CI: (58.7, 68.0) IQR: [52.1, 70.0] $n = 36$	73.0 CI: (71.8, 74.6) IQR: [65.9, 78.0] $n = 260$	69.8 CI: (68.0, 70.0) IQR: [61.6, 74.6] $n = 402$
Rapid	50	80.0 CI: (75.3, 80.0) IQR: [74.2, 82.0] $n = 62$	80.1 CI: (79.0, 84.0) IQR: [75.0, 85.5] $n = 44$	75.0 CI: (73.5, 79.0) IQR: [70.0, 82.3] $n = 36$	80.0 CI: (78.5, 80.0) IQR: [75.0, 85.0] $n = 260$	79.0 CI: (78.0, 80.0) IQR: [73.3, 84.7] $n = 402$
Rapid	90	85.2 CI: (82.2, 90.0) IQR: [80.1, 90.6] $n = 62$	90.0 CI: (87.0, 92.0) IQR: [83.8, 95.1] $n = 44$	85.0 CI: (82.0, 90.0) IQR: [80.0, 90.5] $n = 36$	85.3 CI: (85.0, 87.0) IQR: [80.0, 92.0] $n = 260$	85.6 CI: (85.0, 89.0) IQR: [80.2, 92.0] $n = 402$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Rationale Analysis: Wealth Inequality Forecasters consistently identified AI's tendency to increase returns to capital—held disproportionately by the already-wealthy—as the primary mechanism driving wealth inequality, reinforced by winner-take-all dynamics in the AI sector.[35] Redistribution policy emerged as the key countervailing force, with many expecting that rapid AI-driven displacement would compel governments to respond through policy measures

[35]"I expect wealth concentration to keep rising because AI-driven growth mostly accrues to people who own capital, firms, and intellectual property rather than to wages. Even without fast AI progress, asset appreciation and existing inequality trends push a larger share of wealth toward the top," wrote one AI policy respondent.

like wealth taxation or universal basic income.[36] Some skeptics held that AI would have little effect on distribution, arguing that structural factors like tax policy and historical discrimination are more important.[37] Another concern was white-collar displacement: AI threatens professional roles that have traditionally been the pathway through which the bottom 90% accumulate wealth. Many forecasters noted this could hollow out the middle class even as aggregate productivity rises. A minority questioned whether private wealth would retain its current meaning by 2050, suggesting potential socialization of AI-generated wealth or fundamental redefinition of capital itself.[38]

The shift from labor to capital was the most frequently cited driver for economists and AI industry professionals, with superforecasters and AI policy professionals anchoring more strongly on historical trends and inertia. Economists and superforecasters cited redistribution and tax policy as their second-most frequent driver, which was not the case for the other two groups. Superforecasters were distinctive in flagging 2050 uncertainty as a top-three driver, warning that the rapid scenario could lead to unpredictable political and societal upheavals.

In addition to the rationale examples provided in the footnotes here, more rationale examples can be found in Appendix I.

[36] "This all depends on policy response. If it's a functioning democracy then it's hard to imagine there wouldn't be mass voting support for policies to redistribute wealth in a world of moderate or rapid AI progress and much lower labor force participation," wrote one economist respondent.

[37] "I forecast that wealth inequality will continue to increase steadily but moderately over the next few years. This will be primarily for reasons unrelated to AI progress, such as pre-existing trends in policy, demographic shifts, and sustained asset (stock market and real estate) appreciation," wrote one economist respondent.

[38] "By 2050, I forecast that such massive power concentration will put us in of two extremely different scenarios where either nearly all wealth is captured by a small fraction of the 10%, or this rapid transition has driven historic policy changes leading to unprecedented wealth redistribution across the economy, and a redefinition of wealth and capital itself," wrote one AI policy expert respondent.

D.2.10 Labor Share

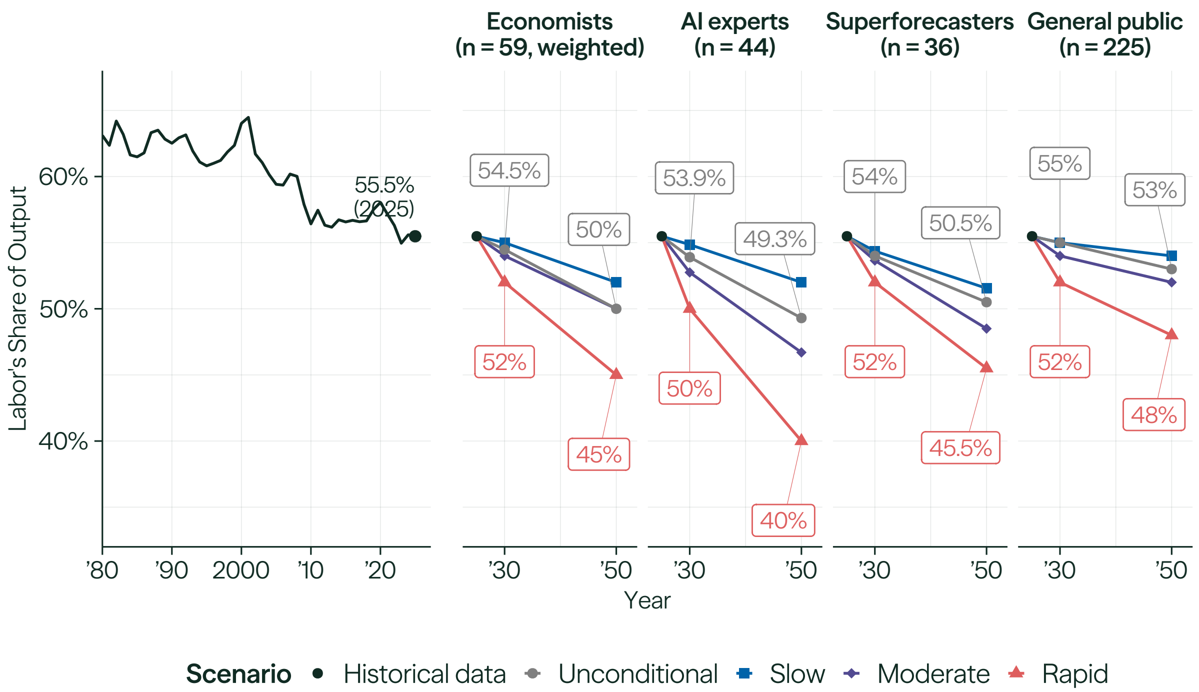


Figure 51: *Forecasts for the labor share of the nonfarm business sector.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Because we elicited only 50th percentile predictions for the labor share, this figure does not show uncertainty. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 39: Labor Share, Non-farm Business Sector (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	54.3 CI: (54.0, 55.0) IQR: [53.5, 55.0] $n = 62$	54.0 CI: (53.0, 54.8) IQR: [53.0, 55.0] $n = 45$	54.0 CI: (53.5, 55.0) IQR: [53.0, 55.0] $n = 36$	55.0 CI: (54.5, 55.0) IQR: [53.5, 56.0] $n = 257$	54.0 CI: (54.0, 54.8) IQR: [53.0, 55.0] $n = 400$
Slow	50	55.0 CI: (55.0, 55.3) IQR: [54.5, 55.3] $n = 62$	54.9 CI: (54.0, 55.0) IQR: [53.4, 55.1] $n = 45$	54.4 CI: (54.0, 55.0) IQR: [53.5, 55.0] $n = 36$	55.0 CI: (55.0, 55.0) IQR: [54.0, 56.0] $n = 257$	55.0 CI: (54.8, 55.0) IQR: [54.0, 55.3] $n = 400$
Moderate	50	54.0 CI: (53.0, 55.0) IQR: [53.0, 55.0] $n = 62$	53.0 CI: (52.0, 54.0) IQR: [51.2, 54.9] $n = 45$	53.6 CI: (53.0, 54.0) IQR: [52.0, 54.5] $n = 36$	54.0 CI: (54.0, 55.0) IQR: [52.0, 56.3] $n = 257$	53.8 CI: (53.0, 54.0) IQR: [52.0, 55.0] $n = 400$
Rapid	50	52.0 CI: (50.0, 53.0) IQR: [50.0, 54.0] $n = 62$	50.0 CI: (48.0, 51.2) IQR: [45.4, 52.6] $n = 45$	52.0 CI: (50.0, 53.0) IQR: [48.0, 54.0] $n = 36$	52.0 CI: (51.5, 52.5) IQR: [50.0, 55.0] $n = 257$	51.3 CI: (50.0, 52.0) IQR: [48.1, 54.0] $n = 400$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 40: Labor Share, Non-farm Business Sector (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	50.0 CI: (50.0, 52.0) IQR: [48.6, 52.2] $n = 61$	49.6 CI: (48.0, 51.5) IQR: [46.6, 53.1] $n = 45$	50.5 CI: (48.0, 51.6) IQR: [45.5, 52.0] $n = 36$	53.0 CI: (52.0, 53.0) IQR: [50.0, 55.3] $n = 248$	50.3 CI: (50.0, 51.1) IQR: [48.0, 53.0] $n = 390$
Slow	50	52.0 CI: (51.4, 53.1) IQR: [50.0, 54.4] $n = 61$	52.0 CI: (50.0, 54.0) IQR: [49.5, 54.6] $n = 45$	51.5 CI: (49.5, 52.0) IQR: [48.1, 53.0] $n = 36$	54.0 CI: (53.0, 54.0) IQR: [51.3, 56.0] $n = 248$	52.0 CI: (52.0, 53.0) IQR: [50.0, 55.0] $n = 390$
Moderate	50	50.0 CI: (49.0, 50.8) IQR: [46.4, 52.0] $n = 61$	47.4 CI: (43.0, 49.1) IQR: [40.0, 51.1] $n = 45$	48.5 CI: (45.0, 50.2) IQR: [43.0, 51.2] $n = 36$	52.0 CI: (51.0, 52.0) IQR: [49.0, 55.0] $n = 248$	50.0 CI: (48.4, 50.0) IQR: [45.0, 52.0] $n = 390$
Rapid	50	45.0 CI: (42.3, 47.0) IQR: [40.0, 48.5] $n = 61$	40.0 CI: (35.0, 47.0) IQR: [30.0, 48.0] $n = 45$	45.5 CI: (35.0, 48.5) IQR: [30.0, 49.0] $n = 36$	48.0 CI: (46.0, 49.0) IQR: [42.0, 55.0] $n = 248$	45.0 CI: (43.0, 46.5) IQR: [35.0, 50.0] $n = 390$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.2.11 Median Household Income

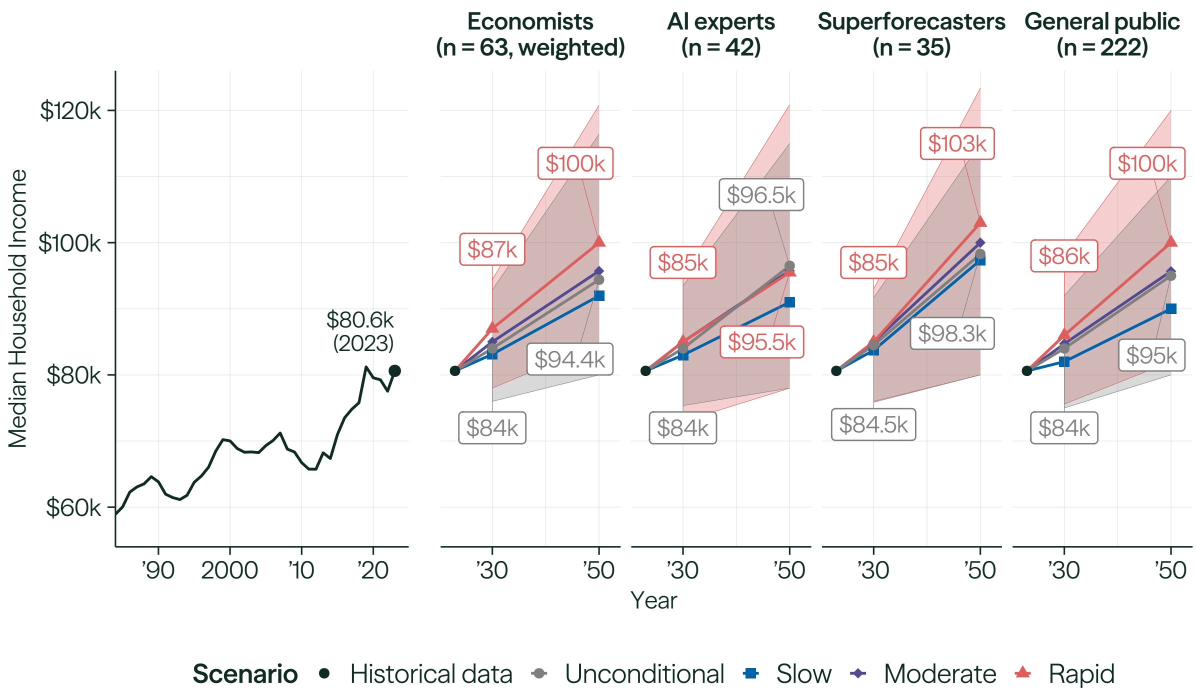


Figure 52: *Forecasts for real median household income.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

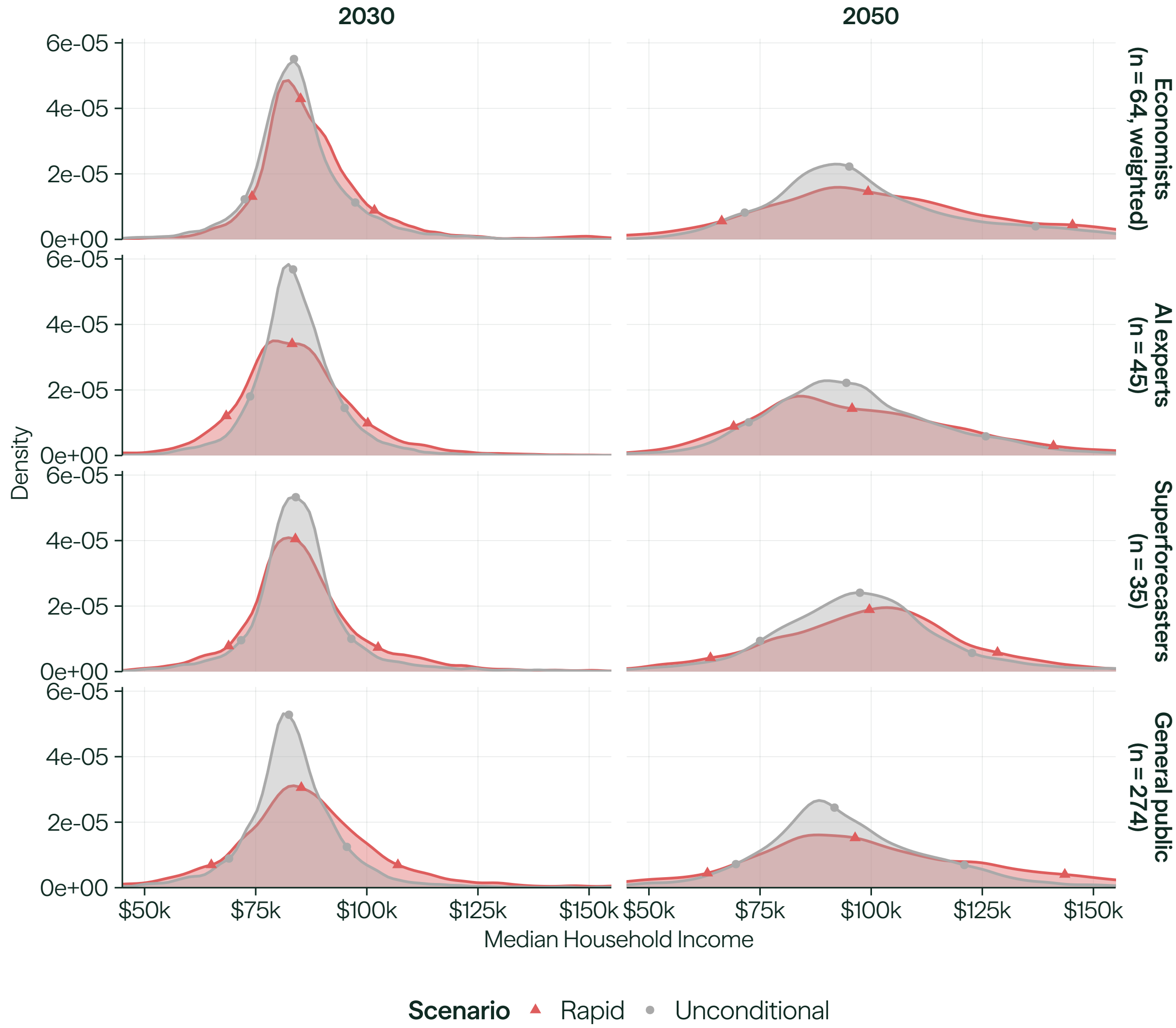


Figure 53: *Distribution of forecasts for real median household income.* Distribution is pooled across participants. Points show 10th/50th/90th percentiles of the distribution.

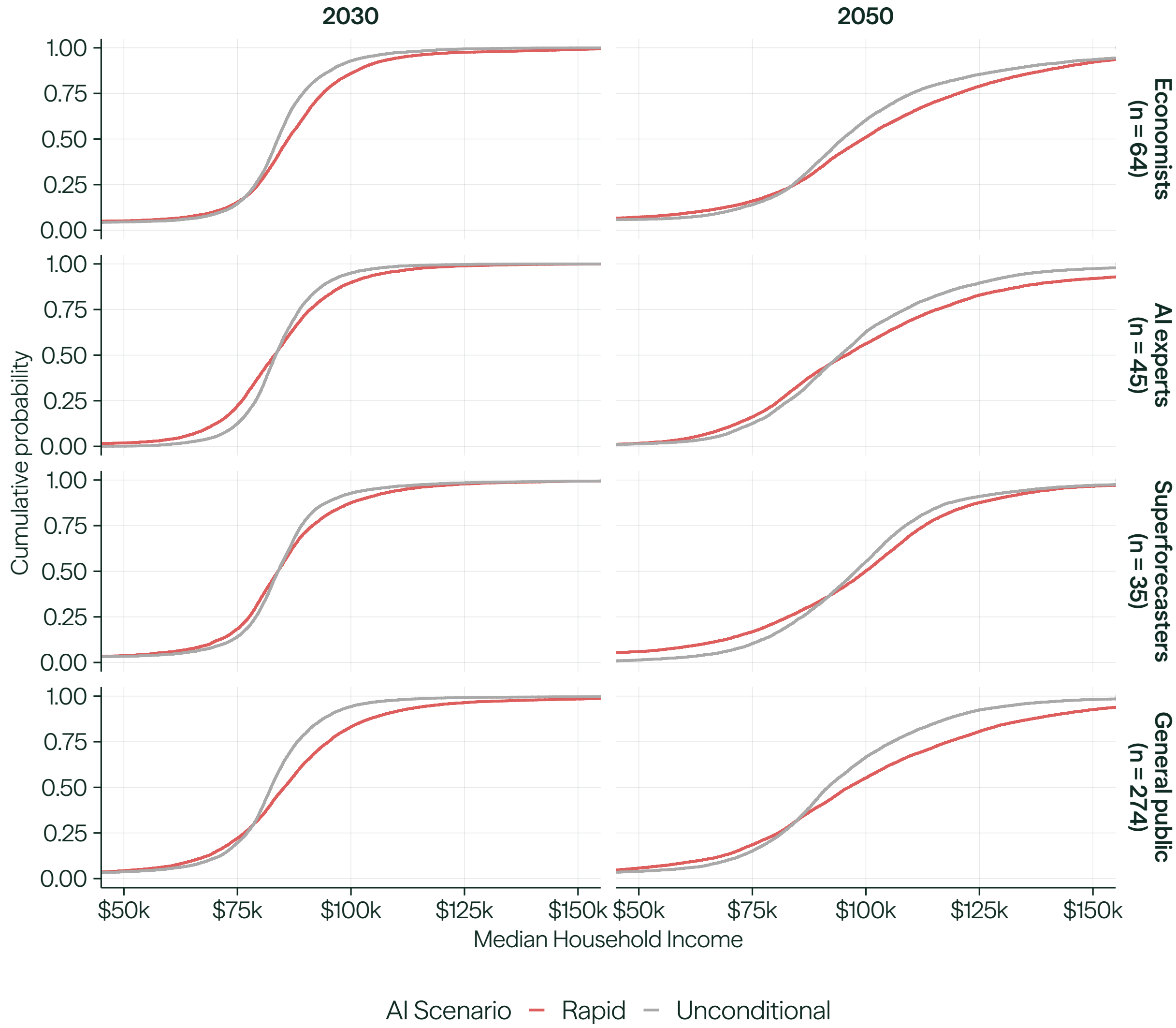


Figure 54: *Cumulative distribution of forecasts for real median household income.*

Table 41: Median Household Income ($1,000s) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	76.0 CI: (72.9, 78.0) IQR: [70.0, 79.0] $n = 64$	75.0 CI: (73.9, 76.0) IQR: [70.0, 78.0] $n = 45$	75.4 CI: (72.0, 77.8) IQR: [70.5, 80.0] $n = 36$	74.3 CI: (72.9, 75.0) IQR: [67.9, 79.0] $n = 253$	75.0 CI: (74.8, 76.0) IQR: [70.0, 79.0] $n = 398$
Unconditional	50	84.0 CI: (82.5, 85.0) IQR: [82.0, 85.4] $n = 64$	84.8 CI: (83.5, 85.0) IQR: [82.6, 86.0] $n = 45$	84.8 CI: (82.5, 85.8) IQR: [81.0, 86.5] $n = 36$	83.0 CI: (82.0, 85.0) IQR: [80.0, 85.5] $n = 253$	84.4 CI: (83.4, 85.0) IQR: [81.0, 86.0] $n = 398$
Unconditional	90	92.3 CI: (90.0, 100.0) IQR: [88.0, 100.0] $n = 64$	94.0 CI: (91.1, 95.0) IQR: [87.8, 98.2] $n = 45$	91.8 CI: (90.0, 95.6) IQR: [89.0, 99.7] $n = 36$	92.0 CI: (90.0, 93.1) IQR: [86.0, 100.0] $n = 253$	92.2 CI: (91.1, 95.0) IQR: [88.0, 100.0] $n = 398$
Slow	50	83.0 CI: (82.0, 85.0) IQR: [81.5, 85.0] $n = 64$	83.0 CI: (82.0, 84.0) IQR: [81.0, 85.0] $n = 45$	83.8 CI: (82.5, 85.0) IQR: [81.2, 86.0] $n = 36$	82.0 CI: (81.0, 83.0) IQR: [80.0, 85.0] $n = 253$	83.0 CI: (82.6, 84.0) IQR: [81.0, 85.0] $n = 398$
Moderate	50	85.0 CI: (83.0, 87.0) IQR: [82.0, 88.0] $n = 64$	85.0 CI: (83.6, 86.0) IQR: [82.5, 87.0] $n = 45$	85.2 CI: (82.0, 86.3) IQR: [80.8, 87.0] $n = 36$	84.0 CI: (82.2, 85.0) IQR: [80.0, 88.0] $n = 253$	85.0 CI: (84.0, 85.4) IQR: [81.0, 87.0] $n = 398$
Rapid	10	78.0 CI: (75.0, 80.0) IQR: [72.3, 81.0] $n = 64$	72.0 CI: (69.3, 75.0) IQR: [65.8, 78.1] $n = 45$	76.0 CI: (71.0, 77.4) IQR: [70.0, 79.0] $n = 36$	75.0 CI: (73.9, 77.0) IQR: [65.0, 81.9] $n = 253$	75.0 CI: (73.9, 76.9) IQR: [69.1, 80.0] $n = 398$
Rapid	50	87.0 CI: (83.0, 88.9) IQR: [82.2, 90.0] $n = 64$	85.0 CI: (80.0, 87.0) IQR: [78.1, 88.5] $n = 45$	85.5 CI: (81.5, 88.0) IQR: [80.0, 88.8] $n = 36$	85.0 CI: (84.2, 87.3) IQR: [78.9, 92.0] $n = 253$	85.0 CI: (84.0, 87.0) IQR: [80.0, 90.0] $n = 398$
Rapid	90	94.0 CI: (89.2, 99.4) IQR: [88.0, 105.6] $n = 64$	95.0 CI: (91.0, 98.0) IQR: [87.8, 100.2] $n = 45$	95.6 CI: (90.0, 100.0) IQR: [88.0, 104.0] $n = 36$	97.3 CI: (95.0, 100.0) IQR: [87.3, 110.0] $n = 253$	95.0 CI: (93.0, 98.0) IQR: [88.0, 105.0] $n = 398$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 42: Median Household Income ($1,000s) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	10	80.0 CI: (77.7, 85.0) IQR: [69.5, 86.0] $n = 64$	78.0 CI: (71.9, 85.0) IQR: [67.8, 88.4] $n = 43$	80.0 CI: (70.0, 88.0) IQR: [66.0, 90.0] $n = 35$	80.0 CI: (77.7, 81.0) IQR: [68.6, 86.7] $n = 249$	80.0 CI: (77.7, 82.3) IQR: [68.9, 89.3] $n = 391$
Unconditional	50	93.2 CI: (90.0, 100.0) IQR: [88.9, 104.4] $n = 64$	96.0 CI: (90.0, 98.0) IQR: [87.7, 104.8] $n = 43$	98.3 CI: (95.0, 102.0) IQR: [92.7, 108.8] $n = 35$	93.0 CI: (90.4, 95.0) IQR: [85.0, 105.0] $n = 249$	96.0 CI: (94.1, 98.0) IQR: [88.1, 105.0] $n = 391$
Unconditional	90	115.6 CI: (101.9, 122.3) IQR: [100.0, 137.2] $n = 64$	115.0 CI: (104.1, 124.0) IQR: [100.0, 133.0] $n = 43$	115.0 CI: (110.0, 125.0) IQR: [106.1, 128.1] $n = 35$	107.3 CI: (105.0, 112.0) IQR: [93.1, 125.0] $n = 249$	115.0 CI: (110.0, 118.8) IQR: [100.0, 130.0] $n = 391$
Slow	50	91.9 CI: (90.0, 99.2) IQR: [88.5, 100.0] $n = 64$	90.0 CI: (88.0, 96.6) IQR: [85.3, 99.5] $n = 43$	97.4 CI: (92.2, 100.0) IQR: [92.0, 101.1] $n = 35$	90.0 CI: (88.4, 92.0) IQR: [83.0, 100.0] $n = 249$	92.5 CI: (91.5, 95.0) IQR: [88.0, 100.0] $n = 391$
Moderate	50	95.1 CI: (90.0, 105.0) IQR: [89.0, 109.3] $n = 64$	94.5 CI: (89.7, 100.0) IQR: [85.6, 105.0] $n = 43$	100.0 CI: (95.0, 105.0) IQR: [91.2, 110.0] $n = 35$	95.0 CI: (91.0, 100.0) IQR: [85.0, 108.2] $n = 249$	97.1 CI: (95.0, 100.0) IQR: [88.2, 110.0] $n = 391$
Rapid	10	83.9 CI: (70.0, 91.8) IQR: [68.6, 100.0] $n = 64$	77.7 CI: (70.5, 84.0) IQR: [63.5, 86.8] $n = 43$	80.0 CI: (65.0, 87.0) IQR: [43.7, 92.6] $n = 35$	80.0 CI: (76.8, 85.0) IQR: [67.7, 95.0] $n = 249$	80.0 CI: (75.0, 84.3) IQR: [63.9, 92.8] $n = 391$
Rapid	50	100.0 CI: (90.4, 116.8) IQR: [81.2, 120.1] $n = 64$	95.0 CI: (86.7, 110.0) IQR: [79.8, 119.3] $n = 43$	103.0 CI: (90.0, 110.2) IQR: [85.1, 122.5] $n = 35$	99.0 CI: (95.0, 100.0) IQR: [84.1, 120.0] $n = 249$	100.0 CI: (95.0, 105.0) IQR: [82.0, 120.0] $n = 391$
Rapid	90	120.4 CI: (107.8, 140.0) IQR: [102.0, 152.7] $n = 64$	120.0 CI: (105.0, 131.1) IQR: [98.1, 147.5] $n = 43$	123.4 CI: (115.1, 155.0) IQR: [113.0, 193.8] $n = 35$	117.3 CI: (111.1, 125.0) IQR: [95.0, 150.0] $n = 249$	120.8 CI: (117.0, 126.5) IQR: [100.1, 153.4] $n = 391$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.2.12 Life Satisfaction

