Generative AI and Economic Growth

A new approach to measuring its potential economic impact

November 2025

Note: Assessment based on productivity estimates focused on GenAI that continue to be changed, especially with AI agents being deployed.

Contents

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Executive Summary

Generative AI (GenAI) and agentic AI are poised to revolutionize global economies and employment landscapes. In the past few years, we've witnessed the launch of large language models, which have grown in sophistication and capabilities. They've scored higher on a variety of tests, advanced from text-based answers to voice, design, and video. This year, the generative AI hype has shifted to agentic AI, which shifts from answering questions or creating content to completing tasks with various levels of sophistication.

With so much changing almost every month, this study develops a novel method for understanding the potential impacts of GenAI adoption in our economy, across industries, and within job roles.

The study employs a dynamic global economy-wide model, specifically the KPMG dynamic economywide model, which is a computable general equilibrium (CGE) model. This model captures inter-industry linkages, disaggregates US households by income and race, and connects the economy globally. The model uses the most recent Global Trade Analysis Project (GTAP) database, widely used data for economywide models.

Importantly, the study incorporates labor productivity estimates at the industry and sector level and within job roles derived from the KPMG patent-pending GenAI value assessment model.

GenAI value assessment is an advanced technological service that offers clients a qualitative, outside-in assessment of GenAI opportunities and the readiness of a target organization. This assessment evaluates the achievable GenAI opportunity that an organization can potentially capture through investments in GenAI, and it also identifies peer benchmarks for comparative analysis.

For this study, we aggregated the GenAI opportunity values by job role and by the North American Industry Classification System (NAICS) industry. Furthermore, based on location of the opportunity values, the industries are mapped to 10 global regions.

This mapping allows us to accurately assess the potential economic benefits of GenAI implementation for specific skill groups within an industry, such as finance professionals in the chemicals industry or human resources personnel in the pharmaceutical products industry.

Leveraging productivity estimates from last year that focus on generative AI—not agentic AI—this study evaluates the potential of AI impacts on our economy using this novel approach to inform policy, business strategy, and workforce development.

Three scenarios were analyzed: a baseline scenario without GenAI adoption, a rapid adoption scenario, and a slow adoption scenario, to project economic impacts from 2024 through 2050. In addition, a rapid adoption scenario without upskilling of labor force was also examined.

To illustrate how findings may evolve over time as large language models and AI agents alter expected productivity impacts, we've also included an analysis of a hypothetical high productivity scenario with rapid adoption.

Importantly, productivity estimates have changed and will continue to change with significant uncertainty today as innovation continues to define the artificial intelligence space. As large language models evolve, we will continue to evaluate how changes in the productivity benefits derived from both GenAI and agentic AI adoption change our economy.

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Key Findings

1 Economic Growth

Our baseline scenario using productivity estimates in 2024 finds that rapid adoption of GenAI could add up to $2.84 trillion to the US GDP by 2030, and $3.37 trillion by 2050. Globally, the economy could see an additional growth of $11.04 trillion by 2050 under rapid adoption, and $9.83 trillion under slow adoption. The US and Europe are projected to gain the most, with $3.38 trillion and $2.72 trillion respectively by 2050.

2 Employment

Rapid GenAI adoption is expected to create a net gain of 8.06 million jobs in the US by 2050, while slower adoption could result in 5.79 million new jobs. However, rapid adoption of GenAI without upskilling, could result in net job loss of about a million by 2050. Key sectors such as education, healthcare, and government are expected to see major job growth.

3 Unemployment Rate

The rapid adoption of GenAI is projected to result in a marginal increase in unemployment rate of 0.15% compared to the baseline in 2050. In contrast, without upskilling, the rapid adoption scenario shows a notable increase in the unemployment rate to 5.55%, with a net increase of 0.51% relative to baseline.

4 Investment Opportunities

Both rapid and slow adoption of GenAI create considerable investment opportunities. Rapid adoption offers gains in investment multiplier effect across most sectors compared to slow adoption. Sectors such as education, healthcare, and transportation show the highest gains from early and extensive implementation of GenAI.

This study showcases the value of a new framework for evaluating the impact of generative and agentic AI on our economy. The study underscores the transformative potential of GenAI in driving economic growth, creating new job opportunities, and enhancing productivity.

However, it also highlights the critical importance of upskilling and reskilling the workforce to fully leverage the benefits of GenAI and ensure equitable distribution of its advantages. Strategic investments in training and infrastructure are crucial to maximize the economic gains from GenAI. Policymakers and stakeholders must focus on creating informed policies that address job displacement, income inequality, and the need for new educational and training programs to foster an inclusive and sustainable economic future.

Going forward, this model will help us better understand the economic implications of AI as it changes our economy.

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

1. Background

In the span of just the past couple of years, Generative AI (GenAI) has moved rapidly from pilot trials to widespread adoption. Consumers adopted GenAI, such as OpenAI's ChatGPT project, at twice the rate of tablets and smartphones.[1] And GenAI is already having an increasing impact on the way organizations do business. It's rare to find an enterprise today that doesn't have its foot on the GenAI accelerator. According to a Q4 2024 KPMG AI Pulse Survey, 68% of leaders will invest between $50-$250 million in GenAI over the next 12 months, up from 45% in Q1 of 2024 (KPMG, 2025).[2] The Q2 2025 KPMG AI Pulse Survey found that 90% of organizations were passed experimenting with agentic AI and were now piloting and deploying.[3]

The study underscores the transformative potential of AI and the pace of innovation.

GenAI is a subset of artificial intelligence that relies on generative models that learn from existing data and patterns to create new content, including text, images, audio, and video. It combines technology and data to drive innovation with great speed and efficiency—and has far-reaching implications for how work gets done in the future. GenAI is already impacting the workforce, with 66% of CEOs surveyed expecting that the implementation of GenAI would require both hiring new talent, as well as training existing talent. GenAI technologies, which include advanced machine learning models capable of generating text, images, and other media, are poised to revolutionize various sectors by enhancing productivity, creating new job opportunities, and driving innovation. However, understanding these impacts requires a nuanced analysis to ensure that the benefits are maximized while mitigating potential downsides such as job displacement and economic inequality.

Globally, the economic impact of GenAI extends beyond national borders, influencing international trade, labor markets, and economic policies. Countries with robust technological infrastructures and policies that support innovation are likely to benefit the most, potentially widening the economic gap between developed and developing nations (Capraro et al., 2024).[4] GenAI's economic implications are particularly crucial in the US, given the country's leading role in technological innovation and its diverse economy. These advancements also necessitate a careful examination of workforce dynamics, as automation may displace certain job categories while creating demand for new skills (Hosseini et al. 2024).[5]

Despite the rapid investment in GenAI, the research on the economic implications of GenAI is still in a nascent stage. Initial findings indicate substantial potential effects on productivity, employment, and inequality (Acemoglu et al. 2022).[6] However, the specifics of where, how and by whom the economic impacts of GenAI will be felt are not well-understood. By studying these impacts, policymakers and stakeholders can better navigate the complexities of GenAI, fostering an inclusive and sustainable economic future.

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[1] Sara Lebow, "Generative AI Adoption Climbed Faster Than Smartphones, Tablets," eMarketer (August 11, 2023)

[2] KPMG (2025a). "AI Quarterly Pulse Survey." Retrieved from: https://kpmg.com/us/en/articles/2025/ai-quarterly-pulse-survey.html

[3] KPMG (2025b). "AI Quarterly Pulse Survey." Retrieved from: https://kpmg.com/kpmg-us/content/dam/kpmg/pdf/2025/ai-quarterly-pulse-survey-q2.pdf

[4] Capraro, V. et al. (2024). "The impact of generative artificial intelligence on socioeconomic inequalities and policy making," PNAS Nexus, 3(6):191. Retrieved from: https://doi.org/10.1093/pnasnexus/pgae191

[5] Hosseini, M.; S.P.J.M. Horbach, K. Holmes, & T. Ross-Hellauer (2024). "Open Science at the Generative AI Turn: An Exploratory Analysis of Challenges and Opportunities." Quantitative Science Studies (Advance Publication), Retrieved from: https://doi.org/10.1162/qss_a_00337

[6] Acemoglu, D.; D. Autor, J. Hazell, & P. Restrepo (2022). "AI and Jobs: Evidence from Online Vacancies." NBER Working Paper 28257, National Bureau of Economic Research, (NBER) Cambridge, MA. Retrieved from: http://www.nber.org/papers/w28257

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1.1 Beyond the Hype: The Imperative behind the GenAI Impact Study

In an era where technological advancements are rapidly reshaping our world, understanding the profound implications of GenAI is more critical than ever. While GenAI continues to evolve, expanding the potential disruptions and changes to the workforce, this study focuses specifically on the impact of productivity as a key metric because of its prominence. Productivity gains are just one aspect of the broader set of disruptions and changes that GenAI brings to the workforce. The insights from this study are based on GenAI impacts, although the rapid emergence of artificial general intelligence (AGI) could soon alter the workforce and productivity dynamics.[7] This research aims to provide a comprehensive analysis that informs policy, business strategy, workforce development, and economic equity. Understanding these impacts is crucial for several reasons:

Shaping Tomorrow—the critical role of GenAI in policy making: Governments and policymakers need to understand the economic implications of GenAI to create informed policies that balance innovation with safety and security. This includes addressing issues such as job displacement, income inequality, and the need for new educational and training programs.

Strategic Edge—how GenAI is revolutionizing business decisions: For businesses, understanding the economic impact of GenAI can inform strategic decisions regarding investment, workforce development, and competitive positioning. Companies that can effectively leverage GenAI are likely to gain significant competitive advantages. There are considerable opportunity costs. The risk of falling behind others and losing trust in your ability to innovate is real and significant. Fast follower advantage continues to erode. It may be too hard to catch up, which is why organizations are investing without the traditional ROI case.