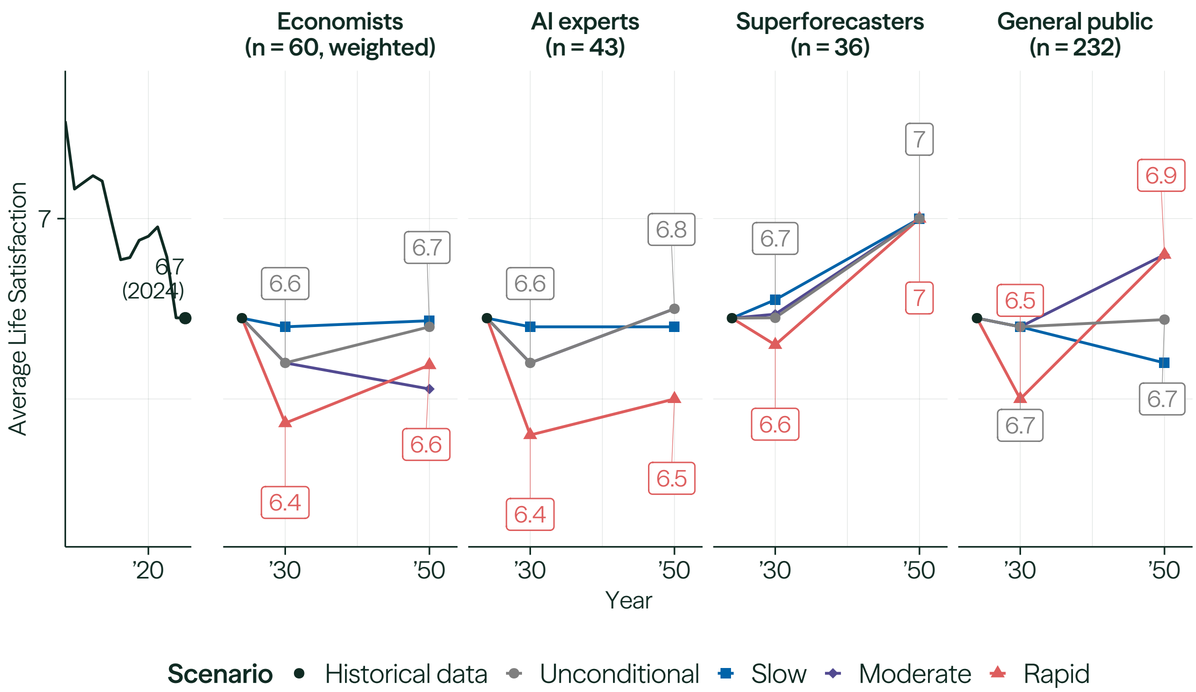


Figure 55: *Forecasts for average life satisfaction on the Cantril ladder.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Because we elicited only 50th percentile predictions for life satisfaction, this figure does not show uncertainty. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 43: Average Life Satisfaction (0–10 scale) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	6.6 CI: (6.6, 6.7) IQR: [6.5, 6.8] $n = 65$	6.6 CI: (6.5, 6.7) IQR: [6.4, 6.8] $n = 46$	6.7 CI: (6.6, 6.9) IQR: [6.5, 7.0] $n = 37$	6.7 CI: (6.6, 6.7) IQR: [6.5, 6.8] $n = 268$	6.6 CI: (6.6, 6.7) IQR: [6.5, 6.9] $n = 416$
Slow	50	6.7 CI: (6.6, 6.7) IQR: [6.5, 6.8] $n = 65$	6.7 CI: (6.6, 6.7) IQR: [6.5, 6.9] $n = 46$	6.8 CI: (6.6, 6.9) IQR: [6.5, 7.0] $n = 37$	6.7 CI: (6.6, 6.7) IQR: [6.5, 6.8] $n = 268$	6.7 CI: (6.7, 6.7) IQR: [6.5, 6.9] $n = 416$
Moderate	50	6.6 CI: (6.5, 6.6) IQR: [6.4, 6.7] $n = 65$	6.5 CI: (6.5, 6.7) IQR: [6.3, 6.8] $n = 46$	6.7 CI: (6.5, 6.9) IQR: [6.5, 6.9] $n = 37$	6.7 CI: (6.6, 6.7) IQR: [6.4, 6.9] $n = 268$	6.6 CI: (6.6, 6.7) IQR: [6.4, 6.9] $n = 416$
Rapid	50	6.5 CI: (6.2, 6.5) IQR: [6.1, 6.7] $n = 65$	6.4 CI: (6.2, 6.6) IQR: [6.0, 6.8] $n = 46$	6.6 CI: (6.4, 6.9) IQR: [6.3, 7.0] $n = 37$	6.5 CI: (6.5, 6.6) IQR: [6.0, 7.0] $n = 268$	6.5 CI: (6.4, 6.5) IQR: [6.0, 6.9] $n = 416$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 44: Average Life Satisfaction (0–10 scale) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	6.7 CI: (6.3, 7.0) IQR: [6.2, 7.0] $n = 62$	6.7 CI: (6.5, 6.9) IQR: [6.2, 7.0] $n = 45$	7.0 CI: (6.8, 7.0) IQR: [6.7, 7.0] $n = 36$	6.7 CI: (6.6, 6.8) IQR: [6.2, 7.0] $n = 254$	6.8 CI: (6.7, 6.9) IQR: [6.3, 7.0] $n = 397$
Slow	50	6.7 CI: (6.4, 6.9) IQR: [6.3, 7.0] $n = 62$	6.7 CI: (6.6, 6.9) IQR: [6.5, 7.0] $n = 45$	7.0 CI: (6.8, 7.0) IQR: [6.5, 7.0] $n = 36$	6.6 CI: (6.5, 6.7) IQR: [6.2, 7.0] $n = 254$	6.8 CI: (6.6, 6.9) IQR: [6.3, 7.0] $n = 397$
Moderate	50	6.5 CI: (6.3, 7.0) IQR: [6.1, 7.1] $n = 62$	6.7 CI: (6.3, 7.0) IQR: [6.0, 7.0] $n = 45$	7.0 CI: (6.9, 7.0) IQR: [6.6, 7.1] $n = 36$	6.9 CI: (6.8, 7.0) IQR: [6.0, 7.2] $n = 254$	6.9 CI: (6.6, 7.0) IQR: [6.2, 7.1] $n = 397$
Rapid	50	6.5 CI: (6.0, 7.0) IQR: [5.7, 7.1] $n = 62$	6.5 CI: (6.0, 6.8) IQR: [5.2, 7.2] $n = 45$	7.0 CI: (6.6, 7.0) IQR: [6.3, 7.2] $n = 36$	6.9 CI: (6.7, 7.0) IQR: [6.0, 7.5] $n = 254$	6.8 CI: (6.5, 7.0) IQR: [5.9, 7.2] $n = 397$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.2.13 Work Hours Assisted by Generative AI

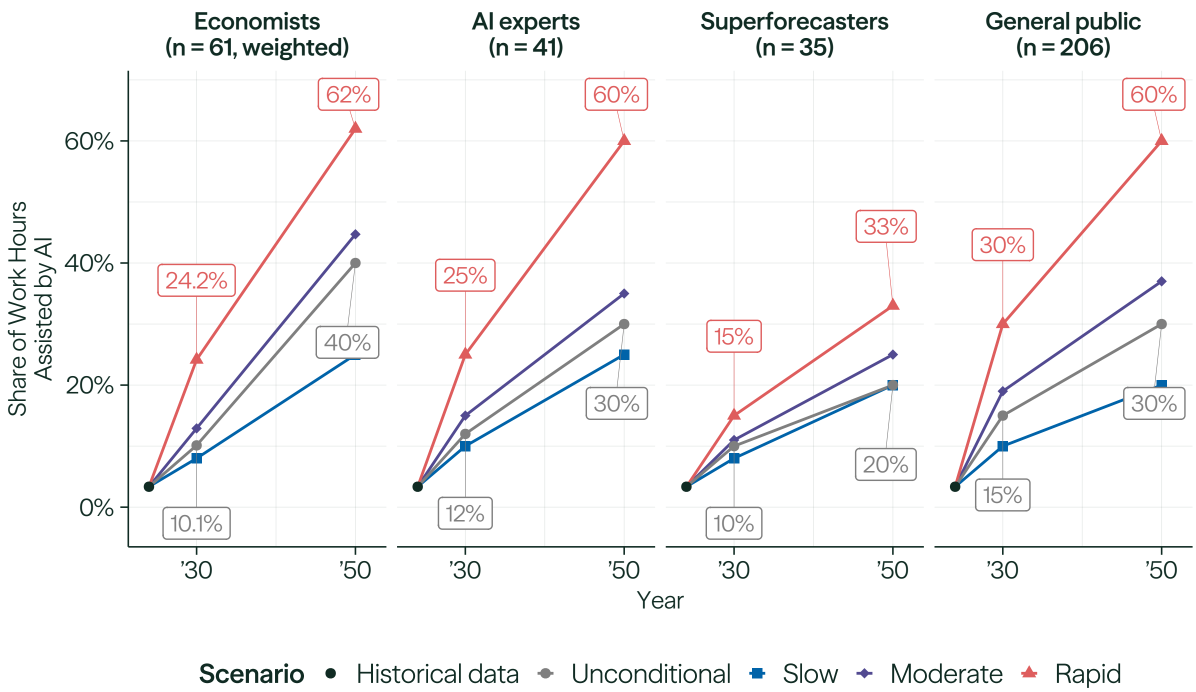


Figure 56: *Forecasts for the share of work hours assisted by generative AI.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Because we elicited only 50th percentile predictions for this outcome, this figure does not show uncertainty. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 45: Work Hours Assisted by Generative AI (%) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	10.1 CI: (10.0, 18.4) IQR: [8.0, 20.0] $n = 61$	12.0 CI: (10.0, 18.0) IQR: [8.0, 20.0] $n = 41$	10.0 CI: (7.5, 13.0) IQR: [6.3, 15.0] $n = 36$	12.0 CI: (8.0, 15.0) IQR: [5.0, 20.0] $n = 230$	10.0 CI: (10.0, 14.0) IQR: [7.0, 18.8] $n = 368$
Slow	50	8.0 CI: (5.7, 12.0) IQR: [5.0, 13.8] $n = 61$	10.0 CI: (7.0, 10.0) IQR: [6.0, 12.0] $n = 41$	8.2 CI: (6.3, 10.0) IQR: [5.0, 12.5] $n = 36$	9.0 CI: (7.0, 10.0) IQR: [4.5, 12.0] $n = 230$	8.3 CI: (7.5, 10.0) IQR: [5.0, 12.2] $n = 368$
Moderate	50	12.9 CI: (10.0, 16.5) IQR: [8.8, 23.3] $n = 61$	15.0 CI: (13.9, 20.0) IQR: [10.0, 25.0] $n = 41$	11.0 CI: (8.5, 15.0) IQR: [7.2, 15.0] $n = 36$	15.0 CI: (13.0, 20.0) IQR: [6.4, 25.0] $n = 230$	14.0 CI: (12.0, 15.0) IQR: [8.0, 22.0] $n = 368$
Rapid	50	24.2 CI: (15.0, 30.0) IQR: [13.0, 40.0] $n = 61$	25.0 CI: (20.0, 30.0) IQR: [15.0, 40.0] $n = 41$	15.0 CI: (12.3, 21.5) IQR: [11.0, 25.0] $n = 36$	25.5 CI: (20.0, 30.0) IQR: [10.0, 40.0] $n = 230$	20.0 CI: (17.0, 25.0) IQR: [12.0, 36.1] $n = 368$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 46: Work Hours Assisted by Generative AI (%) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	40.0 CI: (30.0, 50.0) IQR: [20.0, 59.9] $n = 61$	30.0 CI: (24.0, 45.0) IQR: [17.9, 50.0] $n = 43$	20.0 CI: (15.0, 25.0) IQR: [10.2, 35.0] $n = 35$	30.0 CI: (25.0, 34.0) IQR: [10.0, 45.0] $n = 218$	30.0 CI: (22.0, 35.0) IQR: [15.0, 50.0] $n = 357$
Slow	50	25.0 CI: (15.9, 34.1) IQR: [12.0, 45.0] $n = 61$	22.0 CI: (16.0, 28.0) IQR: [12.5, 33.8] $n = 43$	20.0 CI: (14.0, 25.0) IQR: [9.0, 33.8] $n = 35$	20.0 CI: (18.0, 20.0) IQR: [8.0, 25.0] $n = 218$	20.0 CI: (18.0, 25.0) IQR: [12.0, 35.0] $n = 357$
Moderate	50	44.7 CI: (30.0, 50.8) IQR: [22.4, 66.2] $n = 61$	33.0 CI: (25.0, 48.0) IQR: [21.4, 53.5] $n = 43$	25.0 CI: (18.0, 30.0) IQR: [15.0, 45.0] $n = 35$	35.0 CI: (30.0, 40.0) IQR: [12.0, 52.0] $n = 218$	30.7 CI: (25.9, 40.0) IQR: [18.0, 52.0] $n = 357$
Rapid	50	62.0 CI: (44.6, 80.0) IQR: [37.7, 85.0] $n = 61$	60.0 CI: (40.0, 70.0) IQR: [31.0, 77.5] $n = 43$	33.0 CI: (20.0, 50.0) IQR: [20.0, 67.5] $n = 35$	54.5 CI: (43.5, 62.5) IQR: [20.0, 75.0] $n = 218$	50.0 CI: (40.0, 60.0) IQR: [23.6, 78.0] $n = 357$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.2.14 AI Electricity Consumption

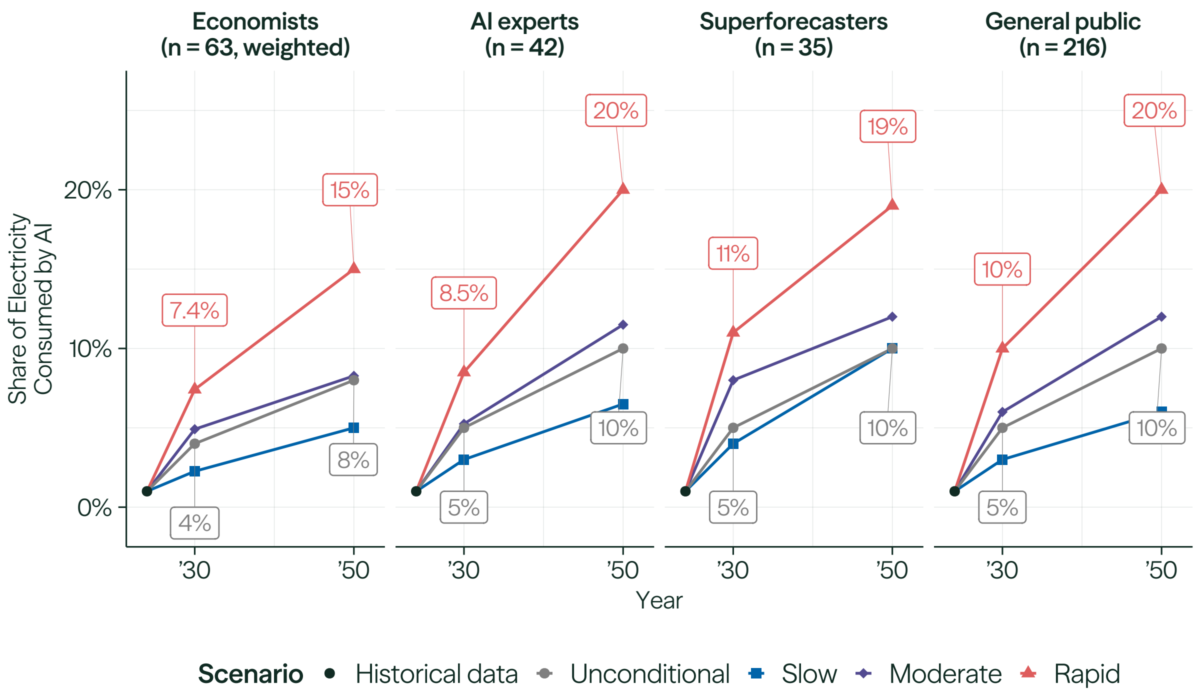


Figure 57: *Forecasts for the share of U.S. electricity consumption used by AI.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Because we elicited only 50th percentile predictions for this outcome, this figure does not show uncertainty. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Table 47: Electricity Consumption for AI Systems (% of total) (2030)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	4.0 CI: (2.1, 6.0) IQR: [2.0, 8.0] $n = 63$	5.0 CI: (3.0, 6.5) IQR: [2.0, 7.5] $n = 44$	5.0 CI: (4.0, 8.0) IQR: [2.3, 9.0] $n = 35$	5.0 CI: (4.1, 6.0) IQR: [2.0, 8.0] $n = 238$	5.0 CI: (4.0, 6.0) IQR: [2.0, 8.0] $n = 380$
Slow	50	2.3 CI: (1.8, 4.0) IQR: [1.5, 5.6] $n = 63$	3.0 CI: (2.0, 5.0) IQR: [2.0, 5.6] $n = 44$	4.0 CI: (2.3, 6.0) IQR: [2.0, 7.0] $n = 35$	3.0 CI: (3.0, 3.0) IQR: [1.5, 6.0] $n = 238$	3.0 CI: (2.3, 4.0) IQR: [1.8, 6.0] $n = 380$
Moderate	50	4.9 CI: (2.5, 6.0) IQR: [2.0, 8.0] $n = 63$	5.3 CI: (3.5, 7.0) IQR: [2.8, 8.0] $n = 44$	8.0 CI: (5.0, 10.0) IQR: [2.8, 10.0] $n = 35$	6.0 CI: (5.7, 7.0) IQR: [3.0, 10.0] $n = 238$	5.8 CI: (5.0, 6.5) IQR: [2.5, 9.0] $n = 380$
Rapid	50	7.4 CI: (4.0, 9.0) IQR: [3.0, 10.0] $n = 63$	8.5 CI: (5.5, 10.0) IQR: [4.0, 11.5] $n = 44$	11.0 CI: (6.0, 13.0) IQR: [4.7, 14.0] $n = 35$	10.0 CI: (9.0, 10.0) IQR: [5.0, 14.5] $n = 238$	9.0 CI: (7.1, 10.0) IQR: [4.0, 13.0] $n = 380$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

Table 48: Electricity Consumption for AI Systems (% of total) (2050)

Scenario	Percentile	Economists	AI Experts	Superforecasters	General Public	Total
Unconditional	50	8.0 CI: (5.0, 15.0) IQR: [3.0, 18.0] $n = 63$	10.0 CI: (8.0, 13.5) IQR: [3.4, 16.0] $n = 44$	10.0 CI: (6.0, 15.0) IQR: [5.0, 17.5] $n = 36$	10.0 CI: (9.2, 12.0) IQR: [5.0, 15.0] $n = 236$	10.0 CI: (8.0, 11.0) IQR: [4.4, 16.4] $n = 379$
Slow	50	5.0 CI: (3.0, 10.0) IQR: [2.1, 10.7] $n = 63$	6.0 CI: (4.3, 10.0) IQR: [2.5, 11.1] $n = 44$	9.0 CI: (5.0, 13.0) IQR: [3.7, 15.0] $n = 36$	6.0 CI: (5.0, 7.0) IQR: [3.0, 10.0] $n = 236$	6.0 CI: (5.0, 8.0) IQR: [3.0, 12.0] $n = 379$
Moderate	50	8.3 CI: (5.0, 15.0) IQR: [4.0, 18.0] $n = 63$	10.5 CI: (9.0, 15.0) IQR: [5.9, 16.5] $n = 44$	12.0 CI: (9.0, 17.0) IQR: [7.6, 20.0] $n = 36$	12.0 CI: (10.0, 14.5) IQR: [7.0, 19.0] $n = 236$	11.0 CI: (10.0, 14.0) IQR: [5.0, 18.0] $n = 379$
Rapid	50	15.0 CI: (8.0, 20.0) IQR: [5.3, 25.8] $n = 63$	19.5 CI: (14.0, 25.0) IQR: [7.4, 30.0] $n = 44$	19.5 CI: (12.0, 25.0) IQR: [10.0, 36.5] $n = 36$	20.0 CI: (17.1, 20.0) IQR: [10.4, 25.0] $n = 236$	19.0 CI: (15.0, 20.0) IQR: [7.5, 30.0] $n = 379$

Note: Median / CI: (95 % CI for median) / IQR: [Q1, Q3] / $n = N$. CI: percentile bootstrap, 3,000 resamples.

D.3 Policy Results

We asked survey participants to predict the marginal impact of six policy proposals—four labor market interventions, one AI-acceleration measure, and one AI taxation measure—under the unconditional and rapid scenarios. All respondents were instructed to estimate the effect of each policy in isolation, setting aside any consideration of conditions, political or otherwise, under which each policy might be adopted. We also asked respondents to indicate their support for implementing each policy without conditioning on any specific AI progress scenario. Finally, we asked respondents to estimate the probability that each policy (or a similar policy, as judged by an economist panel) would be implemented by the U.S. by the end of 2026. The results for 2030 predictions are presented below, along with analyses of the rationales that informed the predicted impacts on GDP and LFPR. Results for expected impact on GDP and LFPR in 2050 are presented in Figure 65 and Figure 67, which appear at the end of this section.

Policy 1: Retraining Support

Unemployed people leaving a job in an industry with high-automation risk are provided with: credits covering up to $25,000 per year for approved training courses, up to two years full-time equivalent in total; career counseling and support for finding retraining opportunities; relocation grants of up to $5,000 covering the costs of moving for a training program

In addition, employees in these industries are allowed to spend up to 50% of their working hours on retraining. For these hours, they are paid 90% of their usual hourly salary. Employers receive tax credits equal to 50% of wages paid during employee training time.

Industries with high-automation risk are identified by a panel of economists. The panel convenes every two years to update its assessments. The program is funded by introducing a retraining payroll tax of 0.5%, split equally between employees and employers (0.25% each).

Economists held modestly positive expectations for the Retraining Support program. The median forecast for the marginal impact on annualized GDP growth was 0.1 p.p. in the unconditional scenario and 0.2 p.p. in the rapid. The median impact on the LFPR was 0.5 p.p. in the unconditional and 1.0 p.p. in the rapid.

Support for implementation was high: 71.8% of economists endorsed the policy, with only 19.9% opposed and 8.3% expressing uncertainty. The median assessed probability of real-world implementation was only 10%, reflecting a common pattern in this survey whereby respondents support a policy but regard political obstacles as substantial barriers to enactment. Enthusiasm for this policy was broadly shared by the other groups surveyed, although superforecasters assigned a notably lower implementation probability of 3.5%; this significantly greater skepticism among superforecasters regarding the political feasibility of the policy proposals persisted across all six policies considered.

Rationale Analysis *Impact on GDP*: Economists frequently cited the likelihood that retraining support would have a positive effect on GDP by upskilling workers, helping to make them more productive, and keeping more workers in the labor pool: "Retraining support modestly raises growth by improving worker–job matching and speeding reallocation from shrinking occupations to expanding ones, with limited fiscal drag given the program's

Figure 58: *Retraining Support*

scale."; "Modest positive effect from smoother labor transitions; workers retrain into higher-productivity roles slightly faster." The 0.5% payroll tax typically attracted little concern—"the tiny payroll tax hardly bites"—but a notable minority of economists questioned whether the policy was "sufficiently large [enough] to meaningfully change the expected GDP growth rate," while others pointed to a potential future where AI is driving automation faster than humans can be retrained, and "human skill levels cease to be the primary driver of output..."

Impact on LFPR: Many economists echoed the sentiment they expressed regarding impact on GDP, i.e. that the policy was likely to lead to a modest upskilling of workers, making them more productive, and therefore more likely to remain in the labor pool: "It raises participation by keeping displaced workers engaged and improving transitions into new roles," wrote one, and another that it will "improve the match between labor supply and demand." A third emphasized that the provision that allows workers to retrain while employed "maintains the employment relationship, countering the job loss expected in declining industries." As with the impact on GDP, however, some economists—in particular when considering the rapid scenario—questioned whether such a policy would be sustainable: "In rapid AI progress, LFPR collapses as AI and robotics automate most jobs... Policy effects on LFPR are modest relative to this massive structural shift."

Policy 2: Modernized Unemployment Insurance

Workers who lose their jobs in an industry with high-automation risk receive enhanced unemployment benefits: unemployment benefits increase from current levels to 75% of the previous salary for up to 18 months; workers who find new employment at lower wages receive wage loss insurance covering 50% of the salary difference for up to 2 years; benefits are portable across state lines to encourage geographic mobility; workers can receive benefits while enrolled in approved training programs without work search requirements; administrative barriers are lowered with simplified applications, automated verification, and reduced reporting requirements.

The program is funded by increasing baseline employer payroll taxes by 9 percentage points from 6% to 15% (on the first $7,000).

Economists forecast the Modernized Unemployment Insurance program would have no impact on either GDP growth or the LFPR in either the unconditional or rapid scenarios.

Despite the null result, support for this policy—while less than for Retraining Support—was robust, with 62.3% of economists in favor, 17.6% opposed and 20.2% unsure. The median probability of implementation was 10%.

Rationale Analysis *Impact on GDP*: Economists who thought this policy would lead to a meaningful increase in GDP were in the minority. A frequently cited concern was that it would dampen job search intensity in ways that offset any positive effects. One wrote that it "would significantly limit incentives to work," and "lead to much slower labor reallocation." The steep employer payroll tax increase also attracted repeated criticism: "Higher employer payroll taxes create a small drag on hiring and investment." For some, the negative view intensified when considering the rapid scenario, as "unemployment insurance stops companies from growing rapidly and limits labor reallocation—this matters more in this [rapid] scenario

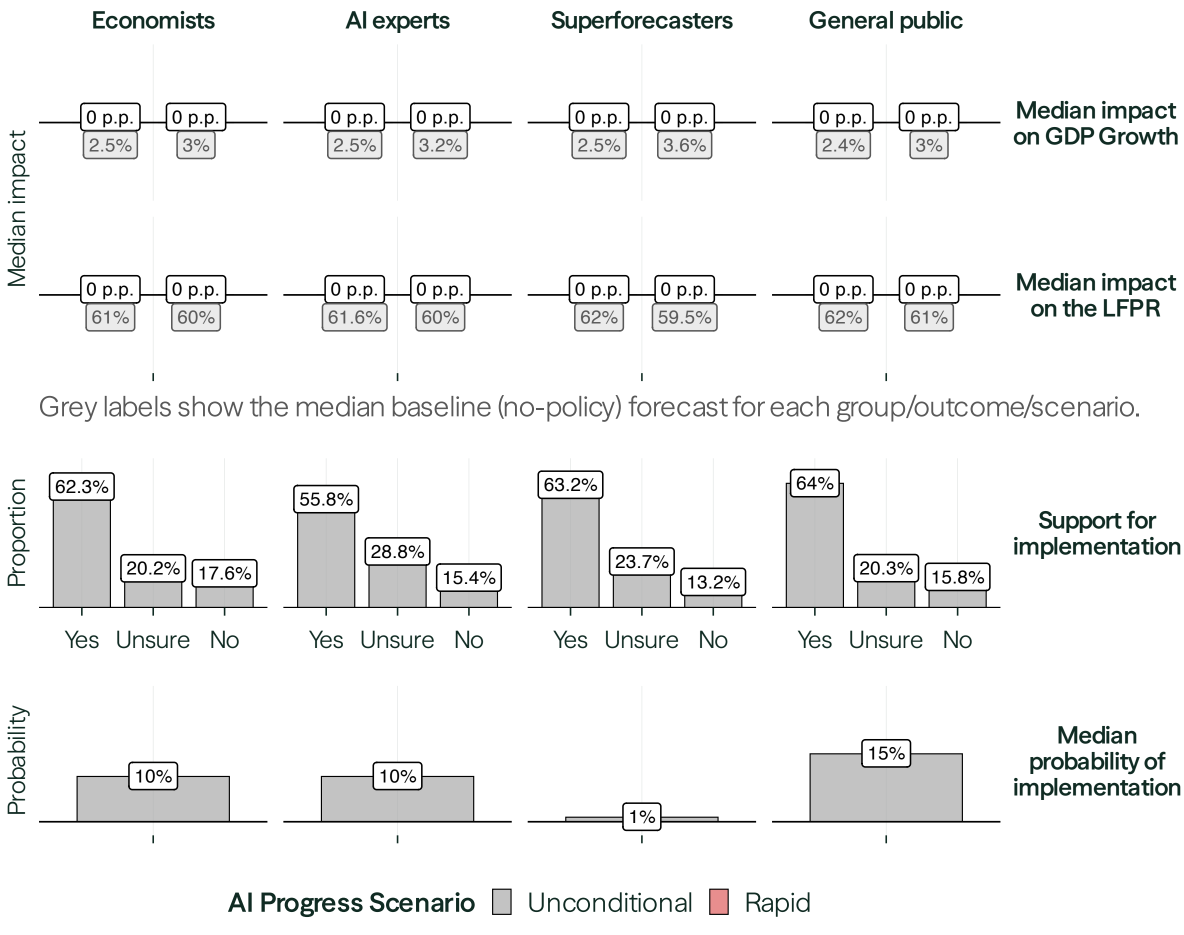


Figure 59: *Modernized Unemployment Insurance*

as there is a lot of reallocation that needs to happen." Some economists did emphasize the policy's ability to "stabilize household demand and reduce scarring by smoothing incomes during job loss." One wrote that the policy is "roughly growth-neutral in the median: it stabilizes demand and improves matching... but also risks longer job search and higher nonwage costs, so the net effect is small."

Impact on LFPR: Economists were split on this measure. The most common positive argument was that because benefit eligibility requires some labor force attachment, this will support the LFPR: "UI keeps people in the labor force for financial reasons—otherwise [they] cannot get UI." The most common negative view was that, "the generous 18-month benefit duration creates some disincentive to work, likely causing a potential reduction on the labor supply." Several economists predicted the tension between these forces would lead to a roughly neutral effect, with one arguing that the policy "improves matching quality" but risks "longer job search" and "higher reservation wages." Under the rapid scenario, one economist warned that "richer UI slows re-entry just as the market is churning," although others noted that "keeping people searching rather than exiting" the labor market is precisely the policy's value in high-displacement conditions.

Policy 3: Universal Basic Income

Every U.S. citizen aged 18 and over receives $1,000 per month.

The program is funded by a 15% value-added tax (VAT) on all goods and services.

Payments are unconditional and do not affect eligibility for other social programs. The amount is indexed to inflation and reviewed every year.

Universal Basic Income was the most negatively received policy among economists in terms of projected economic impact. The median forecast was -2.0 p.p. on the LFPR under either scenario and no effect on GDP growth under either scenario.

Support for this policy among economists was correspondingly low: only 37.4% endorsed it, while 38.2% expressed opposition. Only a 0.4% probability was assigned to real-world implementation.

The divergence between economists and the general public on this policy is among the most striking cross-cohort findings in the survey. Whereas nearly half of economists opposed UBI, 47.6% of the general public supported it, and only 30.5% opposed it—an inversion of the economist distribution. The general public also assigned a meaningfully higher implementation probability of 5%.

Rationale Analysis *Impact on GDP*: The majority of economists questioned UBI's potential to increase GDP, citing work disincentives and the VAT funding mechanism: "UBI would have a large disincentive effect on work and reduce LFPR. This should lead to lower [GDP] growth due to lower capital formation and skill development in the long run."; "The strong income effect discourages some individuals from working, particularly in lower-wage jobs."; "The funding mechanism, a 15% VAT, adds a modest drag on private consumption and production." Those who took a more positive or neutral view tended to argue that "providing unconditional income raises consumption and reduces poverty, stimulating short-run demand." Another, in addition to noting the "demand stimulus" effect, pointed to the potential for

Figure 60: *Universal Basic Income*

"increased entrepreneurial risk-taking [to] boost GDP modestly." Some argued that under the rapid scenario, UBI could "quell social unrest and lower the probability of a catastrophic civil breakdown," which could, in turn, lead to higher GDP growth than otherwise. Another argued that "we will be much richer in the rapid progress scenario and $1,000 won't be as much of a disincentive to work."

Impact on LFPR: Economists were nearly unanimously negative on this policy's impact on LFPR. The income effect argument dominated: "UBI triggers a strong income effect, allowing workers to voluntarily exit the labor force as the necessity to work for survival vanishes." One economist saw it as "accelerating a structural shift toward a leisure society where work becomes optional for many." Several noted the effect would be concentrated among marginal workers—"secondary earners and older workers"—rather than primary breadwinners. A dissenting minority argued the $1,000/month amount is too small to meaningfully change labor supply behavior. As one wrote, "UBI will push some people out of the labor force but not necessarily a ton because the benefits are not particularly large."

Policy 4: Manhattan Project for AI

The federal government will spend approximately 0.4% of the GDP each year (as of 2025, this corresponds to about $120 billion)[39] *with the goal of rapid improvements to AI capabilities.*

This will include the following:

National AI Development Agency, a new federal agency tasked with developing AI capabilities for national security and defense applications. Most development will take place through contracts with companies and universities.

Direct funding to companies and research institutions to develop AI capabilities and applications, with the funding priorities determined by a government board. While companies keep access to any intellectual property they develop, they are required to share key research findings with the government.

Streamlined permitting process for AI-related infrastructure for the private sector. This could include semiconductor manufacturing, data centers, and related energy infrastructure.

The funding represents additional investment on top of existing federal spending. The project is funded by a 0.7% value-added tax (VAT) on all goods and services.

The Manhattan Project for AI was the policy for which economists expressed the strongest positive GDP growth expectations. The median forecast was 0.3 p.p. on annual GDP growth under the unconditional scenario—the highest forecast of any policy—falling modestly to 0.2 p.p. under the rapid scenario. The median LFPR impact was 0 percentage points under both scenarios, however, suggesting economists do not expect the program to meaningfully alter labor market participation even as GDP rises.

Economists were the cohort most supportive of this policy: 55.8% expressed support, with only 17% opposed. The median implementation probability was 15%—the highest assigned by economists to any single policy in the survey. Notably, economists were considerably more bullish on this policy than superforecasters, only 21.1% of whom expressed support,

[39] For context, Epoch estimates that the combined capital expenditures at Alphabet, Amazon, Meta, Microsoft, and Oracle in 2025 were 448.2 billion dollars: https://epoch.ai/data-insights/hyperscaler-capex-trend

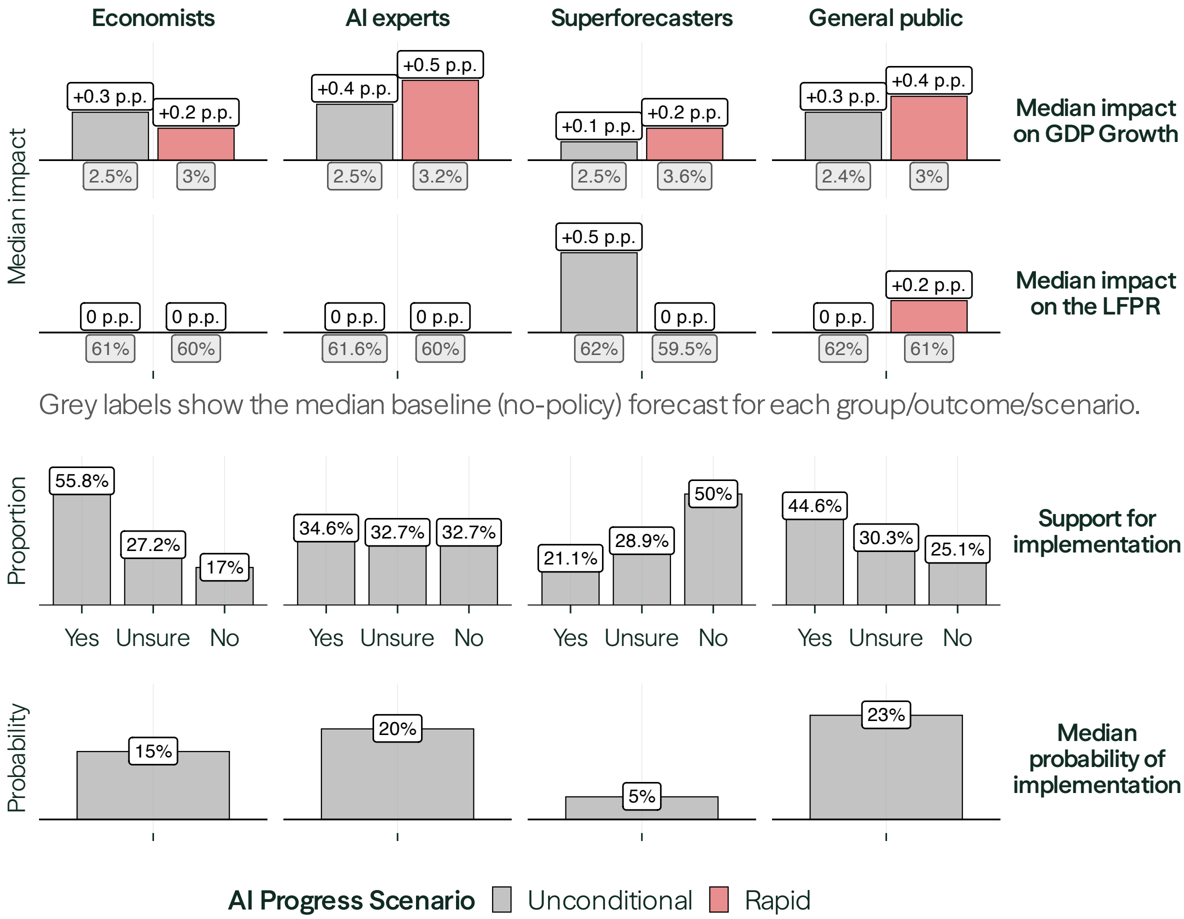


Figure 61: *Manhattan Project for AI*

and who assigned just a 5% implementation probability. AI experts were also less uniformly supportive (34.6% yes, 32.7% no), perhaps reflecting concerns about government-directed research agendas displacing more efficient market-driven innovation.

Rationale Analysis *Impact on GDP*: The dominant view was that this policy would raise GDP: "A 'Manhattan Project' for AI is the most pro-growth policy because it directly accelerates innovation and diffusion and relaxes infrastructure bottlenecks, raising productivity growth, especially over longer horizons."; "[It is] the only policy that directly amplifies the AI growth engine rather than managing its social consequences." One economist noted that it could also "raise expectations of US growth by raising the probability that the US wins the AI race." Still another argued that it "would have a positive impact on GDP growth by increasing the likelihood of the rapid scenario." The permitting/regulatory removal channel also drew praise: "Most of the impact likely would come from the loosening of restrictions on energy etc., not from the likely bad and politicized targeting of subsidies." A skeptical minority placed more weight on this "politicized targeting of subsidies" element, arguing that "the program is likely to be used as a short term cash cow, similar to the Covid support system." One wrote that it "just substitutes government funding for companies' funding," and that diminishing returns were likely in the rapid scenario. The VAT funding mechanism (0.7%) was largely seen as modest relative to the investment scale: "Government spending outpaces the small VAT drag."

Impact on LFPR: Economists were often divided by time horizon on this measure. A common view was that a Manhattan Project for AI could "create new high-skill jobs and attract workers into growing sectors" and precipitate a "massive surge in infrastructure and oversight demand," but that its long-term effect would be negative given the likelihood that it would accelerate AI-related automation: "While I believe that [this] policy will in the short run keep the labor force participation the highest, in the long run it will likely lead to a substantially lower one due to displacement effects."

Policy 5: Compute Tax

Organizations whose AI-related electricity consumption exceeds 100,000 MWh annually pay a tax of $50 per MWh on consumption above this threshold. This tax is indexed to the average electricity price in the U.S. and is updated annually. As of March 2025, the average cost of electricity was $132.7 per MWh according to the U.S. Energy Information Administration.

The tax applies to total electricity consumption regardless of source, including grid electricity and on-site generation. All data centers above 1MW must install certified power monitoring systems and report monthly consumption. AI operations subject to the tax include training and inference for machine learning models with more than 1 billion parameters.

The revenue generated by the tax is distributed to consumers as stimulus checks.

Economists offered a largely neutral assessment of the Compute Tax in terms of aggregate economic impact. The median forecast was 0 p.p. on GDP growth under the unconditional and rapid scenarios. The median LFPR impact was also 0 p.p. under both scenarios.

Normative views were divided: 30.5% of economists supported the policy, 45.9% opposed it, and 23.6% were unsure, reflecting a tension between the effect of distributing tax revenue to consumers as stimulus checks versus the potential costs to innovation and competitiveness. The median implementation probability was 6.6%. Economists were notably less supportive than the general public, of whom 55.2% expressed support.

Rationale Analysis *Impact on GDP*: Economists were largely negative to neutral regarding this policy's impact on GDP, with many emphasizing that the tax would modestly raise the cost of compute-intensive R&D and deployment: "Compute tax distorts AI efforts and reduces investments in the sector, but will likely only modestly reduce high margin AI efforts."; "Increases cost of AI scaling, slowing adoption and innovation at the margin." Others pointed to competitive risks, with one noting the possibility that "datacenter infrastructure gets delayed, downsized or moved offshore." The consumer rebate was widely seen as insufficient to offset the supply-side damage: "Rebates cushion demand but don't fully offset weaker investment and TFP [total factor productivity]." The economists who took a neutral or slightly positive position tended to do so either because they suspected "firms would find ways to avoid [the tax] at pretty low cost," or the tax was "barely enough to matter," or because of

Figure 62: *Compute Tax*

the potential for the stimulus checks and energy efficiency incentives (that might discourage "wasteful investment in AI") would offset the negatives. A few argued the tax could become significantly more damaging under the rapid scenario: "By taxing the core input (intelligence) of the rapid economy, it permanently lowers the ceiling of potential growth."

Impact on LFPR: The most common sentiment among economists was that it would have little to no impact: "I do not see this policy affecting labor force participation."; "Affects firms more than individual labor participation." A notable minority, however, pointed out that by raising the cost of AI relative to human labor, the tax could marginally slow automation and preserve some human employment. "The compute tax will make labor relatively cheaper, increasing demand and wages, and supply of workers," wrote one, and another that it "acts as a labor preservation measure. By taxing the substitute for human labor, it slows the rate of automation and technological displacement." A handful worried the tax would discourage AI investment, cause the US to "lose jobs to competitors who are implementing AI faster," and thereby dampen job creation indirectly.

Policy 6: Job Guarantee Program

Government-guaranteed jobs should pay at least $15 per hour (indexed to inflation) and offer benefits such as federal-employee–level health insurance, paid leave, and retirement contributions.

Projects are chosen through two tracks:

Local track: local employment offices issue open calls for proposals from municipalities, nonprofits, and tribal governments. Projects must (i) be additional to existing public roles, (ii) deliver demonstrable community benefit, and (iii) be approved by a tripartite board representing labor, business, and community members.

Federal track: federal agencies may propose large-scale "national works" (e.g., major infrastructure projects). Proposals are screened for strategic value and additionality by an inter-agency council.

The U.S. Treasury automatically funds 100% of wages, materials, and oversight. Local bodies manage day-to-day operations for community projects, while lead federal agencies manage national works.

The project is funded by a 0.5% value-added tax (VAT) on all goods and services.

The Job Guarantee Program elicited the least support for implementation from the economist cohort of any of the six policies in the survey. Fully 56.8% of economists opposed the program, with only 13.7% in favor. Despite this opposition, economists forecast a modest positive effect on the LFPR: 1.0 p.p. under the unconditional scenario, rising to 2.0 p.p. under the rapid scenario, the latter consistent with the program acting as a significant buffer against automation-driven labor force withdrawal. The median GDP impact was, however, 0 percentage points under both scenarios, suggesting economists do not expect the program to generate meaningful output gains.

The divergence from the general public here is the most pronounced in the survey: 57.1% of the general public supported the Job Guarantee Program, compared to only 13.7% of economists. The median assessed implementation probability among economists was just 0.8%, while for the general public it was 10%.

Figure 63: *Job Guarantee Program*

Rationale Analysis *Impact on GDP*: Economists were divided on GDP, with some noting the potential for a job guarantee program to put "idle labor to work quickly, boosting demand and social stability," and "raise spending and economic activity in the short run." But many economists expressed doubts about the long-term merits of such a program, pointing to productivity and misallocation issues: "job guarantee is expensive make-work, unlikely to be productive, reduces labor supply to productive sectors."; "I highly doubt that the government will be good at finding efficient jobs for people, and combined with the tax necessary to fund the job guarantee program, I think it will drag growth down."; "Government job guarantees add demand but divert labor to lower-productivity jobs." Some argued, however, that under rapid AI, with a collapsing demand for human labor, job guarantees could become pro-growth "by ensuring robust aggregate demand and social stability, allowing the economy to run at full capacity."

Impact on LFPR: This policy generated a strong positive consensus that a standing offer of guaranteed employment would indeed convert a meaningful number of unemployed workers into employed workers, thereby increasing LFPR: "Directly combats nonparticipation by offering a standing option for those otherwise discouraged, preserving routines and attachment." Multiple economists identified it as providing "the largest LFPR lift among the six [policies] because it attacks the participation margin mechanically." One predicted it would "put a floor under the labor market," preventing "the structural decline seen in the baseline." Several noted caveats: that the jobs may be "unpleasant in the long run, leading [workers] to leave the labor force," and the program "needs to be financed and can also distort decisions and ultimately generate less growth and participation." Under the rapid scenario, the floor-setting function was seen as increasingly important, although one economist worried the program would devolve into "make-work programs as AI handles productive tasks."

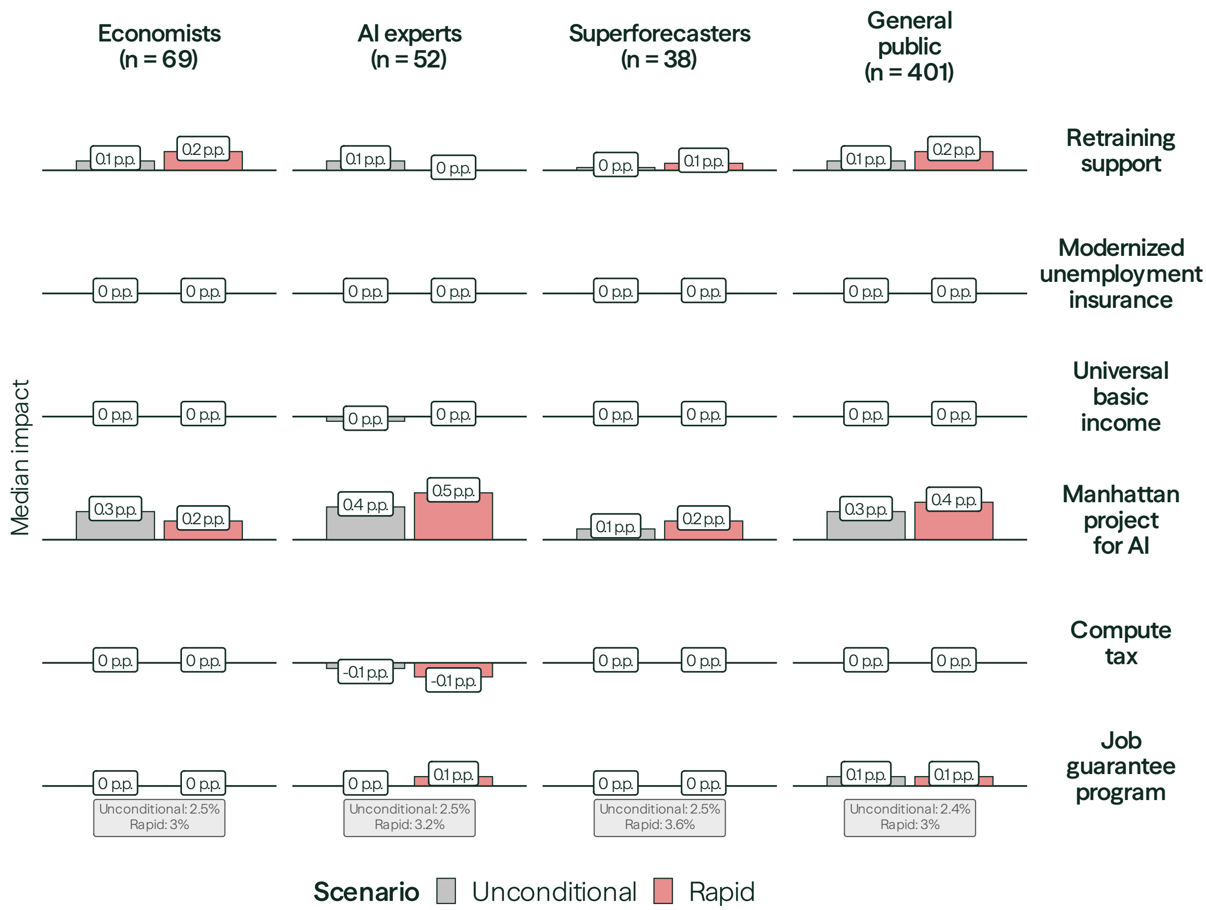


Figure 64: *GDP growth (2030).* Median marginal impact relative to none of the policies being implemented. The gray boxes show forecasts for this baseline for each group.

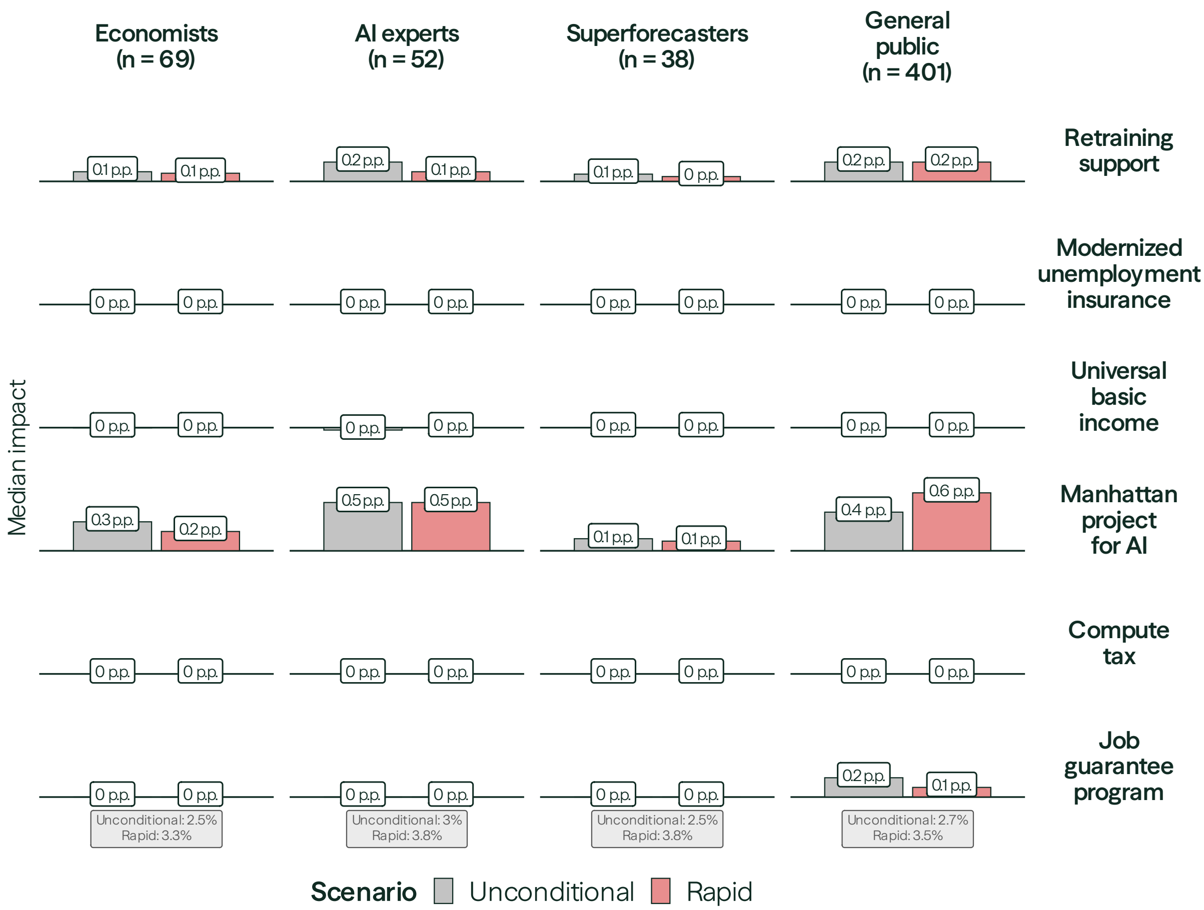


Figure 65: *GDP growth (2050).* Median marginal impact relative to none of the policies being implemented. The gray boxes show forecasts for this baseline for each group.

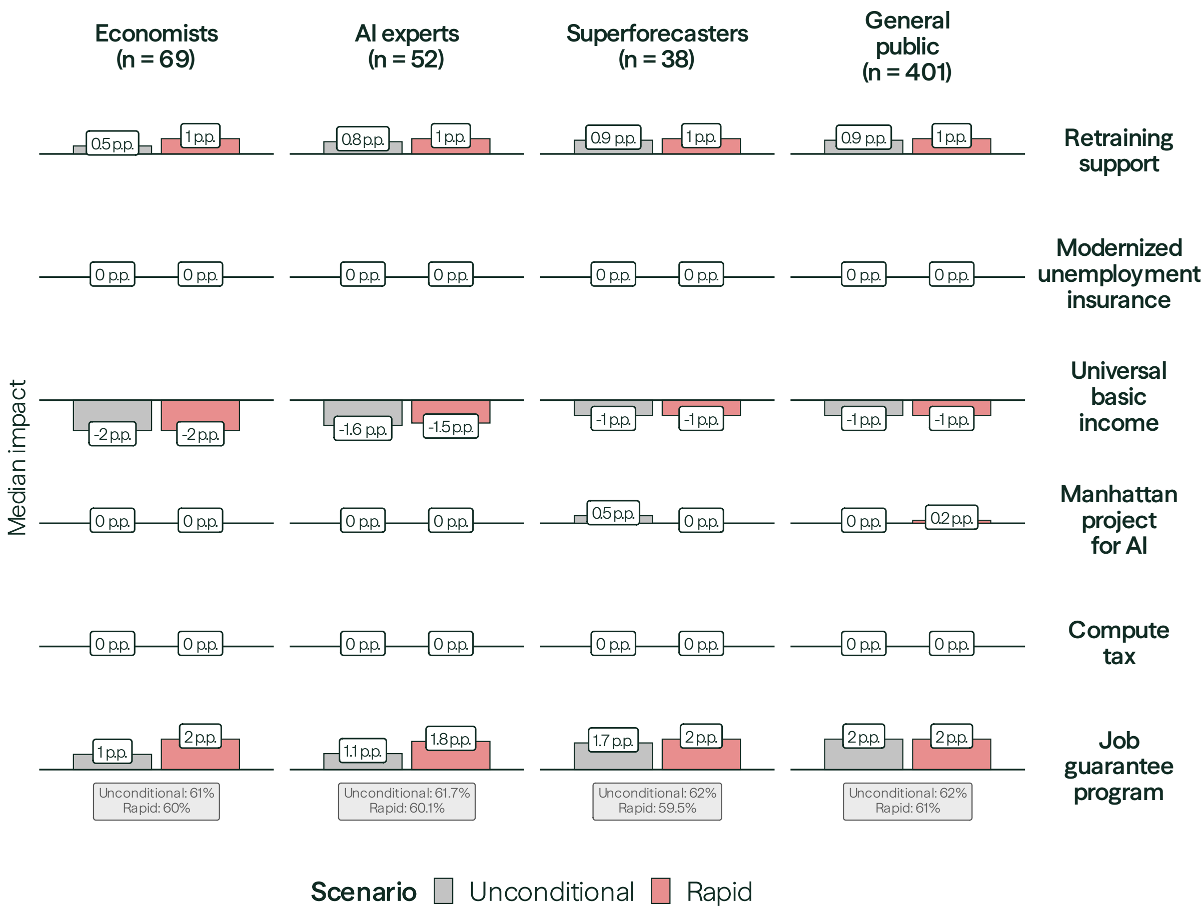


Figure 66: *LFPR (2030).* Median marginal impact relative to none of the policies being implemented. The gray boxes show forecasts for this baseline for each group.

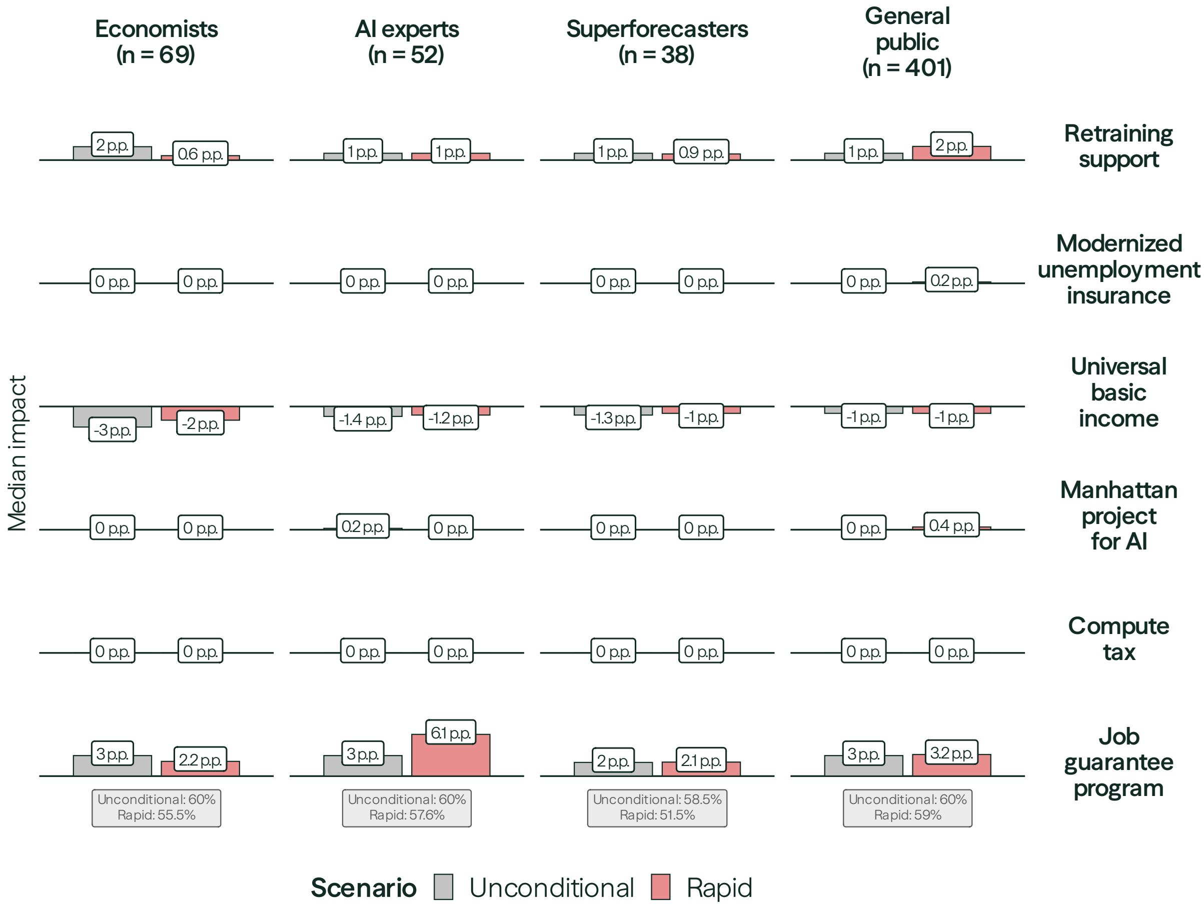


Figure 67: *LFPR (2050).* Median marginal impact relative to none of the policies being implemented. The gray boxes show forecasts for this baseline for each group.

E. Stratification by AI Progress Beliefs

E.1 Rapid Scenario Forecasts

We now stratify our sample by forecasts on the AI progress scenarios to assess if and how these beliefs covary with forecasts for economic outcomes. We first stratify our sample by the probability they assign to the rapid scenario, partitioning the sample into two groups: *strictly above* median or *weakly below* median. First, in Table 49, we summarize the assignment to halves for our expert groups. Economists and superforecasters are concentrated in the slower progress (below median) group, whereas AI experts and the general public are disproportionately represented in the faster progress (above median) group.