Future-Proofing Careers—the essential skills for a GenAI-driven world: As GenAI transforms industries, there will be a growing need for new skills and roles. Identifying these changes early can help educational institutions and training programs adapt to prepare the future workforce.

Bridging the Gap—ensuring economic equity in the age of GenAI: The distributional impacts of GenAI could exacerbate existing inequalities or create new ones. Studying these effects can help ensure that the benefits of GenAI are broadly shared across different communities and demographic groups.

[7] The study primarily considers GenAI as understood by large language models (LLMs) at the time, without agentic capabilities. As agentic capabilities advance, they have the potential to accelerate or shift these dynamics considerably.

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2. Charting the Course

Insights from Past Studies on GenAI's Impact

GenAI, has emerged as a transformative technology with significant economic implications. The literature extensively explores its impact on productivity and labor markets. For instance, Brynjolfsson and Li (2024) found that generative AI tools can significantly enhance worker productivity, especially in technical customer support roles, with a notable 14% increase. These productivity gains are most pronounced among less experienced customer support workers, highlighting the potential of AI to level the playing field in certain job sectors. However, the impact on labor markets is complex, as generative AI can create new job opportunities and enhance existing roles while also posing risks of job displacement. The benefits tend to favor higher-skilled workers and larger firms, leading to uneven distribution across the workforce. The socioeconomic implications of GenAI are equally profound. While AI has the potential to democratize access to information and improve productivity, it can also exacerbate existing inequalities.

KPMG conducted a study with the World Economic Forum (WEF) which provides a comprehensive framework for understanding AI's impact on economies and societies.[8] The framework emphasizes AI's transformative potential in driving economic growth and innovation, provided it is developed responsibly and equitably. The blueprint highlights the importance of building sustainable AI infrastructure, curating high-quality datasets, and establishing ethical frameworks. The study advocates for a collaborative approach involving governments, enterprises, academia, and civil society to ensure inclusive AI development, thereby maximizing benefits for all. Nations face unique challenges in fully leveraging AI's benefits due to various factors. These challenges include securing the substantial investment needed for advancing AI innovation and addressing significant gaps in digital infrastructure, which exacerbates the existing digital divide. In this context, the WEF framework underscores the need for building resilient national AI ecosystems and promoting widespread adoption of AI, which requires coordinated multistakeholder action. The study also emphasizes the need for international collaboration to facilitate global trade and secure cross-border data flows, promoting the development of inclusive AI models and applications.

Recent literature survey reveals that effective policymaking is crucial to harness the benefits of AI while mitigating its adverse effects. The literature underscores the need for interdisciplinary approaches and robust policy frameworks to address these challenges, ensuring that the advantages of AI are more equitably distributed.

The literature on economic impact of GenAI spans several dimensions, including productivity, labor markets, industry-specific impacts, and broader economic growth. A brief survey of literature is listed in Table 2.1.

[8] World Economic Forum (2025) "Blueprint for Intelligent Economies: AI Competitiveness through Regional Collaboration." In collaboration with KPMG. Retrieved from: https://reports.weforum.org/docs/WEF_A_Blueprint_for_Intelligent_Economies_2025.pdf

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Table 2.1: A Review of Literature on Economic Impacts of GenAI

Study	Key Economic Finding	Sector/Focus Area
Brynjolfsson & McAfee (2017)[9]	Productivity increase by up to 40%	Creative industries
Acemoglu & Restrepo (2022)[10]	Displacement of up to 15% of jobs; creation of new roles	Labor market
Goldfarb & Tucker (2019)[11]	Cost reduction by 30%; targeting efficiency increase by 25%	Advertising
Agrawal, Gans, & Goldfarb (2018)[12]	Additional 1.2% annual GDP growth	Broader economy
Bessen, J. (2022)[13]	Net positive job creation in AI-intensive sectors	Various sectors
Cockburn, I., Henderson, R., & Stern, S. (2018)[14]	Accelerated innovation cycles and increased R&D productivity	Technology and R&D
Kaplan, A., & Haenlein, M. (2019)[15]	Enhanced customer engagement and personalization	Retail and customer service
Brynjolfsson and Li (2024)[16]	A 14% increase in productivity	Technical customer support roles
Capraro et al. (2024)	Improvement in productivity, but could widen the digital divide and deepen existing inequalities	Education and healthcare

While there is a growing body of research on GenAI, several gaps remain such as estimating productivity gains across all sectors and regions from adoption of GenAI, linking sector-specific impacts with that of overall economy, impact across developed and developing regions, and equity implications across the US households. By addressing these gaps, this study attempts to provide a more comprehensive understanding of the economic impact of GenAI and help stakeholders navigate the challenges and opportunities it presents.

[9] Brynjolfsson, E., & McAfee, A. (2017). "The Business of Artificial Intelligence: What it Can—and Cannot—Do for Your Organization." Harvard Business Review. Retrieved from: https://hbr.org/2017/07/the-business-of-artificial-intelligence

[10] Acemoglu, D., & Restrepo, P. (2022). "Artificial Intelligence, Automation, & Work." Journal of Economic Perspectives, 36(2):119-140.

[11] Goldfarb, A., & Tucker, C. (2019). "Digital Economics." *Journal of Economic Literature*, 57(1), 3-43.

[12] Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*. Harvard Business Review Press.

[13] Bessen, J. (2022). *AI and Jobs: The Role of Demand*. National Bureau of Economic Research. Working Paper No. 24235. DOI: 10.3386/w24235.

[14] Cockburn, I., Henderson, R., & Stern, S. (2018). *The Impact of Artificial Intelligence on Innovation*. NBER Working Paper No. 24449. DOI: 10.3386/w24449.

[15] Kaplan, A., & Haenlein, M. (2019). "Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence." *Business Horizons*, 62(1), 15-25.

[16] Brynjolfsson, E. & D. Li (2024). "The Economics of Generative AI." The Reporter (1). National Bureau of Economic Research, Retrieved from: https://www.nber.org/sites/default/files/2024-04/2024number1_0.pdf

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

3.1 KPMG dynamic economywide model

The CGE model developed in this study, KPMG dynamic economywide model, is a comprehensive economic model that predicts economy-wide implications of an economic shock. The KPMG dynamic economywide model is developed based on the extended version of Global Trade Analysis Project (GTAP), called MyGTAP model (Walmsley and Minor, 2013)[17] and a recursive-dynamic model (GTAP-RD: Aguiar et al., 2019)[18] enabling it to capture and analyze changes over time. The recursive dynamic features include projecting year-over-year changes capturing the evolution of the economy including capital accumulation, labor productivity and other exogenous macro-economic forecasts such as population growth and changes in global economic conditions. This model combines economic theory and empirical data to account for all trade flow interactions among industries, consumers, and countries globally while simultaneously ensuring economic as well as accounting consistency. The KPMG dynamic economywide model provides a cutting-edge framework for analyzing the comprehensive and dynamic impacts of economic policies, providing valuable insights for policymakers and researchers.

3.2 The CGE Database

The KPMG dynamic economywide model is built upon the most recent GTAP database (Aguiar et al. 2023),[19] a distinctive and extensively utilized database for economywide modeling. The GTAP database is a multi-country, multi-sector dataset that maps the input-output relationships between sectors and the trade connections between countries and regions globally. It integrates policies governing production, consumption, and trade, drawing data from international sources such as UN COMTRADE, the World Bank, the International Trade Commission, and the International Monetary Fund (IMF). This unique, globally balanced database also includes behavioral elasticity parameters for producers and consumers, some of which are econometrically estimated, while others are calibrated to align with economic theories.

The latest GTAP database encompasses 158 global regions and 65 sectors as of 2017. Although running simulations on fully disaggregated data is ideal, it is not feasible due to the high computational resources required. Therefore, we created custom aggregation comprising of 48 sectors (Table B1, in Appendix B) and 10 global regions to capture the economic dynamics of the major global economies.[20] The factors of production in the CGE database typically include land, labor, capital, and natural resources. The International Labor Organization (ILO) classifies labor by skill levels based on educational attainment, and this data is incorporated into the GTAP database as labor endowment across five skill levels. Since the GTAP database used in this study is based on the global economy of 2017, we updated it to reflect the 2022 global economy using a method called entropy optimization. We used Gross Domestic Product (GDP) data from the IMF and sector output data from the Bureau of Economic Analysis (BEA) for 2022.

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[17] Walmsley, T. and P. Minor (2013). "MyGTAP Model: A Model for Employing Data from the MyGTAP Data Application—Multiple Households, Split Factors, Remittances, Foreign Aid and Transfers." GTAP Working Paper No. 78. Center for Global Trade Analysis, Purdue University. Retrieved from: https://www.gtap.agecon.purdue.edu/resources/download/6659.pdf

[18] Aguiar, A., E. Corong, & D. van der Mensbrugghe (2019). "The GTAP Recursive Dynamic (GTAP-RD) Model: Version 1.0." Retrieved from: https://www.gtap.agecon.purdue.edu/resources/download/9871.pdf

[19] Aguiar, A., Chepeliev, M., Corong, E., McDougall, R., & van der Mensbrugghe, D. (2023). The GTAP Data Base: Version 11. Journal of Global Economic Analysis, 7(2), 1-27. Retrieved from https://doi.org/10.21642/JGEA.070201AF

[20] The aggregated 10 regions in the model are: USA, Canada, Mexico, China, India, Brazil, Japan, Korea, Europe, and the Rest of the World (RoW)

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

For estimating the labor productivity, we utilized KPMG's patent-pending GenAI value assessment model[22] solution which evaluates the potential economic growth opportunities attributable to GenAI. GenAI value assessment model is an advanced technological service that offers clients a qualitative, outside-in assessment of GenAI opportunities and the readiness of a target organization. This assessment evaluates the achievable GenAI opportunity ("opportunity") that an organization can potentially capture through investments in GenAI, and it also identifies peer benchmarks for comparative analysis.