Table 49: Composition Within Groups by Rapid Scenario Probability

Group	Below median			Above median		
	N	Share (N)	Share (weight)	N	Share (N)	Share (weight)
Economists	38	55.1%	58.7%	31	44.9%	41.3%
AI experts	24	46.2%	46.2%	28	53.8%	53.8%
Superforecasters	23	60.5%	60.5%	15	39.5%	39.5%
General public	165	41.1%	41.1%	236	58.9%	58.9%

Second, in Table 50 and Table 51, we summarize each group's forecasts for GDP growth in the unconditional case and rapid scenario. Among economists, central forecasts for the 50$^{\text{th}}$ percentile in the unconditional case differ slightly: 2.2% annualized GDP growth in 2030 for the below-median group, compared to 2.6% for the above-median group. However, the interquartile ranges overlap substantially. The degree of overlap is consistent with the results in Section 4: most disagreement is about GDP growth conditional on AI progress, not about the AI progress scenario itself. Different beliefs about AI progress do *not* translate into large, systematic differences in the *conditional* distributions of economic outcomes: below-median economists give a median forecast of 3.5% in the same GDP growth question, compared to 3.3% for the above-median group.

Table 50: Annualized GDP Growth in 2030, 50$^{\text{th}}$ Percentile Forecasts by Rapid Scenario Probability

Scenario	Group	Below median			Above median			Total		
		Median	(IQR)	N	Median	(IQR)	N	Median	(IQR)	N
Unconditional	Economists	2.2	(2.0, 2.9)	37	2.6	(2.0, 3.0)	29	2.5	(2.0, 3.0)	66
	AI experts	2.5	(2.2, 3.0)	22	2.7	(2.1, 3.6)	25	2.5	(2.1, 3.2)	47
	All experts	2.5	(2.0, 3.0)	59	2.7	(2.0, 3.2)	54	2.5	(2.0, 3.0)	113
	Superforecasters	2.5	(2.3, 2.9)	21	2.5	(2.3, 2.8)	14	2.5	(2.3, 2.9)	35
	General public	2.5	(2.3, 3.0)	108	2.2	(1.9, 2.8)	187	2.4	(2.0, 3.0)	295
Rapid	Economists	3.5	(2.6, 5.0)	37	3.3	(3.0, 4.0)	29	3.3	(2.9, 4.5)	66
	AI experts	3.6	(3.0, 7.0)	22	4.0	(3.1, 5.4)	25	3.7	(3.0, 6.0)	47
	All experts	3.5	(3.0, 5.0)	59	3.5	(3.0, 5.0)	54	3.5	(3.0, 5.0)	113
	Superforecasters	4.0	(2.9, 5.0)	21	3.5	(3.1, 5.0)	14	3.7	(3.0, 5.0)	35
	General public	4.0	(3.0, 5.8)	108	3.5	(2.8, 4.3)	187	3.5	(3.0, 5.0)	295

Table 51: Annualized GDP Growth in 2050, 50th Percentile Forecasts by Rapid Scenario Probability

		Below median			Above median			Total		
Scenario	Group	Median	(IQR)	N	Median	(IQR)	N	Median	(IQR)	N
Unconditional	Economists	2.5	(2.0, 3.0)	36	3.0	(2.2, 3.1)	28	2.5	(2.0, 3.0)	64
	AI experts	3.0	(2.0, 4.5)	22	3.6	(2.2, 7.2)	25	3.0	(2.1, 5.5)	47
	All experts	2.5	(2.0, 4.0)	58	3.0	(2.2, 5.5)	53	2.9	(2.0, 4.3)	111
	Superforecasters	2.5	(2.2, 3.0)	21	2.5	(2.3, 5.0)	14	2.5	(2.2, 3.1)	35
	General public	3.2	(2.5, 4.1)	105	2.5	(1.8, 3.7)	181	3.0	(2.0, 4.0)	286
Rapid	Economists	3.3	(2.9, 4.2)	36	4.0	(3.2, 6.0)	28	3.5	(3.0, 4.5)	64
	AI experts	5.4	(3.0, 10.0)	22	5.0	(3.5, 8.9)	25	5.3	(3.1, 10.0)	47
	All experts	4.0	(3.0, 6.0)	58	4.5	(3.3, 7.1)	53	4.0	(3.0, 7.0)	111
	Superforecasters	4.0	(2.5, 5.0)	21	3.7	(2.8, 10.0)	14	4.0	(2.6, 5.0)	35
	General public	5.0	(3.8, 8.0)	105	4.0	(3.0, 6.0)	181	4.5	(3.1, 7.0)	286

We additionally summarize labor force participation rate forecasts in Table 52 and Table 53. We again do not find large differences between the AI progress belief groups. Any group-level differences are masked by large overlap in interquartile ranges.

Table 52: Labor Force Participation Rate in 2030, 50th Percentile Forecasts by Rapid Scenario Probability

		Below median			Above median			Total		
Scenario	Group	Median	(IQR)	N	Median	(IQR)	N	Median	(IQR)	N
Unconditional	Economists	61.4	(60.0, 62.3)	37	60.4	(59.6, 62.9)	26	61.0	(60.0, 62.5)	63
	AI experts	61.0	(60.0, 62.0)	22	61.6	(60.8, 62.4)	26	61.3	(60.0, 62.3)	48
	All experts	61.0	(60.0, 62.0)	59	61.4	(60.0, 62.4)	52	61.1	(60.0, 62.4)	111
	Superforecasters	62.0	(60.0, 63.0)	22	62.0	(60.2, 63.0)	15	62.0	(60.0, 63.0)	37
	General public	62.0	(60.0, 63.0)	103	62.0	(61.1, 62.7)	165	62.0	(61.0, 63.0)	268
Rapid	Economists	59.2	(56.0, 61.1)	37	60.0	(58.0, 61.0)	26	59.3	(56.4, 61.0)	63
	AI experts	58.0	(53.0, 61.0)	22	60.7	(58.0, 63.0)	26	60.0	(56.9, 62.1)	48
	All experts	59.0	(55.0, 61.0)	59	60.0	(58.0, 62.4)	52	60.0	(56.7, 61.9)	111
	Superforecasters	57.8	(55.0, 62.0)	22	59.0	(57.6, 61.8)	15	59.0	(55.5, 62.0)	37
	General public	58.0	(55.0, 62.0)	103	61.5	(59.0, 63.5)	165	60.2	(56.9, 63.0)	268

Table 53: Labor Force Participation Rate in 2050, 50^{th} Percentile Forecasts by Rapid Scenario Probability

		Below median			Above median			Total		
Scenario	Group	Median	(IQR)	N	Median	(IQR)	N	Median	(IQR)	N
Unconditional	Economists	58.0	(53.2, 60.4)	35	60.0	(56.0, 61.7)	25	58.3	(55.2, 60.5)	60
	AI experts	59.0	(55.2, 63.5)	23	60.0	(54.7, 61.4)	26	59.7	(54.9, 62.0)	49
	All experts	59.0	(54.4, 62.0)	58	60.0	(55.0, 61.4)	51	59.0	(55.0, 61.5)	109
	Superforecasters	58.0	(54.2, 61.0)	19	59.5	(51.2, 61.2)	15	58.2	(54.0, 61.0)	34
	General public	60.8	(59.0, 64.5)	99	60.0	(58.5, 61.9)	159	60.0	(58.5, 63.0)	258
Rapid	Economists	54.3	(46.4, 60.0)	35	56.0	(50.1, 63.0)	25	55.0	(50.0, 60.0)	60
	AI experts	53.0	(41.2, 59.8)	23	55.4	(45.0, 61.0)	26	54.0	(44.1, 61.0)	49
	All experts	54.7	(45.1, 60.0)	58	56.0	(50.0, 61.5)	51	55.0	(47.1, 60.0)	109
	Superforecasters	50.0	(36.9, 59.0)	19	58.0	(38.7, 61.2)	15	54.6	(35.9, 60.0)	34
	General public	57.5	(49.3, 62.9)	99	58.6	(53.0, 63.0)	159	58.0	(50.0, 63.0)	258

E.2 Rapid Scenario GDP Growth Forecasts.

Second, we split our sample by 50^{th} percentile forecasts for 2030 GDP growth under the rapid scenario. We compare participants with forecasts of at least 5% to the rest of the sample. First, in Table 54, we summarize the composition of our expert groups. Fewer economists predict rapid growth: only 23% of economists fall in the fast-growth camp, compared to 36% of other experts and 29% of superforecasters.[40]

Table 54: Composition Within Groups by Rapid Scenario GDP Forecasts

	$\geq 5\%$			$< 5\%$		
Group	N	Share (N)	Share (weight)	N	Share (N)	Share (weight)
Economists	16	24.2%	23.2%	50	75.8%	76.8%
AI experts	17	36.2%	36.2%	30	63.8%	63.8%
Superforecasters	10	28.6%	28.6%	25	71.4%	71.4%
General public	83	28.1%	28.1%	212	71.9%	71.9%

Second, in Table 55 and in Table 56, we summarize each group's forecasts for the LFPR in the unconditional and rapid scenarios. Here, we find evidence of correlated beliefs across the conditional distributions: larger GDP growth under the rapid scenario correlates negatively with both 2030 and 2050 LFPR forecasts. Economists in the fast-growth camp give a median 50^{th} percentile LFPR forecast for 2050 of 46.6% in the rapid scenario, compared to 58% in the slower-growth camp.

We additionally summarize these comparisons in Figures 68 to 71.

[40]We report weighted proportions.

Table 55: Labor Force Participation Rate in 2030, 50th Percentile Forecasts by Rapid Scenario GDP Forecasts

		≥ 5%			< 5%			Total		
Scenario	Group	Median	(IQR)	N	Median	(IQR)	N	Median	(IQR)	N
Unconditional	Economists	60.9	(59.8, 62.0)	15	61.1	(60.0, 63.0)	47	61.0	(60.0, 62.5)	62
	AI experts	60.4	(60.0, 61.0)	16	62.0	(60.0, 62.4)	30	61.1	(60.0, 62.1)	46
	All experts	60.8	(60.0, 62.0)	31	61.5	(60.0, 62.5)	77	61.0	(60.0, 62.2)	108
	Superforecasters	60.0	(59.1, 61.0)	10	62.0	(61.1, 62.9)	24	62.0	(60.0, 62.8)	34
	General public	62.0	(60.0, 63.0)	55	62.0	(61.5, 63.0)	167	62.0	(61.0, 63.0)	222
Rapid	Economists	56.6	(51.5, 60.7)	15	60.0	(58.0, 61.8)	47	59.3	(56.4, 61.0)	62
	AI experts	57.5	(52.5, 60.0)	16	60.9	(58.0, 62.8)	30	60.0	(56.9, 62.2)	46
	All experts	57.3	(52.2, 60.2)	31	60.0	(58.0, 62.6)	77	60.0	(56.5, 62.0)	108
	Superforecasters	55.5	(52.0, 58.0)	10	59.6	(57.2, 62.0)	24	58.5	(55.7, 62.0)	34
	General public	58.0	(53.5, 60.0)	55	61.5	(59.0, 63.0)	167	61.0	(58.0, 63.0)	222

Table 56: Labor Force Participation Rate in 2050, 50th Percentile Forecasts by Rapid Scenario GDP Forecasts

		≥ 5%			< 5%			Total		
Scenario	Group	Median	(IQR)	N	Median	(IQR)	N	Median	(IQR)	N
Unconditional	Economists	53.3	(46.2, 57.6)	15	60.0	(56.5, 62.0)	44	58.3	(55.1, 60.5)	59
	AI experts	57.0	(53.4, 62.2)	16	60.0	(57.8, 61.6)	29	60.0	(54.9, 62.0)	45
	All experts	55.0	(51.4, 60.5)	31	60.0	(57.0, 61.8)	73	59.0	(55.0, 61.5)	104
	Superforecasters	50.0	(35.1, 53.8)	10	60.5	(58.0, 62.0)	22	58.0	(53.9, 61.0)	32
	General public	60.0	(55.0, 61.9)	59	60.0	(59.0, 62.0)	157	60.0	(58.4, 62.0)	216
Rapid	Economists	46.6	(36.0, 50.3)	15	58.0	(51.4, 60.0)	44	55.0	(50.0, 60.0)	59
	AI experts	50.0	(36.3, 60.5)	16	57.9	(48.7, 61.1)	29	54.0	(44.1, 61.1)	45
	All experts	48.4	(38.2, 53.9)	31	58.0	(50.3, 61.0)	73	55.0	(47.0, 60.1)	104
	Superforecasters	30.0	(25.0, 35.9)	10	59.0	(54.0, 61.0)	22	54.6	(35.4, 60.0)	32
	General public	52.3	(45.0, 60.0)	59	60.0	(55.0, 62.6)	157	58.0	(51.3, 62.2)	216

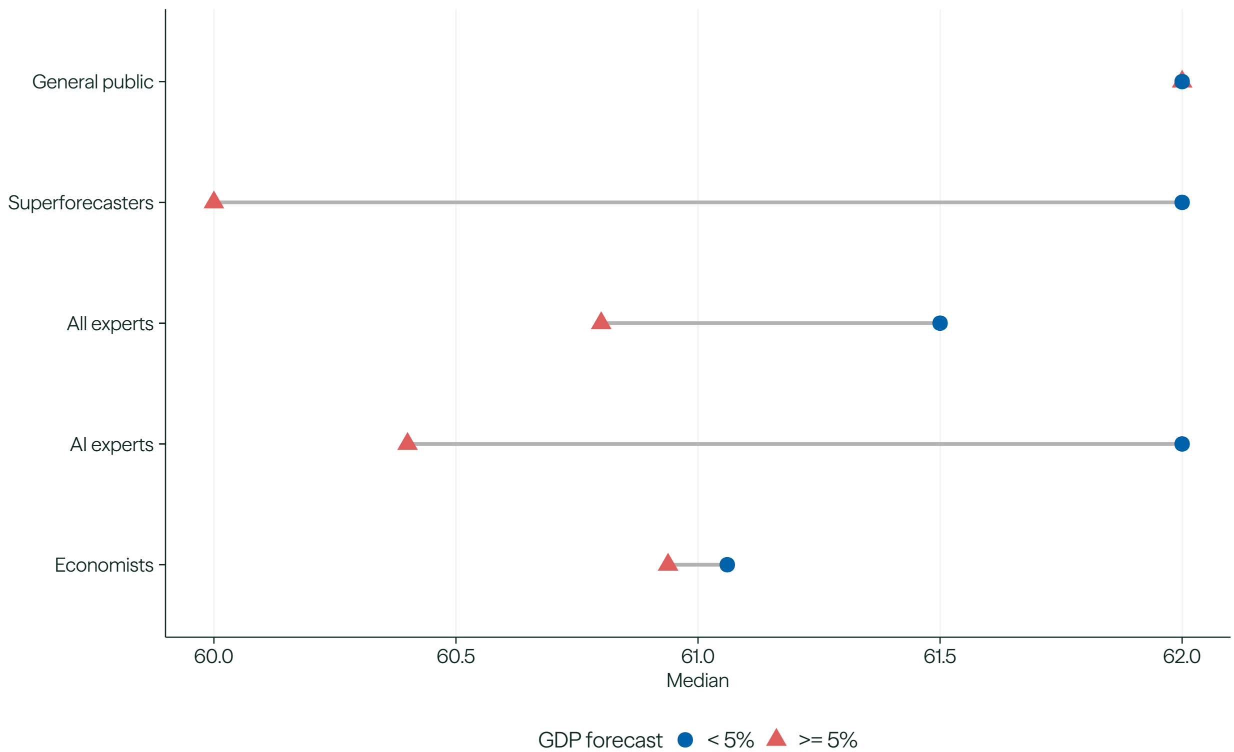


Figure 68: *Labor Force Participation Rate in 2030 in the Unconditional Scenario, 50th Percentile Forecasts by Rapid Scenario GDP Growth Forecasts*

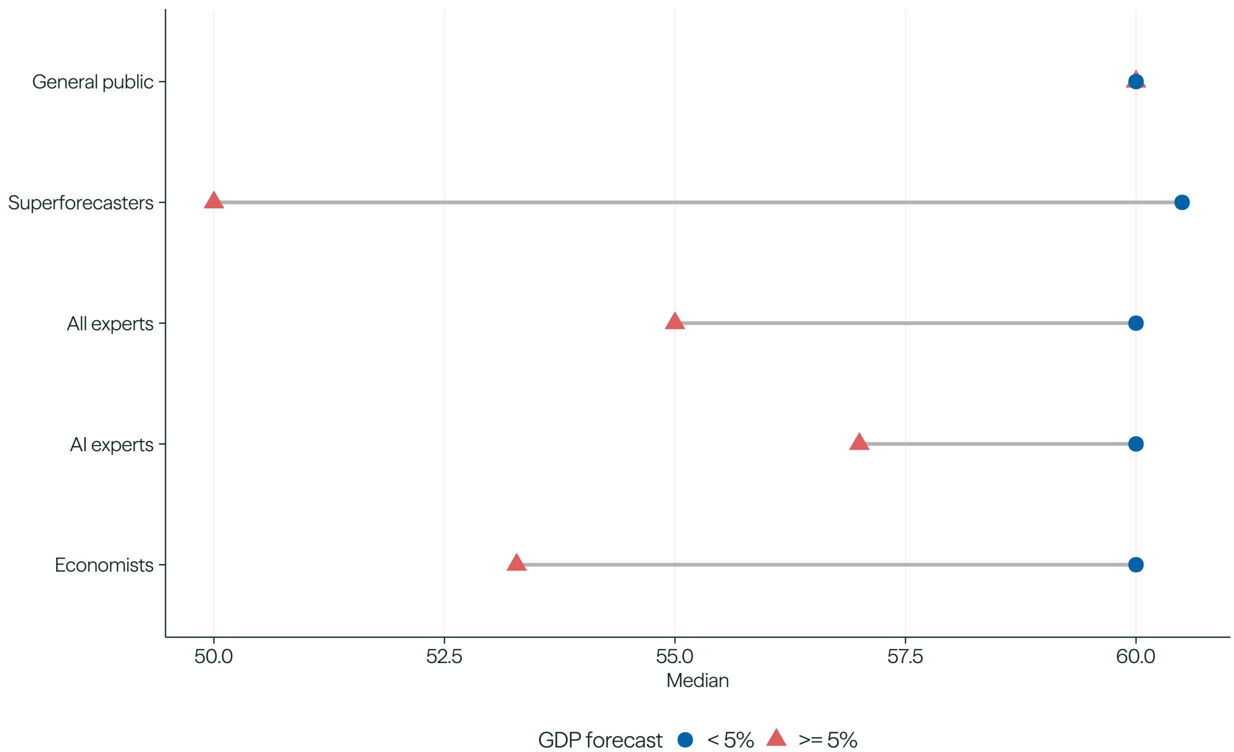


Figure 69: *Labor Force Participation Rate in 2050 in the Unconditional Scenario, 50th Percentile Forecasts by Rapid Scenario GDP Growth Forecasts*

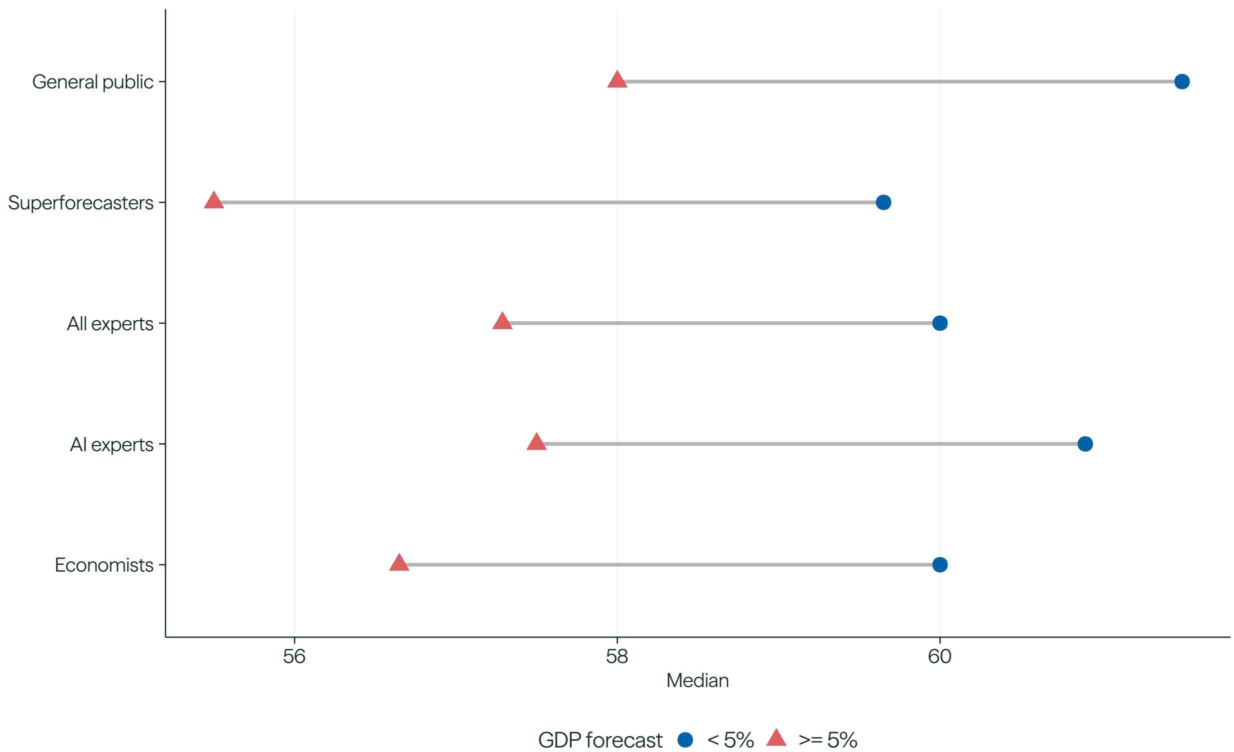


Figure 70: *Labor Force Participation Rate in 2030 in the Rapid Scenario, 50^{th} Percentile Forecasts by Rapid Scenario GDP Growth Forecasts*

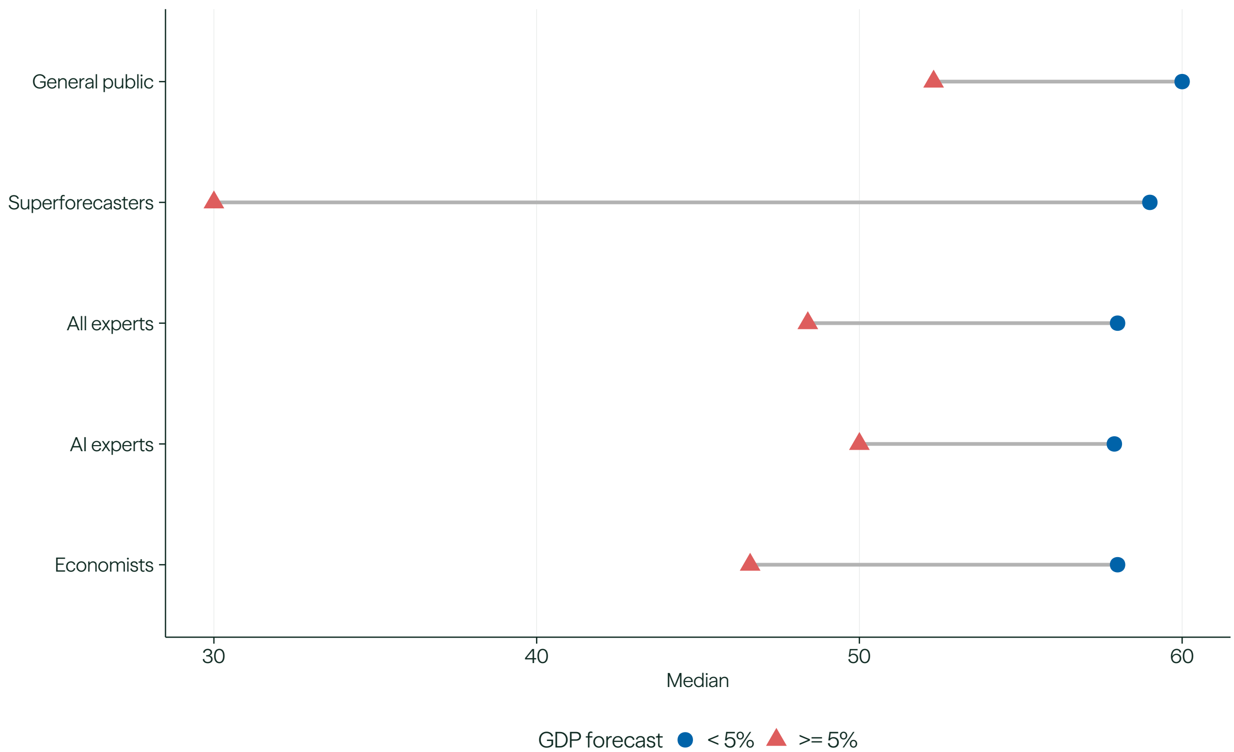


Figure 71: *Labor Force Participation Rate in 2050 in the Rapid Scenario, 50th Percentile Forecasts by Rapid Scenario GDP Growth Forecasts*

F. Coherence Checks and Data Validation

To ensure the quality and internal consistency of participant forecasts, we implemented a series of coherence checks. Some checks look for internal consistency within a participant's forecasts across scenarios and time horizons, while others identify large discrepancies relative to the broader sample or expectations from historical baselines.

We implemented

1. a **feedback stage**, in which participants with flagged responses were contacted and invited to review their forecasts, and
2. a **filtering stage**, in which a subset of remaining incoherent responses were excluded from the analysis.

Only participants from the main expert samples (superforecasters, AI experts, and economists) were contacted in the feedback stage. We did not contact respondents in the larger general public sample, although their forecasts also displayed several of the same incoherences.

F.1 Coherence Checks

For each outcome and policy condition, we evaluated the following flags. These checks were implemented using participants' median (50th percentile) forecasts only, even if 10th and 90th percentile forecasts were available. Note that many of these are not strict logical requirements, and many reasonable forecasts may be flagged. One of our goals was to ensure that any such forecasts were intentional and not mistypes.

Flag 1: Inconsistency Between Unconditional and Implied Forecasts Participants provided:

- an unconditional forecast q_u for each outcome,
- scenario probabilities p_s, and
- scenario-conditional forecasts q_s for each outcome, for $s \in \{\text{slow}, \text{moderate}, \text{rapid}\}$.

Under mild assumptions, these imply an unconditional forecast:

$$\tilde{q}_u = \sum_s p_s q_s.$$

We compare $\tilde{q}_u$ to the reported unconditional forecast q_u. Responses are flagged when:

$$|q_u - \tilde{q}_u| > 5 \cdot |q_u|.$$

This check captures inconsistencies between stated scenario probabilities and conditional forecasts.

Flag 2: Unconditional Forecast Outside Conditional Range The survey asks for three conditional forecasts of each outcome, one for each of the rapid, moderate, and slow progress scenarios. Then, for each participant, let

$$q_{\min} = \min_s q_s, \qquad q_{\max} = \max_s q_s.$$

Given that we define the scenarios to be exhaustive, a condition for coherence is:

$$q_u \in [q_{\min}, q_{\max}].$$

Responses are flagged when this is not the case. This condition follows from the fact that the unconditional forecast represents a mixture over scenario-conditional forecasts.

Flag 3: Non-Monotonic Scenario Ordering For most outcomes, we expect forecasts to be monotonically ordered across scenarios, so that

$$q_{\text{slow}} \leq q_{\text{moderate}} \leq q_{\text{rapid}},$$

or the reverse ordering where appropriate.

Responses are flagged when this ordering is not followed. There exist scenarios in which unordered values represent well-defined and justified world-views, but we found that more often than not, forecasts did follow this trend.

Flag 4: Uncommon Direction of AI Progress Effects For each outcome, we identify the direction of the effect of AI progress (e.g., increasing effects for faster growth scenarios) for each participant. We then compared the direction implied by the participant's forecasts to the modal direction of the broader sample.

Responses were flagged when the participant's implied direction of effect contradicted that of more than 85% of participants.

Flag 5: Timeline Inconsistency Participants provided forecasts for two time horizons: 2030 and 2050. For each outcome, we expected participants to forecast similar directions of AI progress (e.g., increasing effects for faster growth scenarios for both 2030 and 2050). Responses are flagged when this is not the case.

Flag 6: Surprising Magnitudes Forecasts are expected to lie within outcome-specific bounds:

$$q_s \in [L, U].$$

These bounds are not shared with participants, and are chosen to be lenient but exclude clearly implausible values (e.g., annual GDP growth outside $[-2\%, 30\%]$). Responses outside these ranges are flagged.

The bounds were chosen to exclude extreme forecasts that could be results of typos or unit errors while still being flexible to differing beliefs.

The ranges of acceptable values are shown in Table 57.

Table 57: Coherence check bounds for Flag 6. Forecasts outside these ranges are flagged as potentially implausible.

Outcome	**Lower Bound**	**Upper Bound**
Change in Gross Domestic Product	−2 p.p.	30 p.p.
Change in Labor Productivity	−2 p.p.	20 p.p.
Change in Total Factor Productivity	−2 p.p.	20 p.p.
Labor Force Participation Rate	25%	85%
Unemployment Rate	1%	30%
Youth Unemployment Rate	3%	40%
White-Collar Employment Share	8%	40%
Blue-Collar Employment Share	5%	35%
Service Sector Employment Share	20%	70%
Wealth Inequality	50%	90%
Labor Share	25%	70%
Median Household Income	$30,000	$150,000
Life Satisfaction (Cantril scale, 0–10)	4	9
Work Hours Assisted by Generative AI	1%	80%
AI Electricity Consumption	1%	50%

Flag 7: Coherence Between Unemployment and Sectoral Forecasts For labor market outcomes, participants provided forecasts for unemployment (u_s) and employment shares in white-collar (w_s), blue-collar (b_s), and service sector (s_s) jobs.

For each scenario, responses are flagged when:

$$u_s + w_s + b_s + s_s > 100\%.$$

F.2 Participant Update Process

After the initial data collection, we identified all responses that triggered at least one of the flags above. Participants were then contacted via email and provided with:

- a description of the relevant coherence check, and
- the specific responses that were flagged.

In our communication, we encouraged participants to review their forecasts and revise them if the inconsistencies came from misunderstandings or input errors. Participants were explicitly told they were not required to update their responses if they reflected their true beliefs. This approach was intended to improve data quality while preserving differing views from our sample.

Participants who reported spending substantial time reviewing or updating their responses were offered an additional honorarium of $50.

F.3 Filtering for the Main Analysis

After incorporating participant revisions, we applied a final filtering step.

The only exclusion criterion was Flag 2 (Unconditional Forecast Outside Conditional Range), which represents a clear logical inconsistency. For each outcome, if a participant was flagged for this check and did not revise their response, all forecasts for that outcome (across all scenarios and percentiles) were excluded. The two time horizons (2030 and 2050) were treated separately, so one participant may have forecasts for one year but not the other. The exception are the line plots, such as Figure 4, where we filter out all of a participant's forecasts if some are missing. Other outcomes provided by the same participant were treated independently.

F.4 Sensitivity of Results to Coherence Checks

The intervention of checking forecasts for coherence, asking participants to revisit their incoherent forecasts, and filtering out remaining incoherent forecasts did not markedly change the aggregate results.

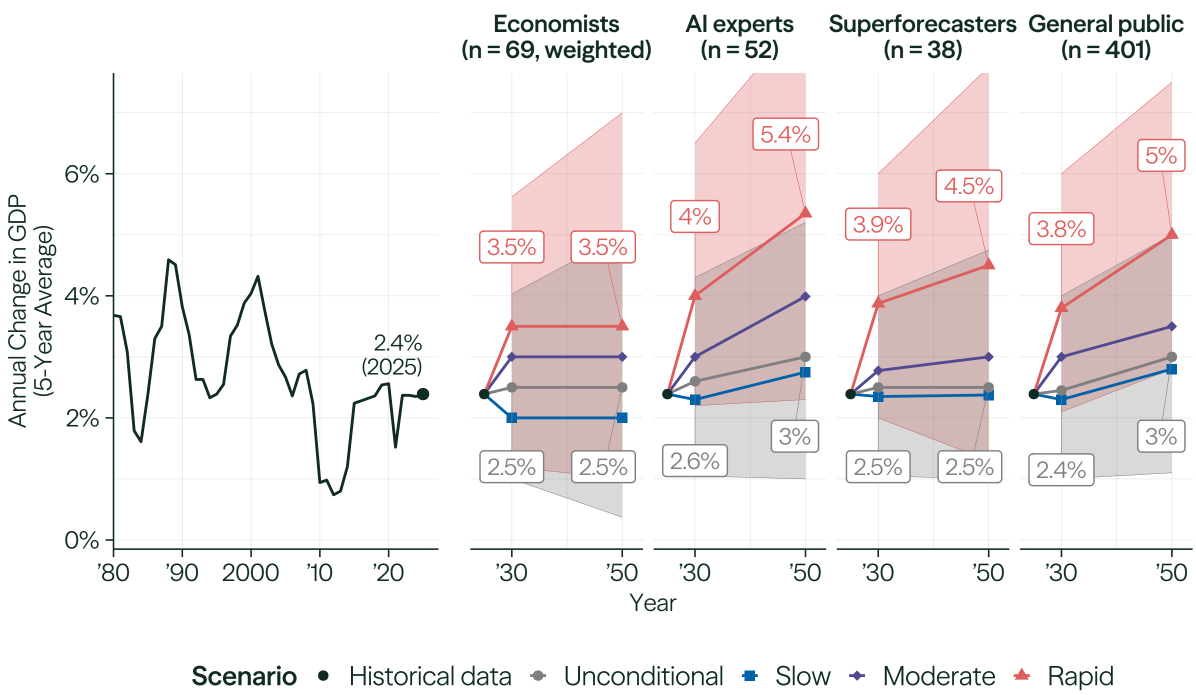


Figure 72: *Forecasts for five-year annualized change in the Gross Domestic Product (GDP), before the coherence-check intervention.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

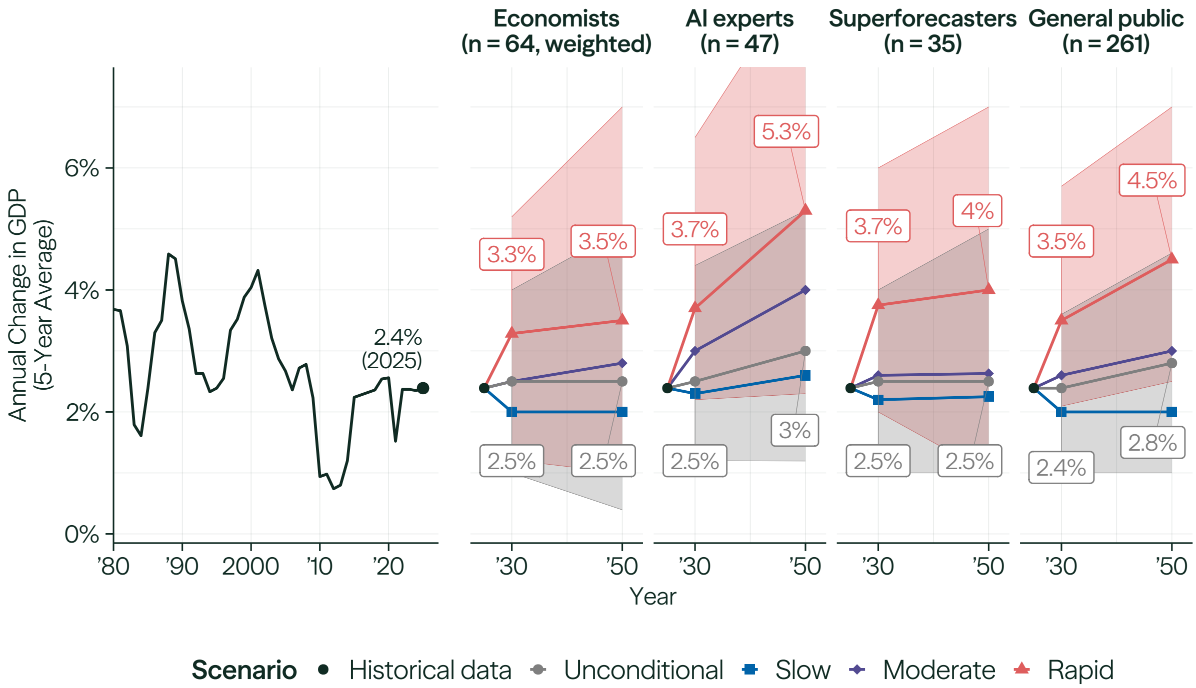


Figure 73: *Forecasts for five-year annualized change in the Gross Domestic Product (GDP), after the coherence-check intervention.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

Figure 72 shows aggregate forecasts for GDP growth before the intervention. Differences to our main filtered results (Figure 73) are small. Economists' unconditional forecasts for both years are still 2.5%, while the pre-intervention forecast conditional on the rapid scenario for 2030 is 3.5% instead of 3.3% in the filtered results. Other groups see similarly small changes. Typically the intervention led to slightly more conservative aggregate forecasts.

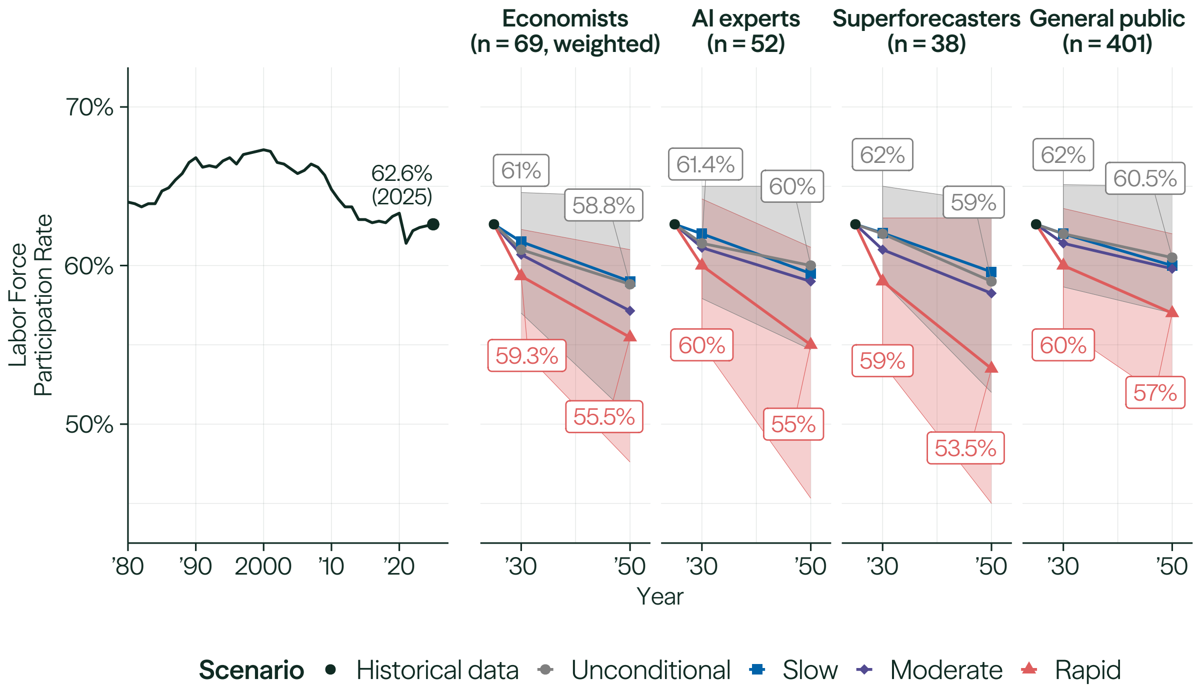


Figure 74: *Forecasts for the labor force participation rate (LFPR), before the coherence-check intervention.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

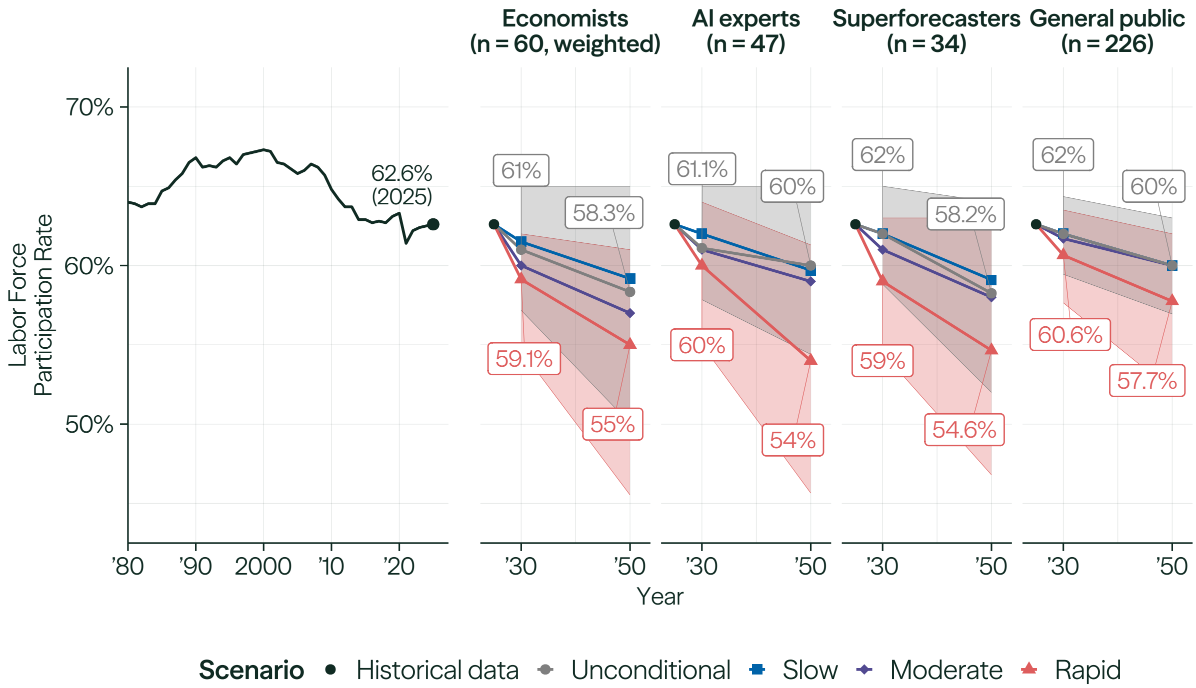


Figure 75: *Forecasts for the labor force participation rate (LFPR), after the coherence-check intervention.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast. The results for economists are reweighted to adjust for non-response bias (see Section 2.3).

The labor force participation results tell a similar story, although here post-intervention aggregate forecasts (Figure 75) tend to be slightly more extreme than pre-intervention forecasts (Figure 74). For example, the LFPR forecast of the AI expert group for 2050 under the rapid scenario is 55.0% pre-intervention, compared to 54.0% post-intervention. However, these differences are small relative to the groups' uncertainty about the outcome, as measured by the aggregate 10^{th}–90^{th} percentile range.

G. Reweighting

We reweight our results to correct for non-response or participation bias: it is possible that the people who participated have systematically different forecasts compared to the people who were invited but chose not to participate.

In reweighting, we choose reweighting variables—factors such as age, years of experience, and gender—that could plausibly correlate with forecasts. To determine the values of these variables for participants and non-participants, we used an AI agent, in conjunction with human assistants, to search the internet for publicly available information. We use a standard approach, iterative raking, to determine a weight for each participant. We used the Weightipy

Python library (Kits, 2026).

We currently reweight the results for the economist sample only; we are planning to extend this later to other expert samples and the general public.

G.1 Economists

The variables we considered, as well as the differences in the variables between our sample and the sampling frame, are shown in Table 58 (and in Figure 1). Due to a relatively small sample size, we had to limit the number of variables we used in reweighting. We eliminated variables that were correlated and prioritized variables with higher discrepancies between the sampling frame and the final sample.

The smallest weight assigned to an economist participant was 0.0047 and the largest was 0.0609 (max/min ratio of 12.9).

G.2 Sensitivity of Results to Reweighting

The reweighting procedure for economists had a small-to-moderate impact on aggregate forecasts, and it did not consistently lead to more conservative or extreme results.

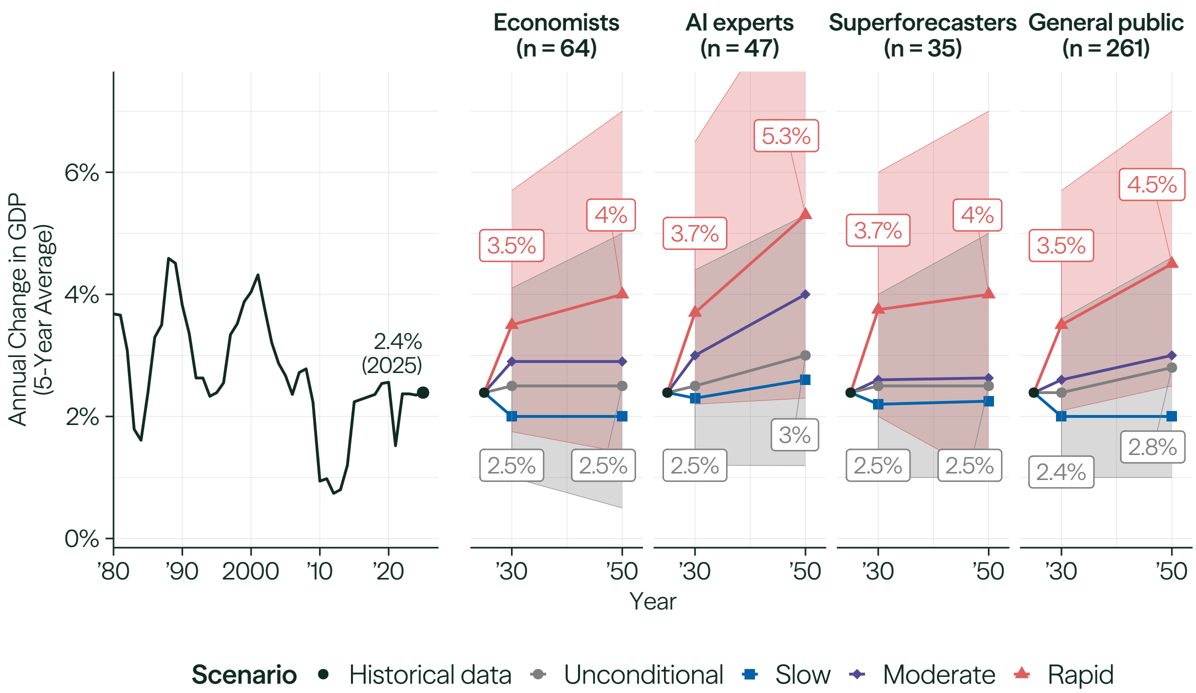


Figure 76: *Forecasts for five-year annualized change in the Gross Domestic Product (GDP), before reweighting.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast.

Table 58: Reweighting Variables: Sample vs. Sampling Frame

Variable	Bin	Sample	Sampling Frame	Reweighted?	Notes
Years of Experience	0-5	12%	4%	**Yes**	Bins collapsed to 0–10, 11–20, and 20+ in reweighting
	6-10	19%	11%		
	11-15	25%	17%		
	16-20	19%	11%		
	21+	26%	57%		
Age	25-34	19%	8%	No	
	35-44	40%	28%		
	45-54	25%	29%		
	55-64	6%	20%		
	65-74	7%	10%		
	75-84	1%	4%		
	85+	0%	1%		
Gender	female	17%	21%	No	
	male	83%	79%		
Continent	North America	35%	55%	**Yes**	Asia and other regions grouped together in reweighting
	Europe	60%	41%		
	Asia	2%	3%		
	Other regions	3%	2%		
Publications in Tier A Journals	0	63%	44%	No	See note[a]
	1-5	34%	42%		
	5-10	3%	10%		
	10+	0%	4%		
Publications in Tier B Journals	0	51%	35%	No	See note[b]
	1-5	45%	53%		
	5-10	5%	9%		
	10+	0%	3%		
Total Citations	<1k	42%	25%	No	
	1k-5k	39%	36%		
	5k-10k	9%	13%		
	10k+	10%	26%		
Group	Well-known	3%	11%	No	
	AI	35%	22%		
	Growth & technology	62%	67%		

[a] Tier A journals: American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics, Review of Economic Studies. Top-5 in Ham, Wright, and Ye (2025)

[b] Tier B journals: AEJ: Applied Economics, AEJ: Macroeconomics, AEJ: Economic Policy, J. Labor Economics, AER: Insights, J. European Economic Association, Review of Economics and Statistics, Theoretical Economics, J. Human Resources, J. Monetary Economics, AEJ: Microeconomics, Quantitative Economics, Economic Journal, J. Economic Growth, RAND J. Economics. Ranks 6-20 in Ham, Wright, and Ye (2025).

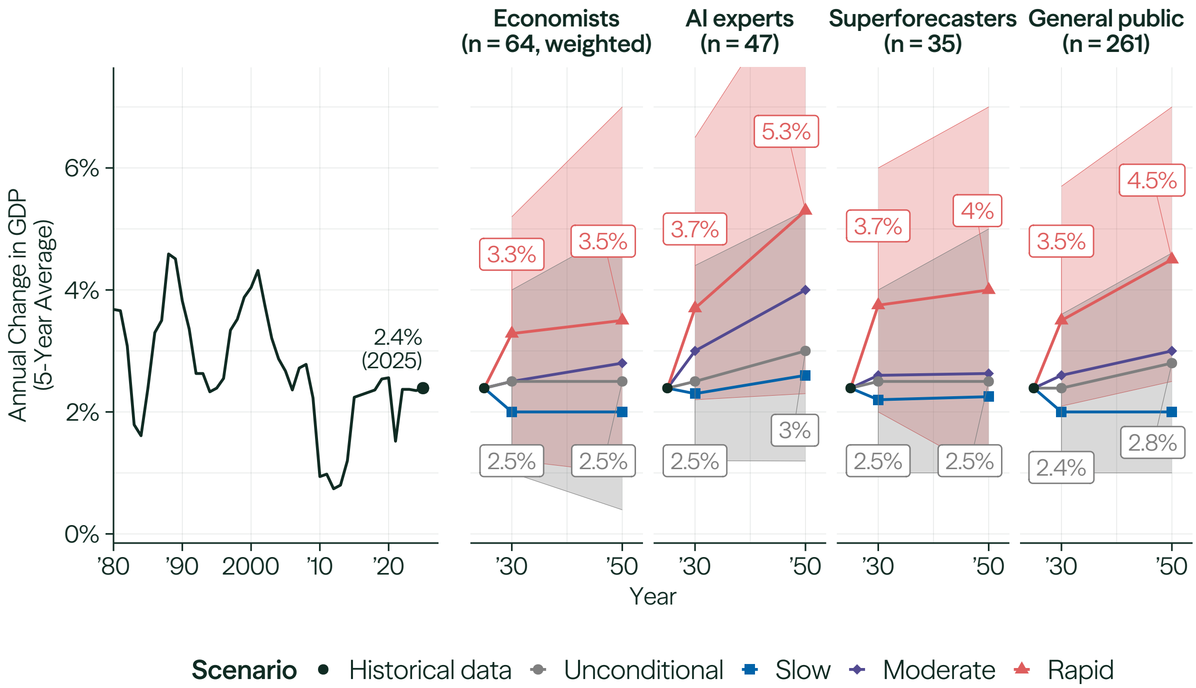


Figure 77: *Forecasts for five-year annualized change in the Gross Domestic Product (GDP), after reweighting (see Section 2.3).* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast.

Aggregate forecasts for GDP growth for economists are shown in Figures 76 and 77.[41] Unconditionally, both the reweighted and non-reweighted results predict 2.5% growth for 2030 and 2050 on the median. In the rapid scenario, the reweighting changes the 2030 forecast from 3.5% to 3.3% and the 2050 forecast from 4.0% to 3.5%. The reweighted results for GDP growth are therefore either unchanged or more conservative, suggesting that the underrepresented groups in our sample—economists with more experience and residing in North America—may have more conservative beliefs than others about growth in the rapid scenario, on average.

[41] Note that other groups were not reweighted and thus show identical results in these two figures.

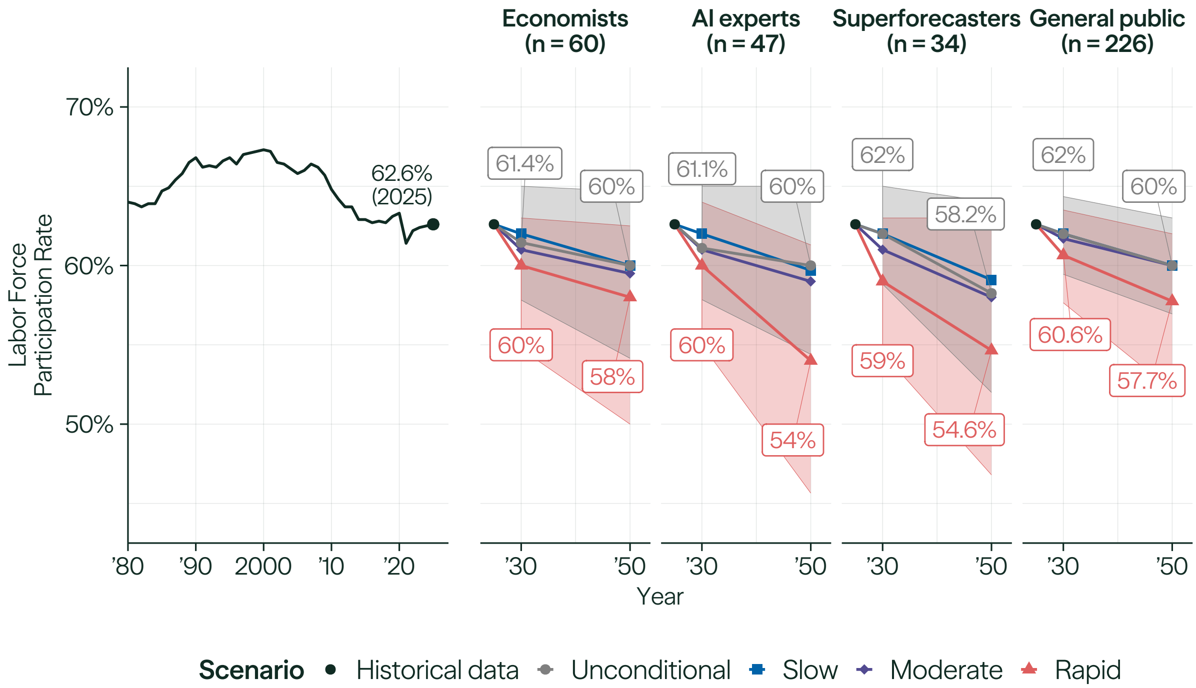


Figure 78: *Forecasts for the labor force participation rate (LFPR), before reweighting.* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast.

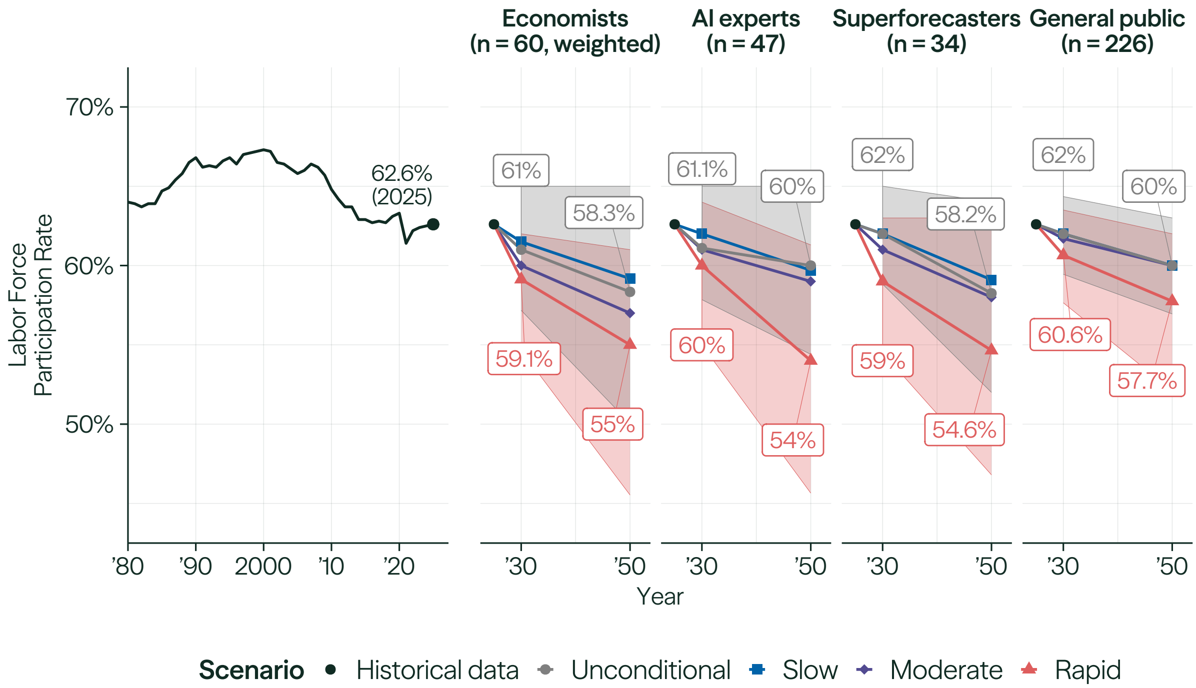
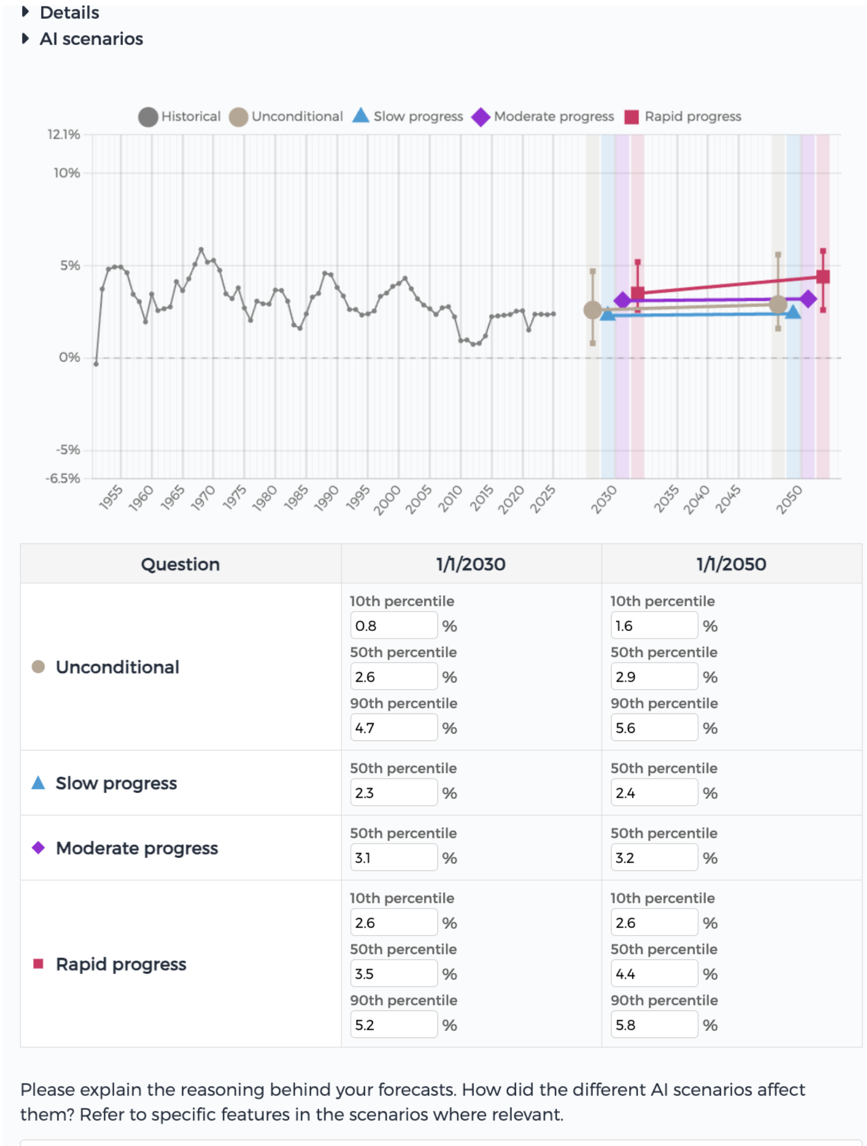


Figure 79: *Forecasts for the labor force participation rate (LFPR), after reweighting (see Section 2.3).* Historical values for the outcome are shown in the left-most panel and with the black points in each panel. Lines show medians of 50th percentile forecasts across participants. Shaded regions span from the median 10th to the median 90th percentile forecast.