The GenAI value assessment process for a target organization involves the following steps:

1	2	3	4
Identifying personnel roles within the organization.	Estimating the expenditure related to each personnel role.	Identifying the activities undertaken by the personnel.	Assessing the GenAI exposure for these activities.

The GenAI value assessment model then calculates the potential GenAI "opportunity" value for each organization based on these factors. This value represents the potential benefit of GenAI as an enabling tool for employees when performing tasks with GenAI exposure, relative to the employee's cost to the organization. KPMG aggregates these opportunity values across all identified personnel within an organization to determine the total realistically attainable opportunity.

For the current analysis, we aggregated the GenAI value assessment model based opportunity values first by functional group within each identified organization, and then by the North American Industry Classification System (NAICS) industry. Furthermore, based on location of the opportunity values, the industries are mapped to the ten global regions. This mapping allows us to accurately assess the potential economic benefits of GenAI implementation for specific skill groups within an industry, such as finance professionals in the chemicals industry or human resources personnel in the pharmaceutical products industry. These productivity estimates are further used to design the scenarios described below.

3.3 Our Scenario Design and Implementation

We created a baseline scenario without GenAI adoption, and counterfactual scenarios based on the pace of GenAI adoption across the industries and regions to be able to estimate economic projections between now and 2050. Though numerous studies have underscored the productivity boost from GenAI adoption, not many provide a precise timeline for full adoption. However, Chui et al. (2023)[23] suggest that half of today's work activities could be automated between 2030 and 2060. This aligns with our assumption of rapid adoption by 2030 and a slower adoption by 2050.

The idea behind the two distinguished timeline in this study is to offer a better understanding of the economic implications of early adoption versus the slower adoption as the GenAI technologies mature and regulatory frameworks evolve.

3.3.1 Baseline or Business-As-Usual Scenario:

The baseline scenario is a standard forecast of a business-as-usual (BAU) growth path across all the global regions for the period 2023 through 2050. The macro-economic forecasts are based on growth in population, labor force, and GDP provided by the widely used Shared Socioeconomic Pathway (SSP-2) data base "Middle of the Road"—intermediate challenges pathway (Oliver et al., 2017).[24] The world energy prices on coal, oil, and natural gas, are assumed to follow International Energy Agency (IEA, 2023)[25] forecasts. This baseline projections mirrors how the global economy is expected to look in the absence of GenAI adoption.

[21] Minor, P. and Walmsley, T. (2013). "MyGTAP Data Program: A Program for Customizing and Extending the GTAP Database." GTAP Working Paper No. 79. Center for Global Trade Analysis, Purdue University. Retrieved from: https://www.gtap.agecon.purdue.edu/uploads/resources/download/6660.pdf

[22] Refer to KPMG's patent pending GenAI value assessment model: https://kpmg.com/us/en/articles/2025/quantifying-the-genai-opportunity.html

[23] Chui, M., E. Hazan, R. Roberts, A. Singla, K. Smaje, A. Sukharevsky, L. Yee, and R. Zemmel (2023). "The Economic Potential of Generative AI—The next productivity frontier." McKinsey & Company.

[24] Oliver F., et al. (2017). "The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century." Global Environmental Change, 42: 251-267, DOI:10.1016/j.gloenvcha.2016.06.004

[25] International Energy Agency (IEA). (2023). World Energy Outlook 2023. Paris: IEA. Retrieved from: https://www.iea.org/reports/world-energy-outlook-2023

3.3.2 Rapid Adoption of GenAI:

GenAI has the potential to profoundly transform various sectors, depending on the level of adoption and the resulting efficiency improvements. In this scenario, we utilize labor productivity estimates from GenAI value assessment model to project the impact of GenAI adoption across all sectors from 2024 through 2030.[26] We assume a "rapid adoption" of GenAI, implying that the estimated labor productivity gains induced by GenAI across global industries will be fully realized over these **seven** (7) years, with equal increments each year. The CGE model incorporates the concept of unemployment closure, which means that while new jobs are created, there may also be job losses. This is a deviation from the standard assumption of CGE models that labor markets clear with full employment in the economy. This reflects the dynamic nature of the labor market as it adjusts especially to disruptive technological advancements.

Additionally, in this scenario, we assume an expanding upskilled labor force to meet the evolving demands of the job market. This ensures that the workforce undergoes a major transformation, with a strong emphasis on upskilling and reskilling programs to equip employees with the necessary GenAI competencies and are equipped with the necessary skills to thrive in a GenAI-enhanced environment, thereby maximizing the potential benefits of GenAI adoption. This scenario assumes that the skilled labor required for these advancements will be available, necessitating ideal conditions in education, economic investments, and supportive policy landscapes.

3.3.3 Slow Adoption of GenAI:

In this scenario, we consider a "slow adoption" of GenAI, extending from 2024 through 2050. We utilize labor productivity estimates from GenAI value assessment model to project the impact of GenAI adoption across all sectors over this extended period. Unlike the rapid adoption scenario, we assume a gradual integration of GenAI technologies, leading to incremental productivity gains across industries globally. The "slow adoption" of GenAI, implies that the estimated labor productivity gains will be fully realized over **twenty-seven** (27) years, with equal increments each year. Industries experience steady but slower improvements in efficiency and innovation, as businesses cautiously integrate GenAI at a conservative pace.

This scenario assumes unemployment closure with expanding upskilled labor force in the model. The slower pace of GenAI adoption allows for a more gradual adjustment of the labor market to technological advancements, potentially mitigating some of the immediate job displacement effects. It also assumes that the availability of skilled labor will gradually improve, relying on consistent efforts in education, economic investments, and policy support over the long term.

The slow adoption of GenAI across all the sectors is assumed mainly due to regulatory barriers, increase in costs of adoption (e.g., Huang, 2023) , and slower investments. For example, IMF reported that AI could potentially increase labor income and wealth inequality and suggested that advanced economies and developed emerging markets should focus on improving regulatory frameworks and support labor reallocation, while the developing economies should prioritize building digital infrastructure and skills (Cazzaniga et al., 2024).[28] The slow adoption scenario highlights the relative missed economic gains that could arise from rapid adoption of AI.

3.3.4 Rapid Adoption of GenAI with No-Upskilling:

We anticipate that implementing GenAI in workplaces would require an investment in personnel skills and abilities to leverage the new technology. Therefore, in addition to the pace of adoption, we also investigate the impact of upskilling (includes reskilling as well) the existing workforce simultaneously with technology investment and adoption. Considering that required investments, educational programs, or policy changes could be very limited or could not be implemented for various reasons, we also include a special case of no-upskilling of labor-force under rapid adoption scenario. This implies that the existing workforce may not fully leverage these advancements, potentially leading to a mismatch between the capabilities of the workforce and the demands of new GenAI-driven technologies. This "rapid no-upskill" scenario underscores the importance of upskilling and reskilling initiatives to ensure that the workforce can effectively utilize and benefit from GenAI advancements. Additionally, the economic environment may limit the potential of the labor force. Factors such as lack of investment in education and training, and inadequate policy support can hinder the workforce's ability to adapt to new technologies. This means that even with the availability of advanced GenAI technologies, the full potential of these advancements may not be realized if the economic conditions are not conducive to workforce development. This aspect is crucial to consider when evaluating the overall impact of GenAI adoption on productivity and economic growth.

Note, we do not implement a no-upskilling scenario under slow adoption of GenAI. While that may be a potential issue, for purposes of this study, we've assumed upskilling will occur in this scenario.

[26] The baseline scenario starts in 2023, while the GenAI adoption scenarios begin in 2024, reflecting the transition from experimentation to widespread adoption of GenAI commenced in 2024.

[27] Huang, H. (2023). "What CEOs Need to Know About the Costs of Adopting GenAI." Harvard Business Review. Retrieved from: https://hbr.org/2023/11/what-ceos-need-to-know-about-the-costs-of-adopting-genai

[28] Cazzaniga, M. et al. (2024). "Gen-AI: Artificial Intelligence and the Future of Work." IMF Staff Discussion Note SDN2024/001, International Monetary Fund, Washington, DC. Retrieved from: https://www.imf.org/en/Publications/Staff-Discussion-Notes/Issues/2024/01/14/Gen-AI-Artificial-Intelligence-and-the-Future-of-Work-542379

4. Our Findings and Insights

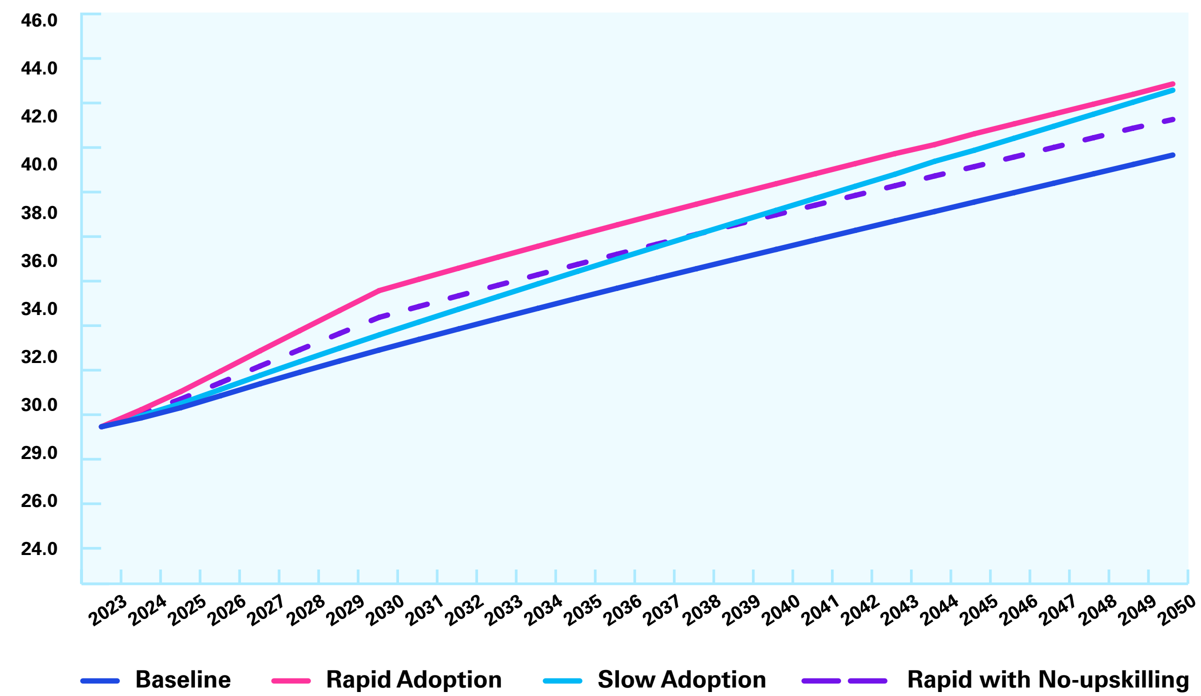
4.1 Impact on the US Gross Domestic Product (GDP)

The main indicator we analyze to quantify the impact of GenAI adoption is the Gross Domestic Product ("GDP"), which measures the monetary value of the goods and services produced within the country. This measure helps to illustrate the productivity gains our model anticipates that would arise from GenAI adoption across all sectors. The top panel of **Figures 4.1a** shows our model's forecast of US GDP from 2023 through 2050. As implied by the **baseline** scenario, the real GDP in the US is projected to grow from $27.5 trillion in 2023 to $40.5 trillion by 2050 (measured in 2024 dollars). In the **rapid adoption** scenario, where GenAI is quickly integrated into all sectors, the GDP sees a more accelerated growth, reaching $43.9 trillion by 2050. This scenario suggests that rapid GenAI adoption could boost US GDP by an additional $2.84 trillion (9 percent) above the baseline by 2030, and by $3.37 trillion (more than 8 percent) by 2050 (see **Figure 4.1b**). This highlights the substantial economic benefits of swiftly embracing GenAI technologies.

In contrast, the **slow adoption** scenario, where GenAI integration is more gradual, results in a GDP of $43.6 trillion by 2050. This is a 7.7 percent increase in real GDP by 2050, but the GDP gains by 2030 is only 2.3 percent relative to the **baseline**. The growth in GDP under the **slow adoption** scenario is more gradual relative to the **rapid adoption** scenario (which is by design), but the economy reaches a similar point by 2050, though not as pronounced (7.7 versus 8 percent). The **rapid no-upskill** scenario, where GenAI is adopted quickly but without corresponding upskilling of the workforce, results in a GDP of $42.2 trillion (4.3 percent) above the baseline by 2050. As shown in the bottom panel of Figures 4.1, the incremental GDP gains converge by 2050 in both the rapid and slow adoption scenarios. However, the rapid no-upskilling scenario considerably stalls this progress in the long run demonstrating the critical role of workforce upskilling in realizing the full potential of GenAI. Without adequate training and education, the economic benefits of rapid GenAI adoption are diminished, emphasizing the need for comprehensive strategies that include both technology integration and human capital development to fully leverage GenAI's transformative potential.

Figure 4.1a: Impact of GenAI Adoption on Real GDP in the US

Real GDP in the US across Scenarios (2024$ trillion)



Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Figure 4.1b: Change in Real GDP relative to Baseline (2024$ trillion) in the US

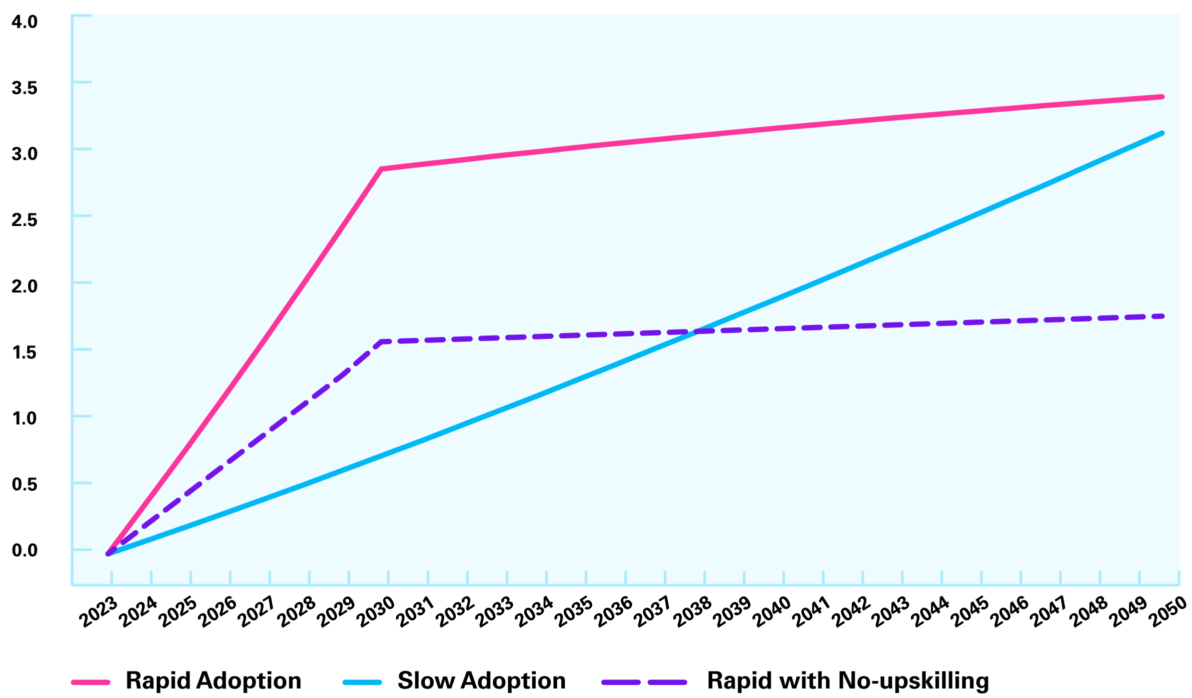


Table 4.1: US Economic Growth due to Generative AI Adoption

AI Adoption Scenarios	US Projected real GDP in 2050 (USD Trillion)	US Real GDP CAGR (2024-2050)	Additional annual growth (%) relative to Baseline (2024-2050)
Baseline—No GenAI Adoption	40.50	1.39%	-
Rapid GenAI Adoption	43.87	1.69%	0.30%
Slow GenAI Adoption	43.61	1.66%	0.27%
Rapid GenAI Adoption—No-Upskilling	42.25	1.54%	0.15%

In **Table 4.1**, we present the compound annual growth rate ("CAGR") of real GDP across the scenarios for the period 2024-2050. Compound Annual Growth Rate (CAGR) is a measure that represents the average annual growth rate of a country's GDP over a specified period, assuming the growth compounds steadily each year. CAGR smooths out fluctuations to show consistent growth over a period of time.

GenAI adoption instigates GDP growth that outpaces baseline GDP growth in every scenario. As a result, we estimate that the US GDP will see a 1.7 trillion to 3.4 trillion dollar increase in GDP relative to baseline growth by 2050. As discussed, the magnitude of this growth is affected by the speed at which Generative AI is adopted, and the human capital investments through upskilling that may coincide with this adoption. The rapid adoption scenario emphasizes the importance of upskilling in the economy which leads to a doubling of the GDP impact (in the sense of net gains) from 1.7 trillion dollars (rapid adoption with no upskilling) to 3.4 trillion dollars (rapid adoption with upskilling) (Table 4.1).

The CAGR tells us how much the economy is expected to grow each year on average. In the baseline scenario with no GenAI adoption, the economy grows at 1.39% per year. With rapid GenAI adoption, the growth rate increases to 1.69% per year, which means the economy grows faster by additional 0.30%. This means if 10 million cars are produced in a year, the additional growth can boost production of 30,000 more cars. Similarly, slow GenAI adoption adds 0.27% more growth, and rapid adoption without upskilling adds only 0.15% more growth each year.

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

4.2 What does GenAI mean for the US Job Market?

Employment impacts of GenAI remain a prominent concern for workers across industries and demographics, especially as the technology improves and is more widely adopted. Recent surveys indicate that, for a significant portion of individuals, job loss to AI is a concern.[29] Studies such as the World Economic Forum (2020)[30] indicated that while automation and AI, including GenAI, might displace certain jobs, they are also expected to create new roles and opportunities in various sectors. The key takeaway from these studies is that the impact of GenAI on employment is complex and multifaceted, often leading to a shift in the nature of work rather than outright job losses. Similar to these studies, our findings suggest that the employment impact of GenAI is likely to result in net employment gains with upskilling of the labor force, rather than substantial job losses.