However, this pattern is reversed for the labor force participation rate. This is shown in Figures 78 and 79. Reweighting changes the 2030 and 2050 unconditional forecasts from 61.5% to 61.0% (2030) and from 60.0% to 58.3% (2050), and the rapid scenario forecasts from 60.0% to 59.3% (2030) and from 58.0% to 55.0% (2050). In this case, reweighting moves the aggregates in the more extreme direction, and especially so for the 2050 forecasts. However, like the GDP growth results, these differences are well within the 10^{th}–90^{th} percentile uncertainty ranges, and thus don't significantly influence our conclusions.

H. Survey Questions



Question	1/1/2030	1/1/2050
Unconditional	10th percentile 0.8 % 50th percentile 2.6 % 90th percentile 4.7 %	10th percentile 1.6 % 50th percentile 2.9 % 90th percentile 5.6 %
Slow progress	50th percentile 2.3 %	50th percentile 2.4 %
Moderate progress	50th percentile 3.1 %	50th percentile 3.2 %
Rapid progress	10th percentile 2.6 % 50th percentile 3.5 % 90th percentile 5.2 %	10th percentile 2.6 % 50th percentile 4.4 % 90th percentile 5.8 %

Please explain the reasoning behind your forecasts. How did the different AI scenarios affect them? Refer to specific features in the scenarios where relevant.

Figure 80: *The forecasting interface used in the survey (shown here for the GDP question).*

H.1 Beliefs about AI and Economic Impacts

Which of the following statements is closest to your views on AI's broader societal impact by 2050?

- AI will be a useful tool that enhances human capabilities, but doesn't fundamentally change social structures or daily life for most people. Its impact on society will be beneficial but limited to specific domains.

- AI will significantly transform several major sectors of society, creating both substantial benefits and adaptation challenges that most institutions will manage successfully.
- AI will fundamentally reshape society in ways comparable to or exceeding the Industrial Revolution, changing how we work, learn, and govern, requiring completely new social and institutional arrangements.

Which of the following statements is closest to your views on AI's impact on economic growth by 2050?

- AI's impact on economic growth will be limited, not significantly different from other recent technological innovations like social media or mobile computing.
- AI will contribute to economic growth similarly to previous major general-purpose technologies like electrification or personal computers, representing a substantial but manageable shift in productivity.
- AI will boost productivity and economic growth more substantially than any previous technological revolution, including the Industrial Revolution and the internet, potentially transforming the economy more fundamentally than any prior innovation.

Which of the following statements is closest to your views on AI's impact on employment by 2050?

- Like previous waves of automation, AI will eliminate some jobs but create others, resulting in minimal net change to overall employment levels. Labor markets will adapt through normal processes.
- AI will disrupt employment patterns more severely than previous technologies, creating significant transitional unemployment, but new job categories will eventually emerge to maintain reasonable employment levels.
- AI will be able to perform the vast majority of current jobs more efficiently than humans, leading to persistent structural changes in employment and requiring fundamental changes to our economic system.

Which of the following statements is closest to your views on AI's impact on economic inequality by 2050?

- AI's effects on inequality will be modest and manageable within existing policy frameworks, similar to previous technological transitions.
- AI will significantly increase economic inequality in the absence of major policy intervention, with benefits primarily accruing to those who own or develop AI systems and related technologies.
- AI will fundamentally transform economic relationships, potentially leading to extreme winner-take-all dynamics, where a small number of AI-owning entities capture an unprecedented share of economic output.

Which of the following statements is closest to your views on the appropriate policy response to AI's economic impacts by 2050?

- Existing economic policy frameworks are largely adequate to address AI's impacts, with minor adjustments to education, tax, and labor market policies.
- Significant policy innovation will be required to manage AI's economic impacts, including substantial expansions of social safety nets, retraining programs, and new approaches to taxation.
- AI's economic impacts will necessitate transformative changes to our economic institutions, potentially including universal basic income, wealth sharing mechanisms, or other novel approaches to ensuring broadly shared prosperity.

H.2 AI Progress

H.2.1 Probability of AI Scenarios

Imagine a panel of experts at the end of 2030, including AI experts from academia and industry, economists, and AI policy experts. The panel is asked which of the three given scenarios best matches the world as it is then, at the end of 2030. **What is the probability that a given scenario will be the most commonly selected option among the panel of experts?**

AI scenarios. We define three scenarios for different levels of AI development:

- Slow progress
- Moderate progress
- Rapid progress

In the following scenarios, we consider the development of AI *capabilities*, not adoption. Regulation, social norms, or extended integration processes could all prevent the application of AI to all tasks of which it is capable.

Reasonable people may disagree with our characterization of what constitutes slow, moderate, or rapid AI progress. Or they may expect to see slow progress observed with some AI capabilities and moderate or fast progress in others. Nevertheless, we ask you to select which scenario, in sum, you feel best represents your views.

We consider a capability to have been achieved if there exists an AI system that can do it:

- **Inexpensively**: with a computational cost not exceeding the salary of an appropriate 2025 human professional using the same amount of time to attempt the task.
- **Reliably**: what this means is context-dependent, but typically we mean as reliably as, or more reliably than, a human or humans who do the same tasks professionally.

The scenarios refer to capability <u>at the end of 2030</u>.

Slow Progress. By the end of 2030 in this slower-progress future, AI is a capable assisting technology for humans; it can automate basic research tasks, generate mediocre creative content, assist in vacation planning, and conduct relatively standard tasks that are currently (2025) performed by humans in homes and factories.

Researchers can benefit from literature reviews on almost any topic, written at the level of a capable PhD student, yet AI systems rarely produce novel and feasible solutions to difficult problems. As a result, genuine scientific breakthroughs remain almost entirely the result of human-run labs and grant cycles. Nevertheless, AI tools can support other research tasks (e.g., copy editing and data cleaning and analysis), freeing up time for researchers to focus on higher-impact tasks. AI can handle roughly half of all freelance software-engineering jobs that would take an experienced human approximately 8 hours to complete in 2025, and if a company augments its customer service team with AI, it can expect the model to be able to resolve most complaints.

Writers enjoy a small productivity boost; models can turn out respectable short stories, but full-length novels still need heavy human rewriting to avoid plot holes or stylistic drift. AI can make a 3-minute song that humans would blindly judge to be of equal quality to a song released by a current (2025) major record label. At home, an AI system can draft emails, top up your online grocery cart, or collate news articles, and—so long as the task would take a human an hour or less and is well-scoped—it performs on par with a competent human assistant. With a few prompts, AI can create an itinerary and make bookings for a weeklong family vacation that feels curated by a discerning travel agent.

Self-driving car capabilities have advanced, but none have achieved true level-5[42] autonomy. Meanwhile, household robots can make a cup of coffee and unload and load a dishwasher in some modern homes—but they can't do it as fast as most humans and they require a consistent environment and occasional human guidance. In advanced factories, autonomous systems can perform specific, repetitive tasks that require precision but little adaptability (e.g., wafer handling in semiconductor fabrication facilities).

Moderate Progress. By the end of 2030, in this middle-of-the-road future, AI is capable of being an effective collaborator across creative, corporate, and technical arenas.

R&D teams can lean on autonomous lab systems with human research assistants to make rapid advances in solar-cell chemistries or fusion-reactor components, although the inventions are improvements rather than revolutions. Almost all freelance software-engineering jobs requiring 5 days or fewer of effort from experienced humans can be tackled by AI, and if a company wants to replace nearly all of its human customer service team with AI, it can probably get away with it, provided customers are not opposed in principle to AI customer service.

AI can draft 100-thousand-word novels solid enough for current (2025) mainstream publishers to release with typical levels of editing by a human publisher and can create a

[42] Level 5 autonomy is defined as, "can operate the vehicle on-road anywhere within its region of the world and under all road conditions in which a conventional vehicle can be reasonably operated by a typically skilled human driver. This means, for example, that there are no design-based weather, time-of-day, or geographical restrictions on where and when the ADS can operate the vehicle. However, there may be conditions not manageable by a driver in which the ADS would also be unable to complete a given trip (e.g., white-out snow storm, flooded roads, glare ice, etc.) until or unless the adverse conditions clear." Source.

5-minute song that humans would blindly judge to have breakout potential, exceptional emotional depth, and be of equal quality to the best songs released by current (2025) record labels. An AI agent can not only craft a well-curated weeklong vacation itinerary, but it can also make last-minute adjustments to bookings in response to unexpected weather, travel delays, or individual requests. Boardrooms are still run by people, but executive teams can delegate multiday operational projects to agentic software that reliably juggles vendors, budgets, and contingencies.

Level-5 robo-taxis that can go anywhere a human driver can go finally exist, as do robots that can navigate any home in the US, make a cup of coffee and unload and load a dishwasher as fast and reliably as most humans and without any human guidance. Robots in advanced factories can adapt to different tasks without extensive reprogramming or equipment changes, making real-time decisions, and have increased physical mobility.

Rapid Progress. By the end of 2030, in the rapid-progress world, AI systems are capable of competing with the best human minds and workers, and can surpass them.

Human creativity and leadership remain valued, but mostly for setting high-level vision—day-to-day execution can be left to silicon-based systems. Autonomous researchers can collapse years-long research timelines into days, weeks, or months, creating game-changing technologies, such as materials that revolutionize energy storage, or bespoke cancer cures. No human freelance software engineer can outperform AI. The same goes for customer service (e.g., call center and support chat), paralegal, and administrative workers (e.g., bookkeepers or scheduling assistants).

Indeed, models have become so capable that AI can create an album of the same caliber as the Grammy Album of the Year. Additionally, a single AI agent can generate a Pulitzer- (or Booker Prize-) caliber novel according to current (2025) standards, adapt the book into an engaging two-hour movie, negotiate the resulting book and movie contracts, and launch the marketing campaigns for both while its sibling agents manage the book publishing company and movie studio at the level of highly competent CEOs.

Not only do Level-5 robo-taxis exist, but they are, on average, 99.9% safer than human-piloted cars and can venture anywhere off-road that a competent human driver can. Meanwhile, robots can navigate an arbitrary home anywhere in the world, make a cup of the most popular local hot beverage, clean and put away the dishes according to the local custom, fix any plumbing issues that arise while they're doing the dishes—and they can do it all faster and more reliably than most humans and without human guidance. Robots in advanced factories can autonomously perform the full range of tasks requiring the highest levels of dexterity, coordination, and adaptive decision-making.

Details: Note that you may be uncertain about two factors:

- the level of AI capabilities at the end of 2030
- the disagreement experts may have given a level of AI capabilities

You should consider both of these factors when giving your forecasts.

In June 2025, a large panel of experts, including top computer scientists, AI industry engineers and researchers, AI policy professionals, economists studying AI and technology, and superforecasters, was asked: *At the end of 2030, what percent of panelists will choose each of the following scenarios as best matching the general level of AI progress?*

According to preliminary results, the average non-superforecaster expert ($n = 361$) estimated that 29.8% of panelists will choose “Slow progress”, 47.9% will choose “Moderate progress”, and 22.3% will choose “Rapid progress”.

H.2.2 Relative Importance of Indicators

The above scenarios are defined using five indicators:

- Research
- Problem-solving
- Creativity
- Agency
- Robotics

When you think about the economic impacts of AI, which of these indicators do you think are the most important? By important, we refer to bottlenecks to impact—if progress was made, relative to current capabilities, in one indicator but not the others, which one would have the biggest impact? Please allocate 100 percentage points across the indicators.

Your allocation should sum to 100%. Don’t spend too much time on this question; we simply want to understand if there are indicators you find more important than others.

H.2.3 Capability in Controlling Physical Systems

What is the probability that the median member of an expert panel will agree with the following at the end of 2030: there exists a commercially available household robot that can reliably (in more than 99% of attempts), and as well as the median human, do at least four out of the following five tasks:

- filling and emptying the dishwasher
- doing laundry (the entire process from hamper to wardrobe)
- unloading groceries
- cooking basic meals
- vacuuming the floor

As above, the panel consists of a mixture of AI experts from academia and industry, economists, and AI policy experts.

Note that we are asking whether the same robot can do the tasks—not whether there exists a (potentially different) robot for each task.

H.2.4 Reliability

What is the probability that the median member of an expert panel will agree with the following at the end of 2030: frontier AI systems generally implement human-requested tasks correctly, avoiding obvious harms. They require minimal oversight for most tasks.

As above, the panel consists of a mixture of AI experts from academia and industry, economists, and AI policy experts.

H.2.5 Current Level of Progress

The following multiple-choice questions aim to get a sense of how familiar you are with the current level of AI capabilities. Please do not look up the answers.

According to the Stack Overflow 2025 developer survey, what fraction of software developers use AI in their development process?

- Very few (less than 10%)
- A minority (10–50%)
- A majority (50–90%) [correct answer, 78.5% to be exact]
- Almost everyone (more than 90%)

According to a research organization called METR (and as of August 2025), how long are the longest software engineering tasks that AI can successfully perform in more than 50% of attempts?

Task length is measured in terms of how long human professionals take to perform the task. Task domains include cybersecurity, machine learning, software engineering, and general reasoning.

- A few minutes
- A few hours [correct answer; GPT-5: 2h 17 min]
- A few days
- A few weeks

According to a meta-analysis reviewing publications from January 2022 to January 2025, how did creative ideas generated by AI models compare to creative ideas generated by humans?

Creative tasks in the reviewed studies included coming up with alternative uses for everyday objects, business and product ideas, and research ideas in the field of natural language processing.

- The analysis found that humans perform significantly better than AI models in generating creative ideas.
- The analysis found no significant differences ... [correct answer]

- The analysis found that AI models perform significantly better than humans in generating creative ideas.

According to an AI art Turing test conducted in October 2024, what percentage of images was classified correctly as either human art or AI-generated content by the median participant (out of 11,000)?

The test was conducted using 50 images curated for quality and the absence of clear signs for either human or AI origin, and included pictures in four styles: Renaissance, 19th Century, Abstract/Modern, and Digital. The score achieved by random clicking is 50%.

- 60% [correct answer]
- 70%
- 80%
- 90%

According to the International Federation of Robotics, which category of professional service robots had the highest global unit sales in 2023?

- Transportation and logistics robots [correct answer]
- Hospitality robots
- Agricultural robots
- Professional cleaning robots

H.3 Short-Term Forecasting

We will ask for 10th, 50th, and 90th percentile forecasts for all questions in this section.

H.3.1 Unemployment Rate

What will be the unemployment rate in the U.S. in March 2026?

Details: The unemployment rate is defined as the fraction of people in the labor force who are unemployed—people who are not working but are actively looking for work.

The labor force includes all people aged 16 and above who are either employed or unemployed and actively looking and available for work, except:

- active duty members of the U.S. Armed Forces
- people confined to, or living in, institutions such as prisons and nursing homes

This definition is sometimes called the U-3 unemployment rate. For more details on how employment is measured, see the U.S. Bureau of Labor Statistics.

If you believe the question becomes invalid—for example, if no human is employed or actively looking for work—please enter 0% for the corresponding percentile and explain your reasoning below.

For example, the civilian unemployment rate in the U.S. was 3.5% in January 2023 and 3.7% in January 2024. The historical data shown in the graph can be found on FRED (data from the U.S. Bureau of Labor Statistics), which we will use to resolve this question.

H.3.2 Inflation

What will be the inflation rate, as measured by the year-on-year percentage change in the Consumer Price Index for all items, in the U.S. in March 2026?

Details: Inflation is the rate at which the general level of prices for goods and services is rising, and purchasing power is falling. For this question, inflation is measured as the year-on-year percentage change in the Consumer Price Index (CPI) for all items in the U.S.

The CPI reflects the average change over time in the prices paid by urban consumers for a representative basket of goods and services. The "all items" CPI includes all categories such as food, housing, apparel, transportation, medical care, and recreation. For more information on how CPI is defined, see the U.S. Bureau of Labor Statistics.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter −100% for the corresponding percentile and explain your reasoning below.

For example, the inflation rate in the U.S. was 6.4% in January 2023 and 3.1% in January 2024. The historical data shown in the graph can be found at the U.S. Bureau of Labor Statistics, which we will use to resolve this question.

H.3.3 Change in Gross Domestic Product

What will be the year-on-year percentage change in the real Gross Domestic Product (GDP) of the U.S. between Q4 2025 and Q4 2026?

Details: Gross domestic product (GDP) measures the total value of goods and services a country produces in a given period of time. Real GDP is the GDP after adjusting for inflation—how much the value of money has decreased during that period—so it captures changes in actual output rather than just price changes.

Here we ask you to forecast the year-on-year percentage change in real GDP between the fourth quarter of 2025 and the fourth quarter of 2026.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter −100% for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph, as well as more information, can be found on FRED (data from the U.S. Bureau of Economic Analysis), which we will use to resolve this question.

H.3.4 Change in Labor Productivity

What will be the year-on-year percentage change in the labor productivity of the nonfarm business sector in the U.S. between Q4 2025 and Q4 2026?

Details: Labor productivity measures how much economic value (goods and services) is produced per hour worked. The nonfarm business sector comprises private businesses and government enterprises, excluding farms, households, nonprofits, and general government.

Here we ask you to forecast the year-on-year percentage change in labor productivity in the U.S. nonfarm business sector between the fourth quarter of 2025 and the fourth quarter of 2026.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter −100% for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph, as well as more information, can be found on FRED (data from the U.S. Bureau of Labor Statistics), which we will use to resolve this question.

H.3.5 Annual Recurring Revenue of the Top AI Company

What will be the Annual Recurring Revenue (ARR) at the end of December 2026 for the AI-focused company with the highest ARR?

Details: Annual Recurring Revenue (ARR) is the value of contracted, recurring revenue of a company, normalized to a one-year period. For AI companies, ARR includes revenue from subscriptions, API usage, licensing, and other ongoing contractual arrangements that renew periodically. It excludes one-time or non-recurring revenue such as professional services, hardware sales, or custom one-off projects.

For the purposes of this question, the "top AI Company" is defined as the AI-focused company (more than 50% of revenue from AI models, tools, or services) with the highest ARR as of December 31, 2026. OpenAI, Anthropic, Cohere, and other companies primarily selling AI model access or AI-powered services are classified as AI-focused companies. Hardware companies such as NVIDIA, cloud infrastructure providers like Amazon/AWS, and broad technology companies such as Google/Alphabet and Microsoft are excluded.

As of the end of August 2025, the top AI company by this definition is OpenAI with ARR of $10 billion in June (Reuters) and $12 billion in July (Reuters). Because the latter of these reports is unconfirmed by the company, we are only showing the former in the graph below.

If you believe the question becomes invalid—for example, if no company qualifies as primarily AI-focused—please enter $0 for the corresponding percentile and explain your reasoning below.

The ARR value will be taken from official public disclosures, press releases, investor updates, or—if unavailable—from the median estimate reported by at least three reputable business news outlets (e.g., The Information, Bloomberg, Financial Times, The Wall Street Journal) by April 2027.

H.4 Economic Outcomes

H.4.1 Change in Gross Domestic Product

What will be the annualized change, in percent, in the real Gross Domestic Product (GDP) of the U.S. between

- *the beginning of 2025 and the beginning of 2030?*
- *the beginning of 2045 and the beginning of 2050?*

Please give your

- unconditional forecast (10th, 50th, and 90th percentiles)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (10th, 50th, and 90th percentiles)

Details: Gross Domestic Product (GDP) measures the total value of goods and services a country produces in a given period of time. Real GDP is the GDP after adjusting for inflation—how much the value of money has decreased during that period—so it captures changes in actual output rather than just price changes.

Here we ask you to estimate the annualized change in the real GDP. We can understand annualization with an example. The GDP in the U.S. increased by 2.5% between 2021 and 2022, and by 2.9% between 2022 and 2023. That means that the total change in the real GDP of the U.S. between 2021–2023 was an increase of approximately 5.47%: $(100\% + 2.5\%) * (100\% + 2.9\%) - 100\% = 5.47\%$. The corresponding annualized change is approximately 2.70%, because constant growth at this rate for two years would lead to the same total growth of 5.47%: $(100\% + 2.70\%)^2 - 100\% = 5.47\%$.

In this question, annualized change can be calculated by the formula

$$(\text{real GDP in 2030/real GDP in 2025})^{1/5} - 100\%$$

for the first question, and equivalently for the second question.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter -100% for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph, as well as more information, can be found on FRED (data from U.S. Bureau of Economic Analysis), which we will use to resolve this question. We show annualized rates over five years. For example, the point dated January 1, 2025, is the annualized change for the years 2020–2024.

H.4.2 Change in Labor Productivity

What will be the annualized change, in percent, in the labor productivity of the nonfarm business sector in the U.S. between

- *the beginning of 2025 and the beginning of 2030?*
- *the beginning of 2045 and the beginning of 2050?*

Please give your

- unconditional forecast (50th percentile)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (50th percentile)

Details: Labor productivity measures how much economic value (goods and services) is produced per hour worked. The nonfarm business sector comprises private businesses and government enterprises, excluding farms, households, nonprofits, and general government.

Here we ask you to estimate the annualized change in labor productivity. We can understand annualization with an example. Labor productivity in the U.S. increased by 0.9% between 2021 and 2022. From 2022 to 2023, it decreased by 1.4%. That means that the total change in labor productivity between 2021–2023 was a decrease of approximately −0.51%: $(100\% + 0.9\%) * (100\% - 1.4\%) - 100\% = -0.51\%$. The corresponding annualized change is approximately −0.26%, because constant change at this rate for two years would lead to the same total change of −0.51%: $(100\% - 0.26\%)^2 - 100\% = -0.52\%$. (The difference is due to a rounding error.)

In this question, annualized change can be calculated by the formula

$$(\text{labor productivity in 2030}/\text{labor productivity in 2025})^{1/5} - 100\%$$

for the first question, and equivalently for the second question.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter −100% for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph, as well as more information, can be found on FRED (data from the U.S. Bureau of Labor Statistics), which we will use to resolve this question. We show annualized rates over five years. For example, the point dated January 1, 2025, is the annualized change for the years 2020–2024.

H.4.3 Change in Total Factor Productivity

What will be the annualized change, in percent, in the total factor productivity of the private nonfarm business sector in the U.S. between

- *the beginning of 2025 and the beginning of 2030?*
- *the beginning of 2045 and the beginning of 2050?*

Please give your

- unconditional forecast (50th percentile)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (50th percentile)

Details: Total factor productivity (TFP) refers to how much output can be generated with a given amount of labor and capital inputs. An increase in TFP represents a higher efficiency in converting inputs to outputs, for example, due to advancements in technology and worker knowledge. The output consists of all goods and services produced by the sector. The private nonfarm business sector comprises private businesses, excluding farms, households, nonprofits, and all government operations, including government enterprises.

Here we ask you to estimate the annualized change in total factor productivity. We can understand annualization with an example. Total factor productivity in the U.S. increased by 3.8% between 2021 and 2022. From 2022 to 2023, it decreased by 1.1%. That means that the total change in total factor productivity between 2021–2023 was an increase of approximately 2.66%: $(100\% + 3.8\%) * (100\% - 1.1\%) - 100\% = 2.66\%$. The corresponding annualized change is approximately 1.32%, because constant change at this rate for two years would lead to the same total change of 2.66%: $(100\% + 1.32\%)^2 - 100\% = 2.66\%$.

In this question, annualized change can be calculated by the formula

$$(\text{total factor productivity in 2030}/\text{total factor productivity in 2025})^{1/5} - 100\%$$

for the first question, and equivalently for the second question.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter −100% for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph, as well as more information, can be found on FRED (data from the U.S. Bureau of Labor Statistics), which we will use to resolve this question. We show annualized rates over five years. For example, the point dated January 1, 2025, is the annualized change for the years 2020–2024.

H.4.4 Labor Force Participation Rate

What will be the labor force participation rate in the U.S. at

- *the beginning of 2030?*
- *the beginning of 2050?*

Please give your

- unconditional forecast (10th, 50th, and 90th percentiles)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (10th, 50th, and 90th percentiles)

Details: The labor force participation rate is the fraction of the civilian noninstitutional population who are in the labor force.

The civilian noninstitutional population includes all people residing in the U.S. aged 16 and above, except:

- active duty members of the U.S. Armed Forces
- people confined to, or living in, institutions such as prisons and nursing homes

The labor force includes people in the civilian noninstitutional population who are employed or unemployed and actively looking and available for work.

If you believe the question becomes invalid—for example, if the size of the civilian noninstitutional population is zero—please enter 0% for the corresponding percentile and explain your reasoning below.

For example, the civilian labor force participation rate was 62.4% in January 2023 and 62.5% in January 2024. The historical data shown in the graph can be found on FRED (data from the U.S. Bureau of Labor Statistics), which we will use to resolve this question.

H.4.5 Unemployment Rate

What will be the unemployment rate in the U.S. at

- *the beginning of 2030?*
- *the beginning of 2050?*

Please give your

- unconditional forecast (10th, 50th, and 90th percentiles)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (10th, 50th, and 90th percentiles)

Details: The unemployment rate is defined as the fraction of people in the labor force who are unemployed—people who are not working but are actively looking for work.

The labor force includes all people aged 16 and above who are either employed or unemployed and actively looking and available for work, except:

- active duty members of the U.S. Armed Forces
- people confined to, or living in, institutions such as prisons and nursing homes

This definition is sometimes called the U-3 unemployment rate. For more details on how employment is measured, see the U.S. Bureau of Labor Statistics.

If you believe the question becomes invalid—for example, if no human is employed or actively looking for work—please enter 0% for the corresponding percentile and explain your reasoning below.

For example, the unemployment rate in the U.S. was 3.5% in January 2023 and 3.7% in January 2024. The historical data shown in the graph can be found on FRED (data from the U.S. Bureau of Labor Statistics), which we will use to resolve this question.

H.4.6 Youth Unemployment Rate

What will be the unemployment rate for 20–24 year-olds in the U.S. at

- *the beginning of 2030?*
- *the beginning of 2050?*

Please give your

- unconditional forecast (50th percentile)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (50th percentile)

Details: For a definition of the unemployment rate, see "Details" under "Unemployment Rate". Instead of the unemployment rate in the entire labor force, here we ask you to forecast the unemployment rate in the group of 20–24 year-olds in the labor force.

If you believe the question becomes invalid—for example, if no human is employed or actively looking for work—please enter 0% for the corresponding percentile and explain your reasoning below.

For example, the civilian unemployment rate for 20–24 year-olds in the U.S. was 7.1% in January 2023 and 6.0% in January 2024. The historical data shown in the graph can be found on FRED (data from the U.S. Bureau of Labor Statistics), which we will use to resolve this question.

H.4.7 Share of Job Categories

What fraction of the labor force will be in [business and analytical / skilled trade and industrial / care and service] occupations in the U.S. at

- *the beginning of 2030?*
- *the beginning of 2050?*

Please give your

- unconditional forecast (50th percentile)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (50th percentile)

Details: For the purposes of this question, the occupation categories are defined as occupations within:

- **Business and analytical occupations**: the following "supersectors" in the private, service-producing industries, as defined by the Bureau of Labor Statistics (BLS): Information; Financial Activities; Professional and Business Services.
- **Skilled trade and industrial occupations**: the private, goods-producing industries, as defined by the BLS. These include the following "supersectors": Natural Resources and Mining; Construction; Manufacturing.
- **Care and service occupations**: the following "supersectors" in the private, service-producing industries, as defined by the BLS: Trade, Transportation, and Utilities; (Private) Education and Health Services; Leisure and Hospitality; Other Services.

For more details on how the BLS defines these "supersectors", see this article. If the definitions change, we will follow the standards adopted by the BLS. We use seasonally adjusted data.

Here we ask you to estimate how the number of these jobs changes as a fraction of the size of the labor force. We can understand this question through an example:

- In January 2024, there were roughly 34.8 million employees in business and analytical occupations; 21.6 million employees in skilled trade and industrial occupations; and 77.5 million employees in care and service occupations (as defined above).
- In the same month, the size of the labor force was roughly 167.3 million individuals.
- Therefore, $34.8/167.3 = 20.8\%$ of the labor force worked in business and analytical occupations; $21.6/167.3 = 12.9\%$ in skilled trade and industrial occupations; and $77.5/167.3 = 46.3\%$ in care and service occupations.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter 0% for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph have been calculated using data found on FRED (employees within industries, size of the labor force; data from the BLS). We will use these sources to resolve this question.

H.4.8 Change in Employment by Occupation

Please rank the following groups of occupations by your forecast of the percent change in employment between the beginning of 2025 and the beginning of 2030[, conditional on the rapid AI progress scenario].

The occupation group with the largest percent increase in employment should be put at the top of the list.

For example, an occupation group with 500,000 employees at the beginning of 2025 and 400,000 at the beginning of 2030 represents a 20% decrease in employment; an occupation group with a change from 500,000 to 600,000 employees represents a 20% increase. The latter should be ranked higher.

The occupation groups shown here are a random subset of the 43 sub-major groups in the International Standard Classification of Occupations, ISCO-08. You can check the standard if the meaning of an occupation group is unclear.

Note: This question is only asked unconditionally and conditionally on the rapid AI progress scenario.