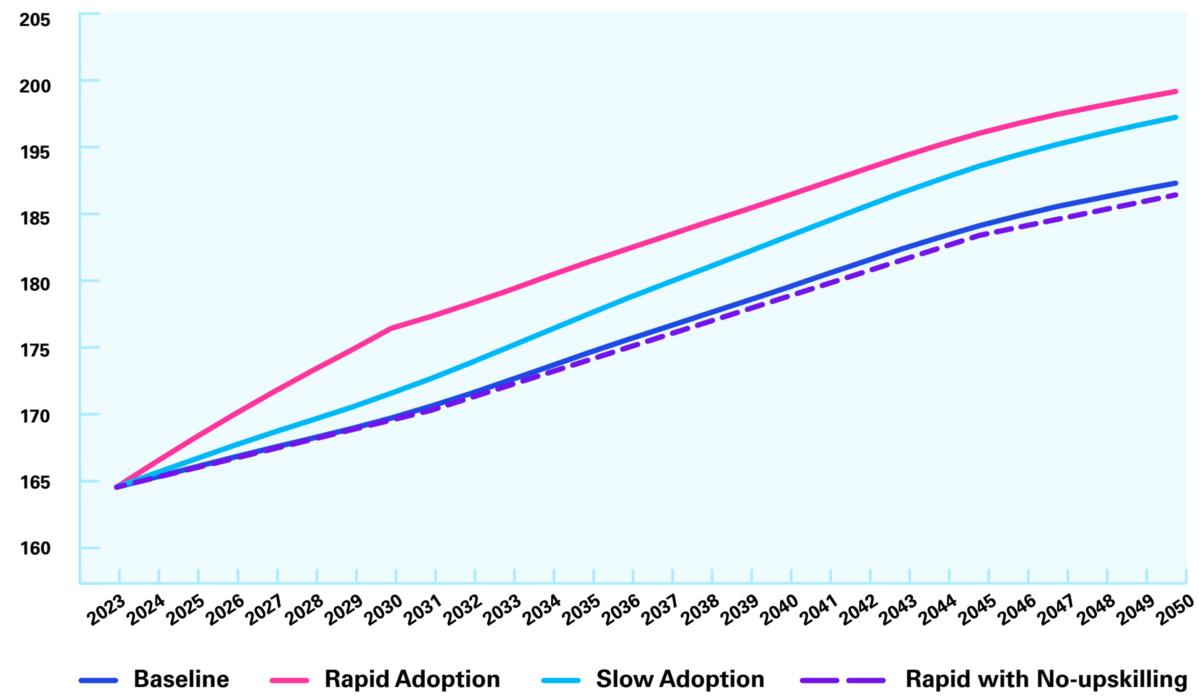
Figure 4.2 presents our employment projections from 2023 to 2050 under the same four scenarios. In the **baseline** scenario, employment grows steadily from 164.7 million in 2023 to 191.4 million in 2050. The **rapid adoption** scenario shows a faster increase, reaching 199.4 million by 2050, indicating that GenAI adoption can significantly boost employment. The **slow adoption** scenario, with a more gradual technology uptake, results in employment reaching 197.2 million by 2050.

[29] Ballard, J. (2024). "How Many Americans feel about AI's role in their Careers and in K-12 Schooling." YouGov. Retrieved from: https://today.yougov.com/technology/articles/49237-how-americans-feel-about-ais-role-in-their-careers

[30] World Economic Forum (2020). "The Future of Jobs Report 2020." World Economic Forum, Geneva, Switzerland. Retrieved from: https://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf

Figure 4.2: Impact of GenAI Adoption on Employment in the US

Total Employment in the US (Million)



In the **rapid adoption with no-upskilling** scenario employment is expected to grow to only 190.3 million by 2050, about a million jobs less than the baseline and substantially lower than the **rapid adoption** and **slow adoption** scenarios. These projections highlight the critical impact of the pace of technology adoption and workforce upskilling on future employment growth.

4.2.1 How will adoption of GenAI impact employment for various labor categories?

Our model's predicted impact on employment by labor skill type in the US is summarized in **Table 4.3.** The rapid adoption scenario showed significant growth across all labor types in 2030 and sustained through 2050, with Managers experiencing the highest increase (3.94 million in 2030), followed by Technicians, Clerks, and Service Workers who also noted substantial

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

job creation. However, Low Skilled jobs show a slight decline by 2050 (-0.12 million), indicating a shift towards more skilled labor requirements. When productivity increases due to GenAI adoption, the CGE model adjusts the production functions to reflect higher output per unit of input. This leads to changes in prices, wages, and employment across sectors, showing how the economy adapts to the new productivity levels. This results in sectoral shifts, with some sectors expanding due to higher productivity and creating jobs, while others contract. The model highlights the importance of upskilling to ensure the workforce can adapt to technological advancements and avoid potential job losses. The net jobs presented in Table 4.3 include all the direct and indirect jobs created by GenAI adoption.

The slow adoption scenario showed more modest job growth across all categories, with Managers projected to have the most significant increase (2.98 million in 2050), followed by positive growth in Technicians, Clerks, and Service Workers jobs. The overall growth in jobs under slow adoption is considerably lower compared to the rapid adoption scenario. The low skilled employment showed the largest decline in 2050 (-0.38 million) under

Table 4.3: Net Creation of US Jobs by Labor Type

Labor by Skill	Rapid Adoption (million)		Slow Adoption (million)		Rapid Adoption with No-Upskilling (million)	
	2030	2050	2030	2050	2030	2050
Technicians	0.69	0.75	0.18	0.59	0.16	0.15
Clerks	1.4	1.49	0.37	1.13	0.17	0.11
Service Workers	1.78	1.89	0.48	1.27	-0.33	-0.5
Managers	3.94	4.18	1.07	2.98	0.27	0.02
Low Skilled	0.06	-0.12	0.02	-0.38	-0.6	-0.79
All Labor	**7.87**	**8.2**	**2.12**	**5.59**	**-0.33**	**-1.01**

the slow adoption scenario. The annual changes in the employment by skill under rapid and slow adoption scenarios are presented in **Figures A2** in Appendix.

The rapid adoption with no upskilling scenario paints a more concerning picture, with negative job growth for low skilled workers and minimal gains for other categories throughout the adoption period of 2024 through 2050. Our results align with broader research on impact of GenAI and automation on the labor market. For example, World Economic Forum (2020) suggests that GenAI could displace certain jobs, but they will also create new opportunities, particularly in sectors requiring higher technical skills and managerial capabilities. These findings highlight the critical importance of upskilling to ensure that the workforce can adapt to the technological advancements brought by GenAI, as failing to do so could result in a potential net loss of jobs by 2050.

4.2.2 How will GenAI adoption Impact Wages

The model predicted effects of GenAI adoption relative to a baseline scenario on real wages across various labor categories in the US are presented in **Table 4.4**. The rapid adoption scenario showed that technicians, clerks, service workers, and managers experience notable wage increases by 2030 relative to the baseline scenario, with technicians seeing the most significant increase at **7.43** percent points in real terms. However, by 2050, the wage growth for these groups diminishes, particularly for service workers and low-skilled labor, who encounter wage declines. In contrast, slow adoption results in more moderate wage increases by 2030 but yields more favorable outcomes by 2050 compared to rapid adoption, indicating a more sustainable long-term benefit.

For example, the growth rate for real wages for technicians in the slow adoption scenario exceeds the rate in the rapid adoption scenario by 2050 (5.57 vs. 3.91 percent). By design, the GenAI-induced productivity growth is concentrated between 2024 and 2030 and does not continue to accelerate (i.e., provide further productivity gains) beyond 2030 under the rapid adoption scenario causing the wage growth to slow down after 2030 compared to the slow adoption scenario. In the slow adoption scenario, the productivity gains are more gradual and thereby resulting in continued wage growth through 2050.

The rapid adoption without upskilling scenario predicts markedly negative impact on wages by 2050 for most labor types, especially service workers and low-skilled workers, who experience highest wage decreases. Even under the rapid adoption with upskilling scenario, low-skilled labor is expected to see a decline in real wages in the long run (-3.26 percent by 2050). This decline is attributed to reduced employment for the low-skilled workers, who are displaced towards more skilled categories. Without upskilling, the long-term displacement effects become pronounced, particularly for lower-skilled workers who are more vulnerable to automation.

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Table 4.4: Impact of GenAI adoption on real Wages by Labor Type in the US (% change relative to Baseline)

Labor Type by Skill	Rapid Adoption		Slow Adoption		Rapid Adoption with No-Upskilling	
	2030	2050	2030	2050	2030	2050
Technicians	7.43%	3.91%	1.96%	5.57%	1.73%	0.73%
Clerks	5.96%	2.38%	1.58%	4.24%	0.73%	-0.28%
Service Workers	5.34%	1.86%	1.44%	3.36%	-1.00%	-2.02%
Managers	6.12%	2.35%	1.66%	4.05%	0.42%	-0.88%
Low Skilled	0.14%	-3.26%	0.06%	-0.82%	-1.45%	-2.13%
All Labor	**4.76%**	**1.27%**	**1.28%**	**3.12%**	**0.00%**	**-1.02%**

4.3 What Industries are impacted the most by GenAI?

Adoption of GenAI is expected to have varied impacts on employment across industries. The results presented in **Table 4.5** illustrate the projected changes in employment across various industries in the US due to the rapid and slow adoption GenAI, relative to baseline. Our results indicate significant variations in employment impacts across different sectors and job categories, reflecting the transformative potential of GenAI on the labor market. A series of KPMG sector-specific studies on a creating value through AI-driven transformation show that AI spending will likely increase significantly in some sectors to set the foundation for growth[31]. For example, the banking sector study suggests as AI is automating repetitive processes such as data entry, document verification, and compliance checks, which may reduce the need for manual roles in these areas. The transformation towards AI-driven processes could lead to a shift in employee roles from traditional functions to managing AI agents and systems. There is an emphasis on upskilling employees to adapt to new roles that focus on strategic decision-making and customer engagement[32]. Similarly, KPMG's insurance sector study indicates that AI is transforming underwriting, claims processing, and fraud detection, potentially reducing the need for manual labor in these areas. As AI systems become more autonomous, roles that involve routine tasks are at risk. However, there is a focus on upskilling employees to handle higher-value tasks and manage AI systems.[33]

This study quantifies the impact across industries. The top panel of **Table 4.5** shows the net change in employment across 17 different industries under rapid adoption scenario aggregated from the 48 granular industries employed in the model (presented in **Table B1** in Appendix B). By 2050, this scenario also results in 8 million additional jobs compared to the baseline, with considerable growth in sectors such as Education (2.15 million jobs), Government & Public Sector (1.9 million jobs), and Consumer & Retail (0.97 million jobs), followed by Finance, and Healthcare & Life Sciences. More than half of the jobs created are for the "Manager" category—which includes various professionals with tertiary education. The increase in employment in these sectors suggests that adopting GenAI will require the managerial category of workforce to facilitate and enhance GenAI based productivity growth. For instance, in the education sector, teaching professionals will play a crucial role in integrating GenAI and enhancing the educational outcome. Similarly, in healthcare sector, GenAI enhances efficiency and patient care, leading to increased demand for various roles including managers, clerks, service workers. The Government & Public Sector also sees a rise in employment to manage and implement GenAI-driven public services. On the other hand, about 1.5 million low skilled workers are displaced from the Other Services sector, which may be attributed to the automation of routine tasks. Some of these workers are absorbed by the Other Manufacturing and Primary sectors. The overall impact of rapid adoption remains considerably positive on most of the sectors indicating net increase in jobs that require highly skilled labor force.

Compared to the rapid adoption scenario, the slow adoption of GenAI showed more gradual and less disruptive impact on employment in the US by 2050. Similar to the rapid adoption scenario, sectors such as Education (1.5 million), Government & Public Sector (1.5 million), and Consumer & Retail (0.7 million) still experience significant job growth, particularly in managerial, clerical, and service worker roles. However, the slower pace of adoption has some of the immediate displacement effects in the short-run. Despite the slower adoption, nearly 600 thousand jobs of low-skilled workers are expected to be lost by 2050 relative to the baseline scenario. Most of these job losses occur in the Other Services and Industrial Manufacturing sectors, where automation and efficiency improvements reduce demand for low-skilled labor. These results suggests that while slower adoption can ease the transition and reduce short-term disruptions, the long-term structural shifts in the economy still lead to a decline in low-skilled employment.

[31] KPMG (2025a) "2025 GenAI Sector Value Reports—Media Resource." KPMG International. Retrieved from: https://kpmg.com/us/en/media/news/2025-genai-sector-value-reports.html

[32] KPMG (2025b) "U.S. Intelligent Banking Report." KPMG International. Retrieved from: https://kpmg.com/kpmg-us/content/dam/kpmg/pdf/2025/us-intelligent-banking-report-web-v2.pdf

[33] KPMG (2025c) "U.S. Intelligent Insurance Report." KPMG International. Retrieved from: https://kpmg.com/kpmg-us/content/dam/kpmg/corporate-communications/pdf/2025/genai-sector-value-reports-insurance.pdf

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

The slow adoption of GenAI in Industrial Manufacturing by 2050 leads to job losses primarily due to the gradual upskilling and replacement of low-skilled roles with automation. As GenAI is incrementally integrated, routine and repetitive tasks become automated, reducing the need for low-skilled labor. This gradual transition allows for some workforce adaptation and retraining, but the overall demand for low-skilled positions still declines as efficiency improvements and automation take hold.

Table 4.5: Change in Employment by 2050 across Industries in the US (thousands of jobs relative to baseline)

Rapid Adoption	Technicians	Clerks	Service Workers	Managers	Low Skilled	All Labor
Education	106.1	352	447.2	1,179.30	59.8	2,144.40
Government & Public Sector	94.4	273.8	433.6	1,077.30	58.5	1,937.50
Consumer & Retail	184.9	183.1	384.3	221.5	-7.3	966.5
Healthcare & Life Sciences	51.9	139	202.7	543.3	8.5	945.5
Finance	94.4	182.3	170.1	458.2	28.2	933.2
Other Manufacturing	19.8	92.3	37.7	220.3	322.7	692.8
Communications	43.9	139.1	23	53.7	98.3	358.1
Recreation	0.4	43.9	63.2	204.2	4.9	316.5
Insurance	29.6	57.6	57.2	136.3	10.5	291.3
Chemicals	3.4	18.7	8.5	53.1	71.9	155.6
Primary	-0.2	-0.2	2	-20.4	140	121.1
Transport	17.7	48.9	7.1	21.5	-5.4	89.8
Pharmaceuticals	1.3	7.5	3.6	20.4	37	69.7
Energy	0.8	2.7	0.4	-0.7	50.1	53.2
Industrial Manufacturing	2.7	15.7	6.5	50.4	-62.1	13.2
Business Services	2.4	-1.8	-24	10.6	-31.1	-43.9
Other Services	106	82	219	109.1	-1500.3	-984.2
All Sectors	**759.6**	**1,636.70**	**2,042.00**	**4,337.90**	**-715.8**	**8,060.30**

Slow Adoption	Technicians	Clerks	Service Workers	Managers	Low Skilled	All Labor
Education	79.4	267.1	314.2	829.8	35.4	1,525.80
Government & Public Sector	74.8	211.7	335.6	820.2	40.6	1,482.80
Consumer & Retail	156.3	149.8	288.3	175.8	-48	722.3
Healthcare & Life Sciences	35.5	85.6	120.4	313.2	-6.7	547.9
Finance	57.7	104	82.5	265.7	0.8	510.7
Other Manufacturing	11.8	51.8	19.2	115.6	85.8	284.2
Communications	38.4	119.6	19	45.1	50.5	272.7
Primary	1	8.2	9.5	138.3	96.1	253.1
Recreation	0.3	27.1	37.2	132.2	0.1	196.8
Insurance	20.8	38.7	36.2	89.6	3.9	189.3
Energy	2.5	8.3	1.6	15.5	30.4	58.3
Transport	15.7	41.4	5.6	18	-23.7	57
Chemicals	1.6	8.9	3.7	24.3	8	46.4
Pharmaceuticals	0.6	3.8	1.7	9.6	12.6	28.3
Business Services	4.3	1.1	-17.9	6.9	-29.6	-35.3
Other Services	87.6	100.5	146.8	184.9	-674.2	-154.4
Industrial Manufacturing	-0.6	-3.4	-2.9	-7.4	-184.6	-199
All Sectors	**587.7**	**1,224.10**	**1,400.50**	**3,177.20**	**-602.7**	**5,786.70**

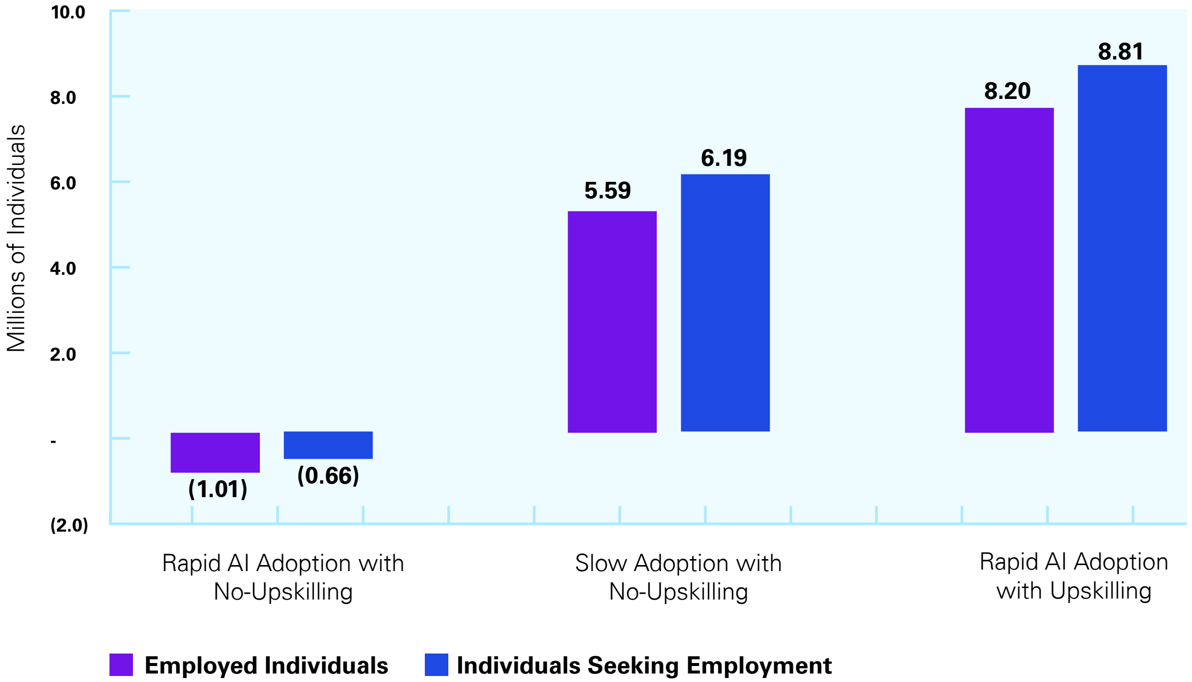
Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

4.4. How will adoption of GenAI impact labor force participation and unemployment?

Overall increase in wages in the labor market is expected to lead to an increase in labor force participation due to individuals seeking better economic opportunities in the sectors with relatively higher wages. This study analyses the productivity based on impact on employment including redistribution of labor force across industries, and net new jobs added due to expanded labor force participation due to upskilling and reskilling. Labor force in the US is expected to increase by approximately a net of 6.2 and 8.8 million by 2050 in the slow and rapid adoption scenarios, respectively **(Figure 4.3)**. However, without upskilling, our analysis projects a net decrease in labor force participation of approximately 0.7 million individuals by 2050. This stark contrast between the upskilled and non-upskilled model variants may be indicative of structural unemployment which may arise from adopting of GenAI with a workforce that is not adequately trained to leverage the technology.

Figure 4.3: Impact of GenAI Adoption on Net Employment in the US by 2050

US Net Employment Impacts of GenAI Adoption by 2050 (Relative to Baseline)



The number of individuals employed or seeking employment increases by a greater amount than the number of employed individuals in both scenarios where upskilling is implemented. This is expected to result in an increase in the unemployment rate relative to the baseline scenario.