H.4.9 Wealth Inequality

What will be the fraction of the national wealth owned by the top 10% wealthiest individuals[43] *in the U.S. at*

- *the beginning of 2030?*
- *the beginning of 2050?*

Please give your

- unconditional forecast (10th, 50th, and 90th percentiles)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (10th, 50th, and 90th percentiles)

Details: The wealth of a household contains the total of all financial and non-financial assets (such as houses, land, deposits, bonds, and others) owned by the household, minus their debts.

Here we ask you to estimate what percentage of the wealth of all U.S. households will be owned by the wealthiest 10% of households. For example, the wealthiest 10% in the U.S. owned 71.2% of the total wealth of all U.S. households in 2023.

If you believe the question becomes invalid—for example, if humans go extinct—please enter 0% for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph, as well as more information, can be found at Our World in Data, which we will use to resolve this question.

H.4.10 Labor Share

What will be the labor share in the nonfarm business sector in the U.S. at

- *the beginning of 2030?*
- *the beginning of 2050?*

Please give your

- unconditional forecast (50th percentile)

[43] This question should have asked about households, like mentioned in the details.

- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (50th percentile)

Details: Labor share is the share of economic output that workers receive in the form of wages, salaries, benefits, and other compensation. It reflects how much of the value produced is distributed among workers.

Here, we ask you to estimate the labor share for workers in the nonfarm business sector in the U.S.. For example, the labor share in Q1 of 2023 was 55.0%. You can find more information about how labor share is defined and estimated in this U.S. Bureau of Labor Statistics (BLS) article.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter 0% for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph are extrapolated from level data shown in this figure, published by the BLS, using index data available on FRED (data from the BLS). We will use data computed in this way to resolve the question, or level data directly from the BLS if these become available.

H.4.11 Median Household Income

What will be the real median household income in the U.S. at

- *the beginning of 2030?*
- *the beginning of 2050?*

Please give your

- unconditional forecast (10th, 50th, and 90th percentiles)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (10th, 50th, and 90th percentiles)

Details: The median household income represents the "middle" annual income of all household incomes—it shows the income for which half of the households earn more, and half less. The prefix 'real' means that this value is adjusted for inflation. Here, the values are adjusted to the value of the U.S. dollar in 2023.

A household consists of all people who occupy a housing unit as their usual place of residence. Income includes all money received, such as earnings, government benefits, rental income, and pensions. It excludes noncash benefits, such as food stamps and subsidized housing, and tax credits such as the Earned Income Tax Credit. For definitions of household and income, see the U.S. Census Bureau.

For example, the real median household income in the U.S. was $77,540 in 2022 and $80,610 in 2023.

If you believe the question becomes invalid—for example, if human economic activity ceases—please enter $0 for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph, as well as more information, can be found on FRED (data from the U.S. Census Bureau), which we will use to resolve this question.

H.4.12 Life Satisfaction

What will be the average life evaluation in the U.S. on the Cantril ladder according to the World Happiness Report at

- *the beginning of 2030?*
- *the beginning of 2050?*

Please give your

- unconditional forecast (50th percentile)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (50th percentile)

Details: The World Happiness Report reports the average response from the previous three years to the Cantril ladder question in the Gallup World Poll. This question, posed to approximately 1000 people in each country, asks:

"Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?"

Here we ask you to estimate the average life evaluation of U.S. respondents as presented in the World Happiness Report. For example, in the 2025 World Happiness Report, the average of U.S. respondents' self-assessed life evaluation was 6.724 for the years 2022–2024.

If you believe the question becomes invalid—for example, if humans go extinct—please enter 0 for the corresponding percentile and explain your reasoning below.

The historical data shown in the graph, as well as more information, can be accessed on the U.S. country profile from the World Happiness Report, which we will use to resolve this question.

H.4.13 Work Hours Assisted by Generative AI

A study by the Federal Reserve Bank of St. Louis estimated that between 1.3% and 5.4% of all work hours in the U.S. were assisted by generative AI in late 2024. This is based on data collected in the Real-Time Population Survey in November 2024 ($N = 1008$) and measures the intensity of generative AI adoption.

What will a future iteration of this study estimate as the percentage of work hours in the U.S. assisted by generative AI at the beginning of 2030?

Please give your

- unconditional forecast (50th percentile)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (50th percentile)

Details: The estimate is based on survey responses to questions about:

- usage intensity: for how long do people use generative AI on the days they use it
- usage frequency: on how many work days they use generative AI
- amount worked: days and hours worked in the previous week

For details, see Section 5.1 in the paper.

If the authors at the Federal Reserve Bank of St. Louis do not run a follow-up study meeting the requirements of this question, the Forecasting Research Institute will appoint a panel of experts to identify an appropriate substitute study.

If you believe the question becomes invalid—for example, if humans go extinct—please enter 0% for the corresponding percentile and explain your reasoning below.

H.4.14 AI Electricity Consumption

What percent of U.S. electricity consumption will be used for training and deploying AI systems in

- *2030?*
- *2050?*

Please give your

- unconditional forecast (50th percentile)
- forecast assuming the slow AI progress scenario (50th percentile)
- forecast assuming the moderate AI progress scenario (50th percentile)
- forecast assuming the rapid AI progress scenario (50th percentile)

Details: AI model training and deployment occur mainly through the use of data centers, which are giant computing centers that host computers ("servers").

Servers in data centers are split into two main categories: conventional and AI-specialized servers, the latter of which are better designed for and dedicated to AI workloads. This question asks about the electricity consumption of AI-specialized servers, regardless of the end application, which is, in practice, difficult to determine.

Historical baselines: There is currently no official reporting on the percentage of U.S. electricity consumption used for training and deploying AI systems. We estimate that this is 1.0% in 2024.

Some relevant sources that estimate future U.S. electricity consumption by data centers and by AI-specific usage:

- Data Centers:
  - The 2024 United States Data Center Energy Usage Report estimates that data centers will consume approximately 6.7 to 12% of total U.S. electricity by 2028.
  - A 2025 report by the National Academy of Sciences estimates U.S. data center demand as a percentage of total U.S. electricity demand under four different growth scenarios as between 4.6–9.1% in 2030.
- AI-specific usage:
  - In February 2025, Epoch AI estimates that "AI could reach fairly eye-popping levels of energy usage by 2030, on the order of 10% of US electricity."
  - A 2024 white paper estimates 40% of AI energy usage by model training and development, and 60% for deployment, based on analysis of existing models.

The question will be resolved by credible reports of total U.S. electricity consumption and fraction of U.S. electricity used for AI training and deployment, by sources such as the U.S. Energy Information Administration, the International Energy Agency, and peer-reviewed publications. If credible reports are not available, FRI will resolve the question with input from at least 3 AI experts selected for expertise in estimating AI's energy consumption.

H.5 Impact of Policies

H.5.1 Probability of Policy Implementation

What is the probability that each policy (or a similar policy, as judged by an economist panel) is implemented by the U.S. by the end of 2026?

H.5.2 Impact of Policies on Economic Outcomes

What will be

- *the annualized change, in percent, in the real Gross Domestic Product (GDP) of the U.S. between*

  - *the beginning of 2025 and the beginning of 2030*
  - *the beginning of 2045 and the beginning of 2050*

- *the labor force participation rate in the U.S. at*
  - *the beginning of 2030*
  - *the beginning of 2050*

if

- *none of the policies described above are implemented*
- *exactly one of the policies described above is implemented [we ask this separately for each policy]*
- *assuming the rapid scenario AND none of the policies described above are implemented*
- *assuming the rapid scenario AND exactly one of the policies described above is implemented*

by the U.S. by the end of 2026?

H.5.3 Policy-Specific Indicators

Impact of Policy 4: Manhattan Project for AI on Scenario Probabilities. Imagine a panel of experts at the end of 2030, including AI experts from academia and industry, economists, and AI policy experts. The panel is asked which of the three given scenarios best matches the world as it is then, at the end of 2030. *What is the probability that a given scenario will be the most commonly selected option among the panel of experts, conditional on Policy 4: Manhattan Project for AI being implemented by the U.S. by the end of 2026?*

H.5.4 Support for Policies

Do you think [policy] should be implemented?

- Yes, with at most minor alterations
- No
- Unsure

Please rank these policies from most preferred to least preferred. [ranking]
What other policies should be considered to address AI's economic impacts? [open response]

H.5.5 Policies

Policy 1: Retraining Support. Unemployed people leaving a job in an industry with high-automation risk are provided with:

- Credits covering up to $25,000 per year for approved training courses, up to two years full-time equivalent in total
- Career counseling and support for finding retraining opportunities
- Relocation grants of up to $5,000 covering the costs of moving for a training program

In addition, employees in these industries are allowed to spend up to 50% of their working hours on retraining. For these hours, they are paid 90% of their usual hourly salary. Employers receive tax credits equal to 50% of wages paid during employee training time.

Industries with high-automation risk are identified by a panel of economists. The panel convenes every two years to update its assessments.

The program is funded by introducing a retraining payroll tax of 0.5%, split equally between employees and employers (0.25% each).

Policy 2: Modernized Unemployment Insurance. Workers who lose their jobs in an industry with high-automation risk receive enhanced unemployment benefits:

- Unemployment benefits increase from current levels to 75% of the previous salary for up to 18 months.
- Workers who find new employment at lower wages receive wage loss insurance covering 50% of the salary difference for up to 2 years.
- Benefits are portable across state lines to encourage geographic mobility.
- Workers can receive benefits while enrolled in approved training programs without work search requirements.
- Administrative barriers are lowered with simplified applications, automated verification, and reduced reporting requirements.

The program is funded by increasing baseline employer payroll taxes by 9 percentage points from 6% to 15% (on the first $7,000).

Similar to Policy 1, industries with high-automation risk are identified by a panel of economists. The panel convenes every two years to update its assessments.

Policy 3: Universal Basic Income. Every U.S. citizen aged 18 and over receives $1,000 per month.

The program is funded by a 15% value-added tax (VAT) on all goods and services.

Payments are unconditional and do not affect eligibility for other social programs. The amount is indexed to inflation and reviewed every year.

Policy 4: Manhattan Project for AI. The federal government will spend approximately 0.4% of the GDP each year (as of 2025, this corresponds to about $120 billion) with the goal of rapid improvements to AI capabilities. This will include the following:

- National AI Development Agency, a new federal agency tasked with developing AI capabilities for national security and defense applications. Most development will take place through contracts with companies and universities.
- Direct funding to companies and research institutions to develop AI capabilities and applications, with the funding priorities determined by a government board. While companies keep access to any intellectual property they develop, they are required to share key research findings with the government.
- Streamlined permitting process for AI-related infrastructure for the private sector. This could include semiconductor manufacturing, data centers, and related energy infrastructure.

The funding represents additional investment on top of existing federal spending. The project is funded by a 0.7% value-added tax (VAT) on all goods and services.

Policy 5: Compute Tax. Organizations whose AI-related electricity consumption exceeds 100,000 MWh annually pay a tax of $50 per MWh on consumption above this threshold. This tax is indexed to the average electricity price in the U.S. and is updated annually. As of March 2025, the average cost of electricity was $132.7 per MWh according to the U.S. Energy Information Administration.

The tax applies to total electricity consumption regardless of source, including grid electricity and on-site generation. All data centers above 1MW must install certified power monitoring systems and report monthly consumption. AI operations subject to the tax include training and inference for machine learning models with more than 1 billion parameters.

The revenue generated by the tax is distributed to consumers as stimulus checks.

Policy 6: Job Guarantee Program. The federal government guarantees a job for any adult who wants one.

- Government-guaranteed jobs should pay at least $15 per hour (indexed to inflation) and offer benefits such as federal-employee–level health insurance, paid leave, and retirement contributions.
- Projects are chosen through two tracks:
  - Local track: local employment offices issue open calls for proposals from municipalities, nonprofits, and tribal governments. Projects must (i) be additional to existing public roles, (ii) deliver demonstrable community benefit, and (iii) be approved by a tripartite board representing labor, business, and community members.
  - Federal track: federal agencies may propose large-scale "national works" (e.g., major infrastructure projects). Proposals are screened for strategic value and additionality by an inter-agency council.

- The U.S. Treasury automatically funds 100% of wages, materials, and oversight. Local bodies manage day-to-day operations for community projects, while lead federal agencies manage national works.

I. Example rationales

I.1 Methodology note

This appendix contains example rationales that respondents provided alongside their forecasts for the four main outcomes: GDP, TFP, LFPR, and wealth inequality. Rationales for each outcome have been sorted into three categories according to whether their accompanying forecast for the relevant outcome in the unconditional 2030 scenario fell into the top 25% of responses ('high'), the middle 50% ('medium') or the bottom 25% ('low').

Rationales were ranked by an LLM tool that assigned rationales a score based on a set of criteria that human markers associate with high-quality rationales: argument quality, clarity, comprehension, and supporting evidence. These rationales are not necessarily associated with higher-accuracy forecasts, but simply provide qualitative coverage describing some of the key arguments respondents brought to bear on their forecasts. This appendix reproduces raw rationale text that has not been adjusted for coherence.

High-scoring rationales were checked for AI-generated content using Pangram, with rationales that were assessed as being majority AI-generated being excluded from this appendix. As such, this appendix contains the three highest-scoring, non-AI-generated rationales for each of the 'high,' 'medium,' and 'low' forecast groups for each of the four main outcomes. Rationales have been lightly edited to correct obvious typographical errors and to adjust language to American English when in British English, for example.

I.2 Gross Domestic Product

- High forecasts: >3% (n = 17)
- Medium forecasts**:** 2 to 3% (n = 68)
- Low forecasts**:** <2% (n =14)

I.2.1 High forecast rationales

Respondent group: Economist
Unconditional 2030 GDP forecast: 4%

My unconditional prediction aligns with the Moderate Progress scenario. I expect AI to raise GDP growth by about 2 percentage points above current levels by 2030, offsetting negative pressures such as demographic decline, climate impacts, and geopolitical instability that would otherwise slow growth. Even though AI capabilities will likely be impressive by 2030, adoption across the economy will remain gradual. Businesses will need to redesign production processes to integrate AI effectively, which will take time. Regulation will also likely slow more disruptive changes in the economy.

Under the Slow Progress scenario, I expect GDP growth to remain roughly at current levels. AI will still contribute to productivity gains, but these will be outweighed by structural headwinds, demographic shifts, climate-related costs, and geopolitical tensions resulting in little or no net acceleration of growth before 2030.

Under the Rapid Progress scenario, I expect a sharp rise in GDP growth by 2030, driven by AI breakthroughs in science, technology, and governance that enable productivity levels unprecedented in human history.

By 2050, I expect all scenarios to converge in terms of AI capability. In every case, AI will likely reach the technological level described in the Rapid Progress scenario, though the timing differs. Median growth rates will vary slightly depending on when this level is achieved. I see an upper limit to sustainable growth at around 20%, constrained by consumption capacity, natural resources, and political or social factors.

Until 2030, I assign a low probability to major global shocks–such as severe climate disasters, large-scale conflicts, or pandemics–and therefore exclude them from the forecast. By 2050, I expect AI to improve our ability to manage these challenges through technology (e.g. cleaner energy), science (e.g. fast vaccine development), and more resilient governance systems.

I see a risk under the Rapid Progress scenario that AI capabilities could advance faster than control and governance mechanisms. In that case, humanity could lose control–either of AI systems themselves or of global stability–potentially leading to catastrophic outcomes such as large-scale conflict, bioweapon misuse, or other AI-related existential threats - potentially destroying most of human civilization and thus reducing GDP growth to 0.

Respondent group: Superforecaster
Unconditional 2030 GDP forecast: 3.84%

If there is rapid progress between now and 2030, my median expectation is that there will be an unprecedented rate of economic growth, though this will probably be tempered by lower growth rates in the early years of this period, and there's still a possibility that AI that's close to artificial general intelligence won't actually impact the GDP figures that much (hence my 10th percentile forecast being within the historical range). My 80% confidence interval for 2050 is extremely wide because it's a long way away, but (based on Ajeya Cotra's Biological Anchors model, Epoch AI's compute-centric model, as well as insiders' and outside views), I expect AGI to more likely than not have arrived by then regardless of whether we're in the slow, moderate or rapid progress scenario and for this to massively boost GDP growth.

My 10th percentiles are at -100 because I think there's a 40% chance that humanity goes extinct conditional on AGI being developed, and I think there's a greater than 50% chance that it will be developed by 2050.

Respondent group: Economist
Unconditional 2030 GDP forecast: 3.5%

I will explain my reasoning in three steps:

First, ignoring AI there has been a slowdown in productivity growth (Jones, Gordon). Coupled with a reduction in immigration to the US, that would lead me to expect a lower growth rate in the coming years without AI. So the baseline is perhaps 2 per cent in the "slow progress".

Second, for standard econ reasons, I think even rapid AI development will take time to be implemented into the economy: it took 50 years for the median manufacturing company to switch to electricity. I don't expect the AI transition to be that slow, but changing organizations, overcoming regulatory burdens etc. will take time. I therefore don't expect dramatic changes over the coming 5 years, though, following my previous comments, a substantial increase in research productivity could improve economic growth in the "rapid progress" scenario, already by 2030, which I give 4 per cent as median and substantially higher 6 in that scenario in the 90th percentile. Since I put some weight on that scenario, I have given a median estimate of 3.5 for the unconditional. The intermediate case is reflected in the 3 per cent for the "moderate progress" scenario.

In the 2050 range, I am highly uncertain.

Regardless of what scenario experts judge in 2030 I think there is still a substantial probability of AI takeoff in the 2030 to 2050 range which I why I have high GDP growth rates in all scenarios. Again, mainly driven by improvements in research productivity.

By 2050, my tails become "weird". I believe that unconditionally, there is at least a 10% risk of a catastrophic outcome which is why the 10th percentile gets -100 and rapid progress does so as well. I might even put that in for the 15th or 20th percentile.

On the other hand, best case scenario is material utopia for all, which I have entered as 20 per cent growth rate, recognizing that these numbers become somewhat meaningless at this point.

I.2.2 Medium forecast rationales

Respondent group: Economist
Unconditional 2030 GDP forecast: 3%

The 2050 forecasts reflect the idea that the level effect of AI would have mostly worked out over the next 25 years. Most other general purpose technologies starting with electrification (motor car, personal computers, wireless telecommunications) had a long lag from invention to widespread implementation to TFP improvement, which worked out over 2-4 decades. I expect that AI will be faster because physical infrastructure is less demanding (other than for the compute providers, which spend massive amounts already but will provide the capabilities through the cloud). As such, differences across scenarios will be small by then.

The 2030 forecasts are more difficult, which is why the bands are larger. Widespread gains through AI adoption and continuous investments towards it are possible. But it is also likely that broad-based productivity effects, outside of AI-intensive companies (producers or users) will be slow, due to implementation lags and unclear gains in low-tech services. It is also possible that we will observe a productivity J-curve (Brynjolfsson et al., AEJ Macro 2021), whereby the productivity effects of general purpose technologies will be initially undermeasured because these technologies rely on intangible assets, which are measured poorly. Demographics may also weigh down growth, especially now that migration is halted. A recession over 2026-27 is not unlikely, and concerns over rising debt are not trivial, affecting also AI hyperscalers more recently. Therefore I expect a base case that is slightly higher than average of the past decade (outside COVID) but with significant uncertainty.

Respondent group: Superforecaster
Unconditional 2030 GDP forecast: 2.5%

We have about 47 months until 2030. As mentioned in my short term forecast on GDP, I am assuming weak to contractionary growth in 2026. With that in mind, I estimate about

1.25% total growth for that year. For 2027, 2028, and 2029, I expect we will see a resurgence in GDP growth of about 2% before AI related GDP growth each year. This article by PWC estimates GDP could be up to 14% higher by 2030. Its methodology seems reasonably sound, so I am going to use it as a basis for additive AI related GDP.

For my slow progress (also my unconditional scenario) I am going to assume 1.0% in 2026, then 3% each following year, which is the sum of 2.0% at baseline, and an additional 1.0% for AI related growth for 2027-2030. Total annualized growth would then be 2.5%. The reason I am picking this for unconditional is that I believe AI is in a 'hype' stage and will probably disappoint for a year or two prior to 2030.

For Moderate progress I will assume 1.0% growth for 2026, then 2.0% baseline growth plus 1.50% AI generated for each year thereafter. Annualized growth for the 50th percentile number would be 2.88%

For Rapid Progress, I will assume customary growth of 2.0% plus 3% AI additive each of the four years. So annualized growth of 5.0% at the 50th percentile. .

Annualized GDP through 2050 is an entirely different matter. Whatever AI is going to add to the economy will be largely realized by that time. If we ever will, we will have super AGI, massively abundant compute through quantum computing, and practically unlimited electrical power from nuclear fusion. By my estimation, we should begin multiplying available compute starting 2030 from ever more capable quantum computers. This should propel us to super AGI by no later than 2035. And by no later than 2050, we will have widely available and abundant electricity from nuclear fusion by 2050. Practically any task will be fully and cheaply automated, and economic growth towards the end of this time range will only be limited by the laws of physics.

Clearly, estimating annualized GDP in such conditions is extremely difficult, so we should approach this with a wide range of possible outcomes.

Slow progress could probably be compared to some of the strongest periods of economic growth in US history. Using data from this Wiki, we can see that the period from 1949 through 1969 (21 years) had an annualized GDP growth rate of 5.3%. I consider this a conservative number because it implicitly assumes AI will not have strong cumulative effects on economic growth, where automation and technological improvement move at a historical rate. The growth seen in the US post-war period was limited by cost of manpower and a slower rate of technological improvement. So 5.3% for the slow growth scenario.

For the moderate growth scenario, which I also consider the unconditional scenario, we are much less encumbered by labor scarcity, as automation will allow much greater increases in productivity. And technological progress will likely speed up considerably, with AIs being able to apply it in much faster time. But there could be conflicts, or other expected or unexpected exogenous shocks that could set things back some years. AI itself could run out of control and cause disruption. There could even be A Luddite revolt that would purposely slow AI progress and usage. With this I am making the general assumption of 1.5X the slow growth scenario. So that would be 8.0% annualized GDP growth.

For Fast Progress, I am assuming earlier timelines for the three points of progress mentioned earlier, which are achievement of strong AGI, super quantum computing, and fusion power. Also, no catastrophes or set-backs, and minimal social disorder. For this scenario it would be 2X slow growth, or 10.4%

Respondent group: Economist

Unconditional 2030 GDP forecast: 2%

My Unconditional scenario is "Slow+", where some of the defined areas capabilities have advanced meaningfully *closer* to the Moderate scenario.

Slow 2030:

10th: 1%

50th: 2%

90th: 3.5%

Moderate 2030:

10th: 1.5%

50th: 3%

90th: 5%

Reasoning: AI ends up complementary and generally enhances worker productivity rather than replacing them. The 50th to 90th percentile estimates reflect such capabilities are [somewhat/widely] and effectively adopted by firms across [some/many] sectors. The 10th percentile estimate reflects lower and/or costly adoption of AI across firms and sectors, potentially with a higher degree of worker displacement, and potentially a higher drag from years of economically harmful tariff/trade and immigration policy.

One of the most potentially economically transformative areas is in personal household robotics, specifically for caretaking purposes. Caretaking is an immigrant heavy labor sector (heavily impacted by current policy), low paid (so the economic feasibility threshold is lower), and is projected to have increasing demand as the population ages.

Rapid 2030:

Reasoning: I think the main upsides here are that the U.S. recaptures significant manufacturing via advanced robotics and can provide significantly more healthcare/personal care at lower cost.

2050 general: The difference in my scenario estimates here is small because I think the state of AI in 2030 has very little bearing on the state of AI in 2050, aside from setting a floor for capabilities (i.e., the Rapid scenario means AI *can* actually do all those things). I think AI capabilities will more or less plateau *somewhere*, with that plateau being hit at different points in time for the different scenarios. I don't think LLM-based AI is capable of hitting the Rapid capability level, because, among other reasons, they won't reach the required levels of generalized problem solving and especially *reliability* without "world models". If new fundamental approaches to AI that successfully incorporate world models are developed, I believe the capability ceiling and therefore impact increases significantly.

The specific timeline of capabilities and especially adoption matters significantly. AI's impact on economic growth will be most significant during the adoption phase. At some point industries/sectors will be effectively saturated with the technologies, and the impact on growth rate will fall as opportunities for low and mid-hanging gains disappear. If the high-growth phase happens 2040-2045 and reaches general saturation at the end of that period, growth 2045-2050 would likely be much lower than if the high-growth adoption phase happens 2045-2050. So on and so forth.

Unconditional 2050: My Unconditional capability level assumes a "Moderate+/Rapid-" level existing by 2045 with widespread adoption, and moderately effective policy interventions to redistribute wealth to the general populace to mitigate labor force displacement (some form of UBI), with a moderately large shift of labor to leisure hours, and corresponding increase of leisure/consumer spending.

Slow 2050:

10th: 1%

50th: 3%

90th: 6.5%

Moderate 2030:

10th: -1%

50th: 3%

90th: 7%

Reasoning: Reflects higher capability floor. The -1% forecast for the 10th percentile reflects that really rapid advanced AI adoption generates massive socioeconomic upheaval faster than society can adapt and consumer spending collapses as gains concentrate without adequate redistribution.

Rapid 2050:

10th: -2%

50th: 3.5%

90th: 7%

Reasoning: Reflects much higher capability floor, mainly for robotics, which are capable enough for advanced manufacturing and can address labor shortages in many industries. The -2% forecast for the 10th percentile reflects that really rapid advanced AI adoption generates massive socioeconomic upheaval faster than society can adapt and consumer spending collapses as gains concentrate without adequate redistribution.

I.2.3 Low forecast rationales

Respondent group: Superforecaster
Unconditional 2030 GDP forecast: 1.8%

I looked at CBO, Fed, and OECD projections for my baseline numbers.

For 2030, I expect increased corruption, decreased consumer confidence, decreased immigration, and decreased government support to reduce potential GDP growth. Spending on AI-related infrastructure has lifted GDP in 2025, but is unlikely to continue unless greater evidence of productivity gains is shown. Minimal effect of AI on GDP growth outside of datacenter buildout.

For 2050, that's a long way away and the US is a large country. Population growth/lack of growth may be the dominant effect, though I also expect a delayed energy transition to weigh on growth. Moving the 10 and 90th percentiles wider apart, too far to know with any certainty what will happen; at least for 2030 we know the starting point.

AI Scenarios:

Slow Progress: This probably doesn't look too different from the unconditional forecast, but might be lower for 2030 because of (presumably) reduced spending on data centers, etc. If AI spending lifted the US GDP growth in 2025, collapse of it would probably mean at least a year in there of low numbers. However, I expect this to improve by 2050.

Moderate progress: For 2030, this would likely mean greater GDP growth than anticipated between now and 2030. Long term, this might be moderated somewhat by costs of climate change and drop in the investment cycle but would be higher on average than in the slow progress case.

Respondent group: Economist
Unconditional 2030 GDP forecast: 1.5%

Rapid progress: For 2030, this would be much higher GDP growth, similar to the effects in the early '90s and around 2000 - when PC's/computer hardware were being adopted and then as more business moved online. But over time, this high growth phase moderates, so that the growth in 2050 is not as high as 2030. On the other hand, 10th and 90th percentiles need to be wider apart for 2050 because who knows - might have another new technology that boosts growth. Also possible that there will be a deep recession.

Structural conditions will continue to put the economy on a low growth path up to 2030, more possibilities for growth could emerge approaching 2050. AI will introduce new sectors of activities with faster growth, but they are likely to be limited in size, while at the same time downsizing other activities; in the slow scenario, this leads to a modest rise of growth rates up to 2030 and a slightly better performance by 2050.

Moderate progress of AI would increase growth in both periods. Rapid progress would further provide incremental improvements. Radical jumps in growth rates are unlikely

Moreover, the way AI improvements could be turned into GDP is not straightforward. A lot of activities do not increase monetary transactions, value added and incomes as recorded by GDP (e.g. many uses of ChatGPT). I may also reduce prices of some activities (e.g. medical diagnoses), resulting in a fall of the value added in some fields.

The increase in sales and value added of AI-related firms is likely to be limited - and increase slowly - as a share of the total economy, with modest impacts on GDP trends. A major effect of AI companies is on the asset and stock market capital values, that however affect GDP only when dividends are distributed or assets are sold. The effects of AI could be therefore greater on capital values than on GDP income flows.

On the downside:

GDP will be slowed by the decline of activities affected or replaced by AI (more labor-intensive ones). The rise of GDP requires a parallel rise of both supply capabilities (driven also by AI) and of demand - for consumption, investment and government expenditures; the concentration of gains from AI and greater income inequality are likely to reduce the space for demand growth; a new major role of public expenditures is unlikely to emerge in the US now, with the dangerous exception of military expenditures. GDP growth may therefore be constrained by limited demand growth.

Finally, the rise of world GDP up to 2050 will continue to be concentrated in China and East Asia, with a lower scope for US growth.

Respondent group: Superforecaster
Unconditional 2030 GDP forecast: 1.95%

Unconditional: Developed economies are growing at a slower rate for various reasons (secular stagnation?), so I expect growth in 2030 to be lower than the historical average of around 2% to 3%. Growth in 2050 should be even worse because the long-awaited effects of global warming should have started to kick into full gear by then. Economists have determined that the effects of a 2C or 3C above the 1880 baseline world would have the same economic effect as a war. I have a wide range of growth scenarios because it is impossible to pinpoint the timing of the next economic crash or boom so precisely so far in advance.

My numbers for the slow, moderate and rapid progress follows this logic: AI will have its most positive effect on the economy on shorter timescales. For my 2030 forecast, I have assumed 0.25% improvement under the slow progress scenario and a 1.0% under the moderate progress scenario. If there is rapid progress in that time, the economic boom will be like no other. I would be surprised, given how revolutionary the event would be, if economic growth in the rapid progress resulted in less than a 2.0% increase in GDP. These are just guesses, however. I haven't done the research necessary to see if my numbers are valid. Still, I think the more progress there is, the wider the intervals (or possibilities for higher growth) will get.