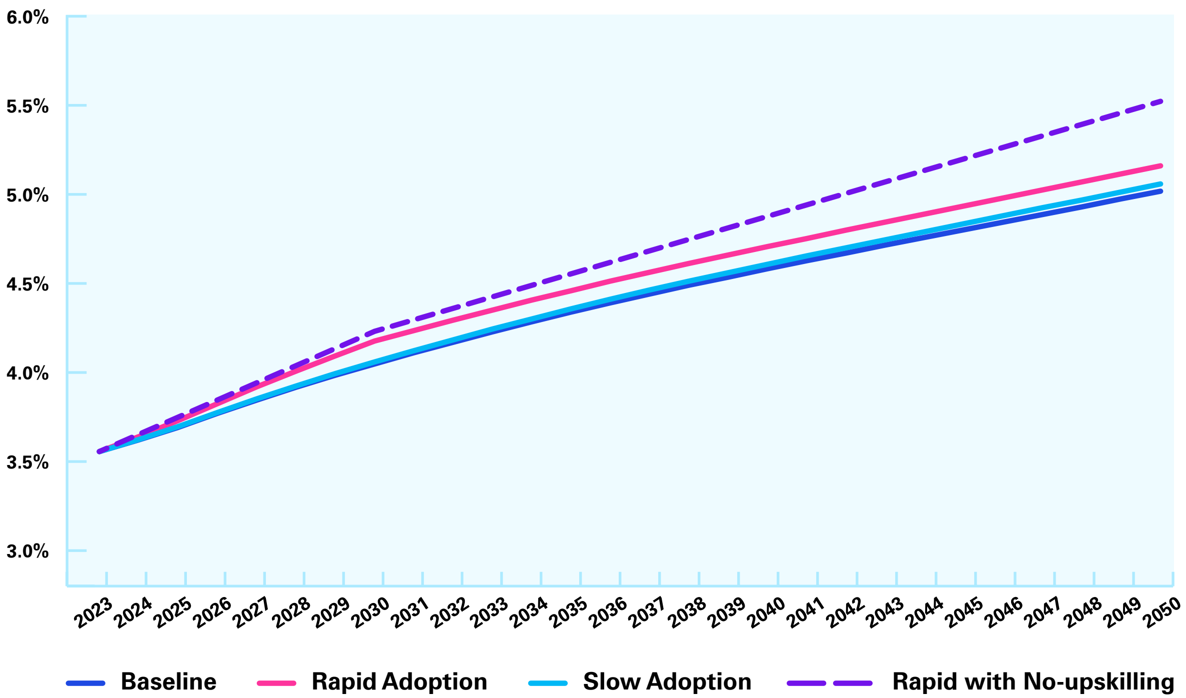
The model results on year-on-year changes on the unemployment rate in the US across all the scenarios (top panel) and change in unemployment relative to the baseline (bottom panel) are provided in **Figures 4.4.** Under the baseline scenario, the unemployment rate in the US is projected to gradually increase from 3.56 percent in 2023 to 5.04 percent in 2050. This steady rise reflects an underlying trend in the labor market without the influence of GenAI adoption.

The unemployment rate increases slightly more than the baseline, reaching 5.08 and 5.18 percent in the slow and rapid adoption scenario by 2050, respectively -- difference of about 0.04 and 0.15 percentage points by 2050. Overall, GenAI adoption will expand job opportunities (measured in total employment) and generate additional growth in the economy while increasing the unemployment rate slightly relative to the baseline scenario at the same time. This aligns with the literature that suggests that technological advancements can lead to short-term job losses but may be offset by new job creation in the long term (Acemoglu & Restrepo, 2018).

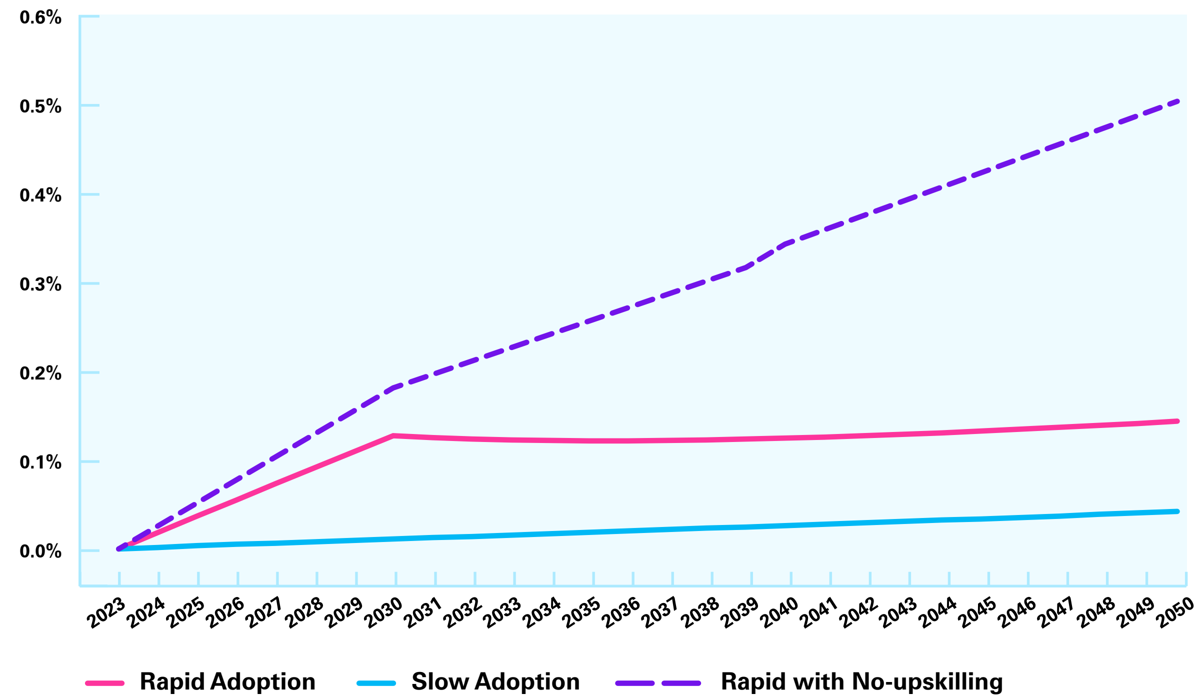
Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Figures 4.4: Impact of GenAI Adoption on Unemployment in the US

US Unemployment Rate (%) across Scenarios



Net Change in US Unemployment Rate (%) Relative to Baseline



The most notable impact is observed in the rapid adoption with no-upskilling scenario, where the unemployment rate reaches 5.55 percent by 2050, with a net increase in unemployment of 0.51 percentage points by 2050. This scenario highlights the critical importance of upskilling and reskilling initiatives to counteract the negative employment effects of technological adoption. Without such measures, the displacement of workers by GenAI adoption is more pronounced, leading to higher unemployment rates.

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

4.5 What are the Costs of Adopting GenAI?

GenAI adoption could potentially involve significant costs across various domains including labor, capital investment, and other intermediate inputs (operating expenses). Labor costs are a major component, driven by the need for highly skilled professionals and experts. The skilled labor force is essential for developing, training, and maintaining GenAI models. Zhang et al. (2020)[37] estimates that salaries for AI specialists can range significantly, depending on the level of expertise and geographical location. Additionally, continuous professional development and training are necessary to keep the workforce updated with the latest advancements in AI technologies, further adding to labor costs. It is important to note that recent advances in the costs of GenAI, such as DeepSeek, likely will alter the competitive landscape and the rate of AI adoption. In this context, Jevons Paradox may apply which states increased efficiency in GenAI technologies could lead to greater overall consumption and demand for GenAI.

Capital investment is another substantial factor in the adoption of GenAI, which include investments such as high-performance computing infrastructure, such as GPUs and TPUs, which are crucial for training large-scale AI models. Li et al., (2021)[38] estimate that the cost of setting up and maintaining such infrastructure can be significant, with expenses potentially reaching millions of dollars for large-scale operations. In addition, intermediate inputs which comprise the operating expenses attributed to improve productivity of the workforce including information technology (IT) related costs. The CGE models help identify the cost implications related to shifts in labor, capital, technology and other intermediate inputs, providing insights into efficiency and productivity changes. The model allocates the resources based on relative returns across the sectors in an economy. In **Figures 4.5**, we present the model predicted change in costs associated with GenAI adoption relative to baseline. As the top panel of the figure shows the net change in costs associated with rapid adoption of GenAI, the wage bill constitutes the substantial cost peaking about $700 billion in 2030, resulting from absorption of additional workforce. The rapid adoption creates an opportunity for capital investment starting at $48 billion in 2025, and peaking at $282 billion by 2030, and gradually tapers off. This peak suggests that 2030 is a critical year for stakeholders to capitalize on GenAI advancements. In addition, the technology costs attributed to GenAI, while steadily increasing from $6 billion in 2025 to $40 billion in 2030, remain relatively stable thereafter. Smith et al. (2022)[39] highlight that companies investing in AI technologies experience improved decision-making capabilities, increased revenue growth, and better market competitiveness. Our analysis underscores the substantial initial investments required to integrate GenAI, with the most significant opportunities for returns and growth concentrated around the year 2030.