My 2050 forecast differs from my 2030 forecast in that it factors in the detrimental effects from years-long high-energy consumption by data centers. These effects include exacerbating climate change because of the amount of energy required to run these data centers; water shortages for the same reason; and mass layoffs and changes to the way Americans work.

My base case is the higher the level of progress, the greater the negative impacts to both will be, with the net negative impact to the economy eventually exceeding the productivity and other gains derived from AI.

Still, I could be wrong. That is why my distribution of probabilities for the "rapid progress, long timescale (2050)" scenario is so wide.

Addendum: The direction of change as AI progresses is inconsistent across time horizons because I believe the rapid progress scenario would have potentially severe negative consequences to growth in the long term.

I.3 Total Factor Productivity

- High forecasts: >1.5% (n = 19)
- Medium forecasts: 1 to 1.5% (n = 55)
- Low forecasts: <1% (n = 22)

I.3.1 High forecast rationales

Respondent group: Economist
Unconditional 2030 TFP forecast: 2%

Under the Slow Progress scenario, I do not expect significant impact before 2030. Under the Moderate Progress scenario, I expect factor productivity to rise slightly above historical trends, driven by technological improvements. Under the Rapid Progress scenario, I expect a large jump in total factor productivity (TFP) resulting from major technological innovation, with labor input becoming increasingly irrelevant for production.

Between 2045 and 2050, I expect the AI economy to pick up speed. In the Rapid progress scenario the AI economy is in full swing by then. TFP is exploding. Labor input plays a marginal role for production.

Respondent group: Superforecaster
Unconditional 2030 TFP forecast: 1.9%

The median TFP near 1.3-1.4 % = a modest bump above historical 1.1 % because of some AI adoption but hedged by capital, regulation, and saturation.

Rapid AI could plausibly lift the trend to $\tilde{2}$ % by 2030, but long-run median tails off slightly by mid-century as frontier benefits diffuse and slow.

Slow AI is below 1 %, as assistive tools alone don't change long-run productivity trends much.

Respondent group: Superforecaster
Unconditional 2030 TFP forecast: 2%

In the slow progress condition, total factor productivity growth will probably be in line with the recent average of $\tilde{1}$%. In the moderate progress condition, it seems reasonable that TFP growth will be higher than we have seen in the history of this data series. AI advances seem particularly well suited to improve the rate at which new technologies–hard tech as well as advances in culture and organizational patterns–are discovered and spread throughout the economy. In the rapid progress condition, this is even more so the case. The same amount of TFP growth that occurs in 5-10 years should instead occur in one year (or less, but we are only looking for 50th percentile forecasts here). In all cases there should be some slowdown going out to 2050 (note that TFP will be high to staggeringly high with sustained growth rates higher than this data series's history).

I.3.2 Medium forecast rationales

Respondent group: Economist
Unconditional 2030 TFP forecast: 1.35%

Historically, TFP growth has been a little less than half (0.45) of labor productivity growth over five-year horizons, the rest given by improvements in labor quality and capital deepening. Over the next five years, the path of capital deepening is highly uncertain; massive investment for AI-related purposes has already taken place, and it is unclear whether it will continue. At the same time, as firms ramp-up AI adoption, investment may rise outside the hyperscalers. Intangible capital, including things like cloud services but also higher employee retooling will also likely rise.

As such, and given the productivity J-curve mentioned above (TFP undermeasured initially and overmeasured over the long-run for general purpose technologies), it seems likely that TFP growth will be a little lower relative to labor productivity growth until 2030 (0.4), but a little higher by 2050 (0.5). These figures come from the model of Brynjolfsson et al, and correspond to 5% undermeasurement in the early years, and 10% overmeasurement after 25-30 years. Note of course that one also has to assume that any divergence between labor productivity and TFP due to utilization will have evened-out over five years.

Respondent group: Economist
Unconditional 2030 TFP forecast: 1%

In the slow 2030 scenario, I forecast near-zero TFP growth (0.6%). When firms shift to AI, they accumulate intangible capital (new business processes, re-training) which is not counted as an asset in GDP accounts. This makes TFP look low initially (inputs rise, output stays flat). By 2050, this hidden capital is activated, leading to a delayed TFP boom (1.5%) as the slow progress world finally converges to the frontier.

For the moderate scenario the same considerations hold. In addition, while AI helps finding ideas faster, the underlying complexity of science is also potentially rising exponentially. Therefore, after an initial higher level in the period 2025-2030 (1%), TFP growth normalizes to 1.5% in the period 2045-2050. Even in the rapid scenario, I forecast in 2045-50 TFP growth at 2% due to two structural drags: if high inequality (assumed in particular in my rapid view) persists, economies may suffer from massive allocative inefficiency (i.e. in human capital). Talent risks being locked out of the innovation economy, reducing aggregate TFP below its potential. In addition TFP is a residual that captures shocks. Severe climate volatility (e.g., crop failures, disrupted logistics) appears in data as a 'negative technology shock' we put in the same inputs but get less output. This will likely eat away a portion of the gross efficiency gains from AI by 2050.

Respondent group: Superforecaster
Unconditional 2030 TFP forecast: 1.5%

Up until 2030, we should see a relatively small increase in total factor productivity under the moderate progress scenario. While AI is making a small difference in productivity now, it will be far more pronounced through 2050.

The 4 years leading up to 2030 will be a period of immense investment with much less return, compared to the period from 2030 to 2050. By 2030 we should be at or near the dawn of quantum computing, which will propel AI forward to AGI, this in turn will lead to a wide range of scientific breakthroughs that will lead to a major increase in all factor productivity; both because of improvements in manufacturing efficiency, but also a reduction in more expensive employee headcount.

But after 2030, the combination of completed hard work to adapt AI to the work, and successive technological breakthroughs throughout the 2030s, will tremendously improve total factor productivity. By 2050, virtually every commercial activity will be transformed to be far more productive with the same amount of labor and capital.

I.3.3 Low forecast rationales

Respondent group: Economist
Unconditional 2030 TFP forecast: 0.8%

Between 2025 and 2030, TFP growth in the U.S. private nonfarm sector is likely to remain modest. Without major breakthroughs, demographic trends and slower innovation diffusion will weigh on productivity. AI could offset this slowdown, maintaining or slightly boosting growth but only in a scenario of rapid technological progress.

Between 2045 and 2050, the outcome will depend on how deeply AI is integrated into production. In a moderate-progress world, productivity gains will stabilize; under rapid progress, AI could drive a significant acceleration in TFP, comparable to past industrial revolutions.

Respondent group: Economist
Unconditional 2030 TFP forecast: 0.9%

TFP growth from AI requires building data centers, electrical power plants etc. - which looks like high capital growth, but modest TFP growth in the short run. In the long run, electricity drives output, which (I think) looks like TFP growth in growth accounting as it's neither capital nor labor.

Robotics advances in the moderate scenario will make the productivity of capital higher (both in factories and other settings).

Under the slow scenario, we are overinvesting in compute right now, so TFP growth will be slower.

Respondent group: Superforecaster

Unconditional 2030 TFP forecast: 0.7%

One thing is whether the large rise in investment in 2025 is going to dampen TFP at the start of the 2025-2030 period. I tend to think that substantial capital will be required in advance of the economic gains (this is clearly what is happening now and consistent with building a new layer of infrastructure). Hence my TFP forecasts show this growth consistent with previous periods (or lower) and don't differ that much between scenarios.

I am not sure how to think about capital productivity in the longer term. Capital could drive higher output and the labor cost differential that drove manufacturing overseas may (it is not certain at all) superseded by other factors–notably energy costs, material availability, technology ownership and so on. It is also conceivable that output increases substantially, but capital productivity much less so depending on up-front costs and the replacement cycle of the underlying materials (which people will only be able to guess at).

I.4 Labor Force Participation Rate

- High forecasts: >62.68% (n = 26)
- Medium forecasts: 60 to 62.68% (n = 63)
- Low forecasts: <60% (n=9)

I.4.1 High forecast rationales

Respondent group: Superforecaster
Unconditional 2030 LFPR forecast: 62.8%

In 2030 the rapid progress scenario may have a roughly covid-sized impact (a drop of about 3%) in reducing the LFPR in the 10th percentile case. More likely, the rapid progression hasn't had a chance yet to disrupt the labor force. In 2050, with virtually all work (including physical work) being possible to do by AI, there would be few industries with human workers remaining. Some of them may be:

1. "organic" artists (actors, writers, that cater to an audience that prefers a human voice)
2. politicians (perhaps to ensure that human alignment is maintained)
3. certain legal professionals for a similar reason (e.g. AGs, judges)
4. certain professionals in the food industry? even if robots can cook as well as humans and can taste food the same way, some may prefer "organic food" (similar to 1)

I'll estimate 10% for all these industries together, and perhaps another 15% for jobs that don't quite exist yet (alignment professionals? at least in a more practical rather than philosophical sense)

Respondent group: Economist
Unconditional 2030 LFPR forecast: 64.2%

a) At the beginning of 2030:

Unconditional forecasts: 10th percentile = about 65%; 50th percentile = about 64%; 90th percentile = about 63%,

Slow AI progress: 50th percentile = 62%,

Moderate AI progress: 50th percentile = 64%,

Rapid AI progress: 50th percentile = 61%,

b) At the beginning of 2050:

Unconditional forecasts: 10th percentile = about 66%; 50th percentile = about 65%; 90th percentile = about 64%,

Slow AI progress: 50th percentile = 63%,

Moderate AI progress: 50th percentile = 65%,

Rapid AI progress: 50th percentile = 62%,

Forecasts are based on the following aspects.

1. The 2030 scenario is more anchored to current evolution compared to later scenario

2. In 2050, labor market participation will depend on different factors, including immigration and demographic evolution, that can very depending on policies, other confounding factors different from AI

Respondent group: Economist
Unconditional 2030 LFPR forecast: 63.7%

Note that in the case of a rapid progress of AI, the disruptive effect on the labor market can be high in the short run, with a negative effect on the dependent variable. However, in the short run, the positive effect is expected to be large (the increase in labor productivity will increase GDP and aggregate demand, with new jobs creation).

I.4.2 Medium forecast rationales

Respondent group: Economist
Unconditional 2030 LFPR forecast: 60%

Until 2030, I expect the impact of AI on the labor participation rate to be low because of slow diffusion and regulatory barriers. Only under the Rapid Progress scenario do I expect a major downward trend. Many people will still work, mainly because integrating AI capabilities into production processes takes time and policymakers will try to maintain employment.

By 2050, labor force participation will drop considerably. Under the Slow and Moderate Progress scenarios, a significant share of the population will still work, protected by regulations or due to preferences for humans to perform certain roles (e.g., doctors). This share might decline further in the future. Under the Rapid Progress scenario, only a few humans will still work in the traditional sense, mostly in areas where society chooses to keep humans in the loop (politics, parts of teaching, medicine). I expect most people to remain active, but not through conventional employment.

My prediction is based on the assumption that high levels of unemployment beyond 15-20% are not sustainable for any government in the U.S. and we would therefore see a separation of income from employment (in one form or another).

Respondent group: Economist
Unconditional 2030 LFPR forecast: 60.8%

The effect of aging increases as large cohorts retire. This is the main force pulling participation down. Immigration offsets it a bit, but I expect inflows to slow under the current administration. Better senior health and remote work slightly slows participation decline.

Slow progress: By 2030 AI handles routine tasks (text writing, information gathering, summaries, basic customer chat and other simple chores). While productivity rises moderately, impact on labor demand and supply stays low. By 2050 AI starts enhancing workforce participation for groups such as parents, older workers, people with disabilities, but demographic trends continue to dominate.

Moderate progress: In this scenario, the effects on workforce participation seen by 2050 in the slow progress scenario are already evident by 2030. Advanced tools, seamless remote work platforms and level 5 autonomous robo-taxis enable parents, people with disabilities and seniors to join or remain in the workforce supporting labor force participation rates against ageing. By 2050, steady AI improvements offset a considerable part of the demographic drag. Routine roles start disappearing but new, better paid AI jobs fill the gap.

Rapid progress: In 2030 AI outperforms human freelance software engineers. The same goes for customer service (e.g., call center and support chat), paralegal, and administrative workers (e.g., bookkeepers or scheduling assistants). Displacement beats reskilling and participation drops. By 2050 job markets adapt. AI makes jobs safer, better paid and less tiring, health outcomes improve, work-life balance strengthens, education pivots to AI skills and higher wages pull in more immigrants, lifting participation above the early dip.

Respondent group: Economist
Unconditional 2030 LFPR forecast: 62%

Labor force participation in 2030 is unlikely to radically change from its current level because of the lag in adoption and efforts of displaced workers to find alternative employment. For 2050, there is substantial uncertainty over whether individuals will completely drop out of the labor force or will work fewer hours and how tied health care is to being employed. By 2050, it is clear that AI will have greatly impacted the number of jobs with large scale employment (ranging from commercial drivers to fast food to nursing homes) in sectors where employees are not getting substantial utility from "working" other than through their financial remuneration. The ability of the economy to generate jobs (even part time jobs) that provide such utility is a deep source of uncertainty. However, labor force participation has a low bar - 1 hour per week worked.

Keynes' predictions about people working 15 hours and spending the rest on leisure in 2020 may not be far off.

I.4.3 Low forecast rationales

Respondent group: Superforecaster
Unconditional 2030 LFPR forecast: 59.1%

As a baseline, labor force participation peaked around 2000 and has since been in decline from 67.3% to the 2024 number of 62.6%, resulting in an annualized decline of 0.2 percent. Demographics will continue to drive this, which is to say we are experiencing an aging population. Even with the robust immigration the US has experienced, we should see the average age of the US population continue to rise, reducing the overall number of available workers accordingly. As Drucker once observed, demographics is destiny. Implications of these trends are the easiest things to forecast.

As this paper points out, the skilled labor gap will be of greatest concern. And now we have AI entering the workforce, so to speak. To a very large extent, these trends can be seen as complementary and will tend to drive one another forward more forcefully. That is to say, we will see a significant increase in the rate of reduction of the labor force participation rate as older workers are forced to retire earlier, and then those higher cost positions are taken up permanently by AI. This is likely how the skill gap will be easily filled. On the other hand, while higher paying, full-time positions will greatly reduce over time, part-time and casual labor positions will increase. This will somewhat offset the AI driven reduction in employment.

By 2030, we will see the trend accelerating, but it will not be at peak by that time. Businesses will focus on replacing those positions that have the most AI friendly aspects (digital based / requires analysis / detailed oriented repetitive work), especially those paying the most. But there are likely whole labor categories that can be completely done away with eventually. However, this will take time. The current generation of LLMS are capable of being extremely good at specific things, though they still require close monitoring by humans, and will need to be specifically applied to a given area. So it will take some time to implement all of this tremendous potential, and that will slow the inevitable trend for the next five or so years.

Even so, the 2030 Slow Progress scenario (which I see as the unconditional scenario) will still increase the baseline reduction trend by 0.3%, bringing it to a 0.5% annual reduction for the 50th percentile, or a 2.5% cumulative reduction down to 60.1%. For the 10th percentile, I am adding a full percent reduction. And for the 90th percentile, I am assuming virtually no AI effect, leaving it at near baseline reduction of 61.0%.

Moderate Progress (also my unconditional scenario) would allow much more ambitious human labor replacements. But still, the work of implementation will slow things for at least the next few years. It just takes time to build clever systems that are at once resilient and completely reliable. Some areas will allow easy replacement. But no business will risk disaster for quick conversions in all cases. Also, for at least a few years, there will be a poverty of imagination that will slow things. Many business leaders will not be able to comprehend how to do any of this, and they will need to be replaced by those that can and will. Still, better business cases from better progress will likely increase the reduction rate to 0.7 percent per annum, resulting in a 3.5% reduction to 59.1%.

Rapid progress would bring annual reduction to 1.0 percent for the 50th percentile, which would be significant, but nowhere near what we would see by 2050.

By the beginning of 2050, we will likely be through the most major reductions in labor force participation. I would assume that aging of the US population would have accelerated the baseline rate of 0.2% to 0.3%. But that will be dwarfed by the effects of full AI implementation. By 2050, AI will pervade practically every area of life. There will be very few professions that AI cannot do better, faster, and cheaper. But on the other hand, labor productivity will explode higher and economic activity will grow at a rate that is even higher than the peak of industrialization. While we will see a reduction in labor force participation, it will be mostly in what used to be full-time employment. There will be a partial offset from all sorts of odds and ends type part-time and / or casual labor. I assume this source of poor substitution will offset 50% of the brutal reductions we can expect from AI.

For even slow progress, labor force participation will fall off tremendously, both from continued aging trends and outright population decline, and strong AI implementation. By this time, AI solutions will have been implemented in every area that they can be, but the effects were less impressive than expected because of myriad practical realities. Still, we will have the baseline reduction of 0.2 for demographics, and then at least 0.8 percent percent per year reduction (1.6 percent offset by 0.8 part time) from increasing AI implementation.

For Moderate Progress, AI implementation has gone a bit better and more areas were successfully replaced almost entirely by AI. But even then, there are just some positions where AI either cannot replace, or where we still need the human in the loop. And then we will have great need drive many into any kind of part-time or casual labor possibly available. With that in mind, I am assuming an annual drop of 0.2 percent for demographics, and 1.0 percent from AI in the labor force participation rate.

Rapid progress at 50th percentile means that AI has been entirely successful in replacing practically everything it can in terms of human labor. And what's more, the human often is worse being in the loop than not. However, we will be nearing a frictional area of labor participation, where rock bottom is likely around 25%. For some professions, there is no human replacement, for aesthetic reasons if nothing else. And since even minor part-time or casual labor counts as participation, we could still have higher participation where such work is more of a hobby than a meaningful source of income.

Respondent group: Superforecaster
Unconditional 2030 LFPR forecast: 57.3%

In the baseline scenario, LFP has been trending down since 2005, and this trend of decline will accelerate in the next years. This is because many people will retire in the next few years due to demographic change. In the base line scenario, there isn't much change to this small trend until 2050.

But in the rapid progress scenario, all bets are off. Actually, it is the same even with moderate progress. One theme that is underrated in this environment is that AI might enable extreme longevity. This will mean retirement becomes obsolete. It's impossible to provide a pension for people whose life expectancy is indefinite. So everybody might work, except of course children, caregivers like mothers (it's a definition thing I guess to say they are "not in the labor force" for their kids), and privatiers with wealth sufficient to sustain them forever just on the interest. Working might also become much easier and more pleasant, with much shorter workweeks due to productivity, which might lure people into the labor force.

OTOH, transformative AI (TAI) could just need a small cadre of managers/dexterity workers to do the things it can't do. So in the long run, most people will live a life comparable to today's retirees forever. It's hard to say; both scenarios to me are comparably plausible with TAI!

Respondent group: Superforecaster
Unconditional 2030 LFPR forecast: 58.8%

By 2030, I expect labor force participation to have trended downward in all scenarios because of retirements and I expect there may be another significant recession before then that permanently lowers the participation rate. In the rapid progress scenario, my 10th percentile is at 0 because it's possible that AGI will have arrived and displaced humans from the workforce by then, especially given that the scenario includes advanced robotics.

By 2050, my 10th and 50th percentiles are 0 because I expect AGI which has displaced humans from the workforce to have arrived by then (this is based on a number of things, including Ajeya Cotra's biological anchors model, Epoch's Direct Approach, insiders' views and outside views such as semi-informative priors). My 90th percentiles are still within the historical range because it's possible that I'm wrong about AGI's economic impact or its impact on labor markets and that it enhances rather than displaces human labor.

I.5 Wealth Inequality

- High forecasts: >74.98% (n = 25)
- Medium forecasts: 72 to 74.98% (n = 49)
- Low forecasts: <72% (n = 24)

I.5.1 High forecast rationales

Respondent group: Economist
Unconditional 2030 wealth inequality forecast: 75%

For sure, wealth inequality will increase, regardless of the scenario. This is really well analyzed in the Cazzaniga report. Essentially, wealth inequality increases because the owners of capital receive high returns in any AI scenario. Even without AI, in the absence of policies countervailing the concentration of wealth, the concentration of wealth at the top will continue. In Europe, people have started talking about limitarism and redistribution, etc. But I also do not expect that there will be much change on this front, and AI will make matters worse.

Respondent group: Economist
Unconditional 2030 wealth inequality forecast: 75%

I expect wealth inequality to increase as AI raises the importance of capital in production at the expense of labor. People who own capital, especially land, will be better positioned to expand their wealth. Since overall wealth is likely to rise significantly, most people will still be better off, and therefore the increase in inequality will most likely not cause major social unrest.

Until 2030, changes will likely be moderate. By 2050, I expect wealth inequality to have increased significantly.

Respondent group: Economist
Unconditional 2030 wealth inequality forecast: 75%

a) At the beginning of 2030:

Unconditional forecasts: 10th percentile = about 72%; 50th percentile = about 75%; 90th percentile = about 77%,

Slow AI progress: 50th percentile = 72%,

Moderate AI progress: 50th percentile = 77%,

Rapid AI progress: 50th percentile = 80%,

b) At the beginning of 2050:

Unconditional forecasts: 10th percentile = about 72%; 50th percentile = about 75%; 90th percentile = about 77%,

Slow AI progress: 50th percentile = 72%,

Moderate AI progress: 50th percentile = 77%,

Rapid AI progress: 50th percentile = 80%,

In 2030, the share of wealthy individuals is likely, in my opinion, to rise given that there are no expected counteracting policies. A rapid adoption of AI tools (rapid progress scenario) probably would lead to more inequality given the concentration of this market in few firms. Making predictions for 2050 is difficult given that confounding factors can influence this specific variable.

I.5.2 Medium forecast rationales

Respondent group: Economist
Unconditional 2030 wealth inequality forecast: 73.5%

1) Anchor: we're starting from an already extreme level.

The survey notes 71.2% in 2023 for the U.S. top 10% wealth share (OWID/WID-based). With a starting point that high–no big change–is not 60%, it's low-70s. (And different measurement systems can give different levels: e.g., the Fed's Distributional Financial Accounts put the top 10% share of household wealth lower, around the high-60s in some recent summaries, but the survey's resolution source is OWID/WID, so I'm forecasting that concept).

2) Why AI progress affects wealth much more than income (and why 'agency' matters).

Wealth concentration is fundamentally about who owns the scarce assets that capture rents: equities, private business ownership, IP, and (increasingly) intangible capital. In the rapid scenario, the economically salient capability shift is high agency + problem-solving, which makes AI a closer substitute for broad task bundles. That raises the expected surplus accruing to owners of scalable capital and platforms, and weakens labor's outside option, exactly the mix that pushes a larger share of national wealth to the top.

3) Scenario wedges (what changes across slow/moderate/rapid).

- Slow: AI remains largely assistive; the economy looks like a continuation of current trends. Wealth concentration still rises somewhat (asset-price dynamics, existing market power), but not dramatically: from 72% to 76% by 2050.

- Moderate: enough capability to compress many white-collar job ladders (even without full robotics), increasing the capital share and the value of incumbent intangibles; compounding over 25 years gives a meaningful rise: from 73.5% to 80.5%.

- Rapid: the combination of (i) faster automation of cognitive production, (ii) winner-take-most platform dynamics, and (iii) politically resilient rents (IP, data, compute, distribution) produces a much higher endpoint: 79% by 2030 and $\tilde{8}$8% by 2050 on the median path, unless checked by aggressive redistribution/competition policy. I am also assuming that such stark wealth inequality doesn't lead to major social upheaval, or worse.

4) Why the distributions are not symmetric (upper tail fatter, especially under Rapid).

Wealth concentration has a natural convexity: when returns to capital rise, the top benefits disproportionately because portfolios are more equity-/business-heavy and can leverage opportunities; that compounding produces 'runaway' scenarios (hence 93% as a plausible 2050 Rapid P90). The downside tail is thinner because reversing wealth concentration requires sustained policy (tax, competition, corporate governance, housing, education/asset-building) and/or long periods of weak asset returns, both possible but harder to sustain than continued drift upward.

5) Internal consistency with the rest of my forecasts.

Given Moderate = 74% in my scenario-weighting, the unconditional median = Moderate median (by construction). And the Rapid scenario's higher unemployment/lower participation I already forecast is exactly the environment where wealth shares can rise even if GDP rises: output becomes less labor-intensive and rents accrue to owners.

If I were to explicitly build in a 'political-economy constraint'(extreme wealth concentration raises the probability of backlash / instability), then the shape of the forecast distribution would change, especially by 2050.

This is how it would change conceptually:

1) The upper tail gets endogenously truncated.

My earlier Rapid P90 of $\tilde{9}$3% for 2050 is essentially a 'no-binding-constraint' extrapolation: rents compound, and nothing forces mean reversion. If one allows that very high concentration is itself destabilizing, then once the top share pushes into the high-80s, the likelihood of redistributive regimes (tax, antitrust, partial socialization of AI rents, wealth/estate policy, tighter corporate governance) rises sharply. I mean, a civil war could lead to drastic redistribution. That makes outcomes like >90%less likely.

2) The distribution becomes more nonlinear (often bimodal).

One gets two qualitatively different regimes:

- Rent persistence regime: concentration continues to rise (platform rents + capital-biased automation + weak bargaining power).

- Backlash regime: either (a) policy rebalancing that pushes the top share down, or (b) social breakdown that can push it either way (expropriation reduces top share; but chaotic inflation/asset destruction can wipe out middle wealth and perversely raise the share held by the top if they can protect assets).

So the right way to think about 2050 is less 'smooth compounding' and more 'fat-tailed politics.'

3) The median may move only modestly, but confidence in it should fall.

I really don't know how to quantify the political risk. I do think backlash is plausible but not dominant, which would mean the median wealth share under Rapid might not change dramatically; what changes most is that my earlier very high P90 is less defensible, and I would need to acknowledge the regime-switch risk.

I incorporate this explicitly into my forecasts, I would mainly adjust 2050 (2030 is too soon for the constraint to bite hard).

- Rapid AI scenario (2050): from 82 / 88 / 93 to something like 78 / 85 / 90

– P90 falls because ever-higher concentration is less stable.

– P10 falls too because strong backlash becomes more plausible (a more equal outcome is no longer 'rare'.

– P50 dips a bit because some probability mass shifts from 'continued drift up' into 'policy mean-reversion.'

- Unconditional (2050): I would say the same logic applies but more weakly (since Rapid only has $\tilde{8}$% weight in my panel-scenario beliefs). So I'd trim the unconditional P90 a little and trim the P10 a little, with the median still essentially pinned by the Moderate scenario.

Respondent group: Economist

Unconditional 2030 wealth inequality forecast: 72%

I think the realized distribution of wealth depends mostly on policy (education, taxation, etc), and not on technological progress. That is, for a given level of technological progress, policy can achieve many different levels of wealth inequality. The US appears to have reached a level of wealth inequality that a large share of the population is unhappy with and feels is unfair. While I don't necessarily foresee a definite decrease given how high taxes already are and how unpopular tax increases tend to be, I see a decrease as more likely than an increase, both in the short run and the longer run. Of course, policy responses are a choice, so it's possible for wealth inequality to increase on net. And policy responds with a lag, which is why I think we might see a larger increase in equality in the short run compared to the longer run. With rapid AI progress, growth may be higher (making redistribution feel less costly) and the returns to human capital may be lower. For this reason, I see a larger possibility of a meaningful long-run decrease in inequality in the rapid progress scenario.

Respondent group: Economist
Unconditional 2030 wealth inequality forecast: 72%

Asset prices keep outpacing wage growth. Aging increases large inheritances.

In the slow progress scenario AI is mostly a helper. The rich gain only slightly faster than average households, inequality rises but slowly.

In the moderate progress scenario the effect is more notable. Productivity increases and capital owners as well as high skilled workers capture the biggest slice.

The rapid progress future might create "winner takes most" platforms. Equity and data assets surge, human labor becomes highly replaceable, concentrating wealth sharply at the top.

I.5.3 Low forecast rationales

Respondent group: Superforecaster
Unconditional 2030 wealth inequality forecast: 70.3%

Generally, people think two things about redistributive effects of TAI. One, the rich might get richer and the poor have no comparative or absolute advantage any more, so they would languish in poverty. Unless there is massive redistribution. This is the view of Dario Amodei in Machines of Loving Grace most prominently.

I view the situation differently. Comparative advantage and trade have held since the dawn of humanity. Even in the 19th century with its household servants, inequality wasn't as high as Amodei predicts for TAI. There might be redistribution or not, but the rich will get richer as they have always. The poor will get richer too, though, because of the rising tide lifting all boats, even if they are not very productive in the transformed economy. TAI will be the first time you can become rich even though it is not off the back of others; you can become rich off the back of AI and today everyone can share in Musk's wealth by just buying Tesla shares or being a diffuse claimant to Tesla's tax revenues.

Respondent group: Economist
Unconditional 2030 wealth inequality forecast: 71%

The top-10% wealth share changes slowly, so by 2030 it remains close to recent levels. Under slow AI progress, limited effects on returns to capital keep concentration near trend. Under moderate progress, higher returns to skilled labor and capital modestly increase concentration.

Under rapid AI progress, advances in problem-solving, agency, and AI-driven research raise the value of scalable assets and IP, increasing wealth concentration.

Respondent group: Economist
Unconditional 2030 wealth inequality forecast: 70%

I think much of the public debate on this is mistaken. For two reasons.

First, it is by no means a given that the AI companies will become tremendously profitable. The three leading companies are neck to neck and have alternated between first place in the past year. The competitive structure might end up being closer to Bertrand competition than anything else. If AI / compute becomes a commodity then the entire benefit will accrue to the users of the AI, not the producers, and consequently be much more broadly spread.

Second, a future with abundant and cheap compute will drive down the price of the very things where compute is valuable.

It is by no means a given that Amodei will own the world.