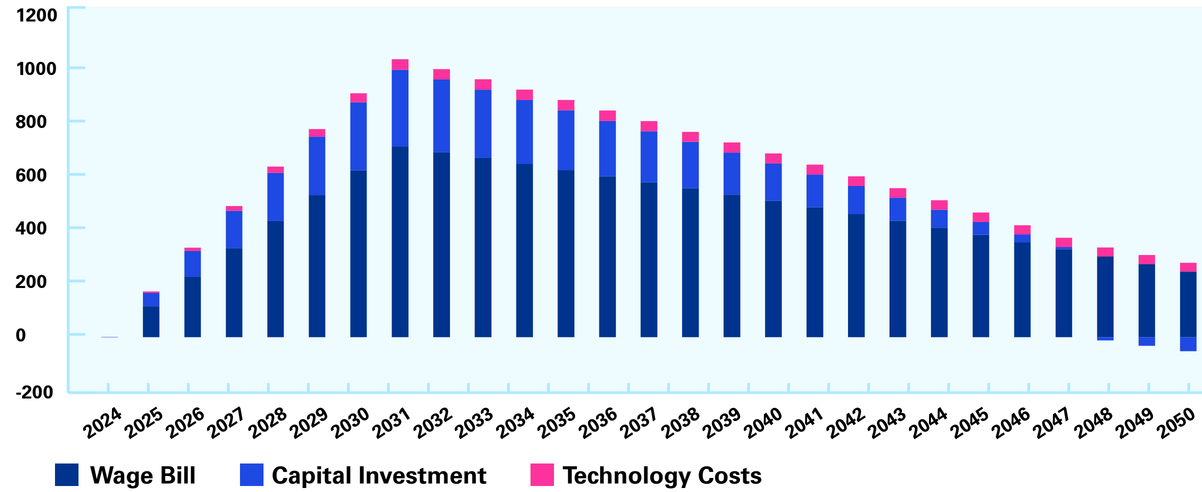
[37] Zhang, Y., Chen, X., & Liu, Y. (2020). "Economic Impacts of AI Adoption: A Labor Market Perspective." Journal of Artificial Intelligence Research, 69, 123-145.

[38] Li, J., Wang, H., & Zhou, X. (2021). "Cost Analysis of High-Performance Computing for AI Workloads." Journal of Parallel and Distributed Computing, 145, 1-12.

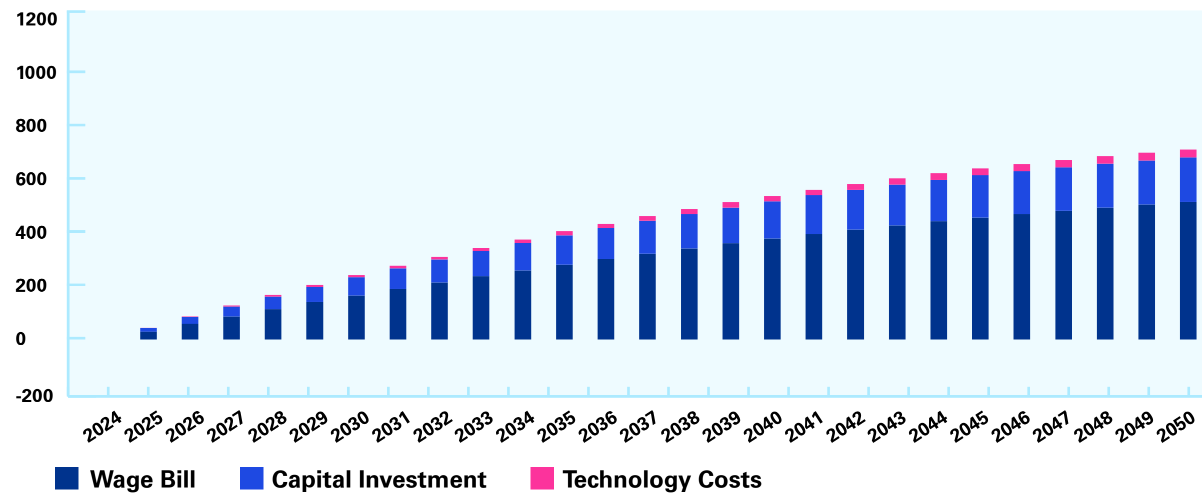
[39] Smith, A., Jones, B., & Roberts, C. (2022). "The Financial Implications of AI and Data Science Investments." Journal of Information Technology, 37(2), 89-105.

Figures 4.5: Costs associated with adoption of GenAI in the US

Net Change in Rapid Adoption Costs (2024 $ Bill)



Net Change in Slow Adoption Costs (2024 $ Bill)



The bottom panel of **Figures 4.5** shows the net change in costs associated with slow adoption of GenAI, which indicate a steady and gradual increase across wage bills, capital investment,

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

and technology costs. The wage bill incrementally rises to $512 billion, while the opportunity for capital investment increases to $164 billion by 2050. The technology costs of slow adoption of GenAI grow to $30 billion by 2050. These results emphasize that the slow adoption of GenAI creates a continuous and stable investment opportunity, enabling stakeholders to gradually integrate GenAI advancements.

4.6 What Investment Opportunities does GenAI create?

An investment multiplier measures the increase in economic output from an investment in a specific sector. **Table 4.6** presents these multipliers as output-to-investment ratios for each sector. The baseline multipliers for 2024 indicate that sectors such as education, and healthcare & Life Sciences have high multipliers, suggesting relatively larger economic returns from investments in these areas. These estimates are based on base year data, reflecting the technology matrix in the US economy's input-output structure (regardless of the scenarios). In the baseline scenario, many sectors show a decreasing trend in investment multipliers by 2030 and 2050, indicating diminishing returns, except for the energy and transport sectors. In contrast, the rapid adoption scenario shows increases in multipliers of 3-7 percent for energy, transport, consumer & retail, business services, education, healthcare & life sciences, and government sectors. Although the rapid adoption scenario peaks in 2030, it slows by 2050 but remains higher than the slow adoption scenario, enhancing economic returns on investment. These results underscore the importance of strategic technology investments to maximize economic growth, especially in sectors poised for GenAI integration.

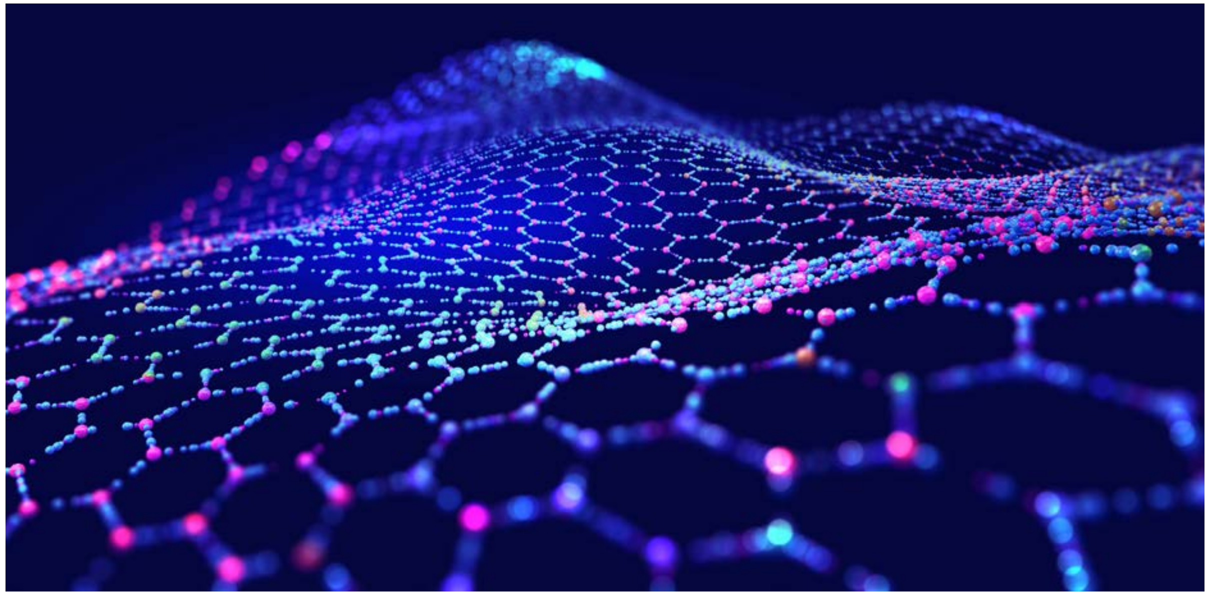


Table 4.6: Investment Multiplier across US Industries

Industry	2030			2050		
	Baseline	Rapid adoption	Slow adoption	Baseline	Rapid adoption	Slow adoption
Education	15.76	16.17	15.86	15.17	15.87	15.73
Healthcare & Life Sciences	9.61	9.93	9.69	9.13	9.55	9.47
Transport	8.16	8.43	8.23	9.35	10	9.76
Industrial Manufacturing	7.19	7.23	7.2	7.45	7.59	7.5
Energy	5.79	5.91	5.82	7.54	7.94	7.8
Chemicals	5.73	5.75	5.74	6.57	6.74	6.66
Primary	5.36	5.36	5.36	6.35	6.57	6.51
Recreation	5.03	5.14	5.06	4.88	5.04	5.01
Insurance	4.88	4.94	4.9	4.8	4.91	4.89
Government & Public Sector	4.81	4.9	4.83	4.72	4.91	4.87
Business Services	4.69	4.8	4.72	4.56	4.69	4.66
Consumer & Retail	4.55	4.7	4.59	4.36	4.53	4.49
Finance	3.73	3.79	3.75	3.67	3.76	3.75
Other Services	3.47	3.44	3.46	3.46	3.44	3.45
Communications	3.46	3.45	3.46	3.43	3.46	3.43
Other Manufacturing	2.72	2.7	2.71	2.76	2.78	2.76
Pharmaceuticals	2.3	2.28	2.30	2.39	2.38	2.38
All Sectors	**4.44**	**4.49**	**4.45**	**4.53**	**4.64**	**4.61**

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Interestingly, the education sector showed highest investment multiplier in 2024. This is because, the labor-centric structure of the sector has a lower capital-to-labor ratio, where human resources such as teachers, administrators, and support staff are essential for delivering educational services. For instance, Moretti (2004)[40] provide evidence of the significant returns on investment in education, highlighting its broad economic benefits. Further, Luckin et al. (2016)[41] suggests that the integration of GenAI in education not only supports teachers but also necessitates new roles that focus on the development and oversight of AI-driven educational tools. The multiplier effect is particularly pronounced in education, because the sector not only directly impacts the workforce but also has long-term benefits for economic growth.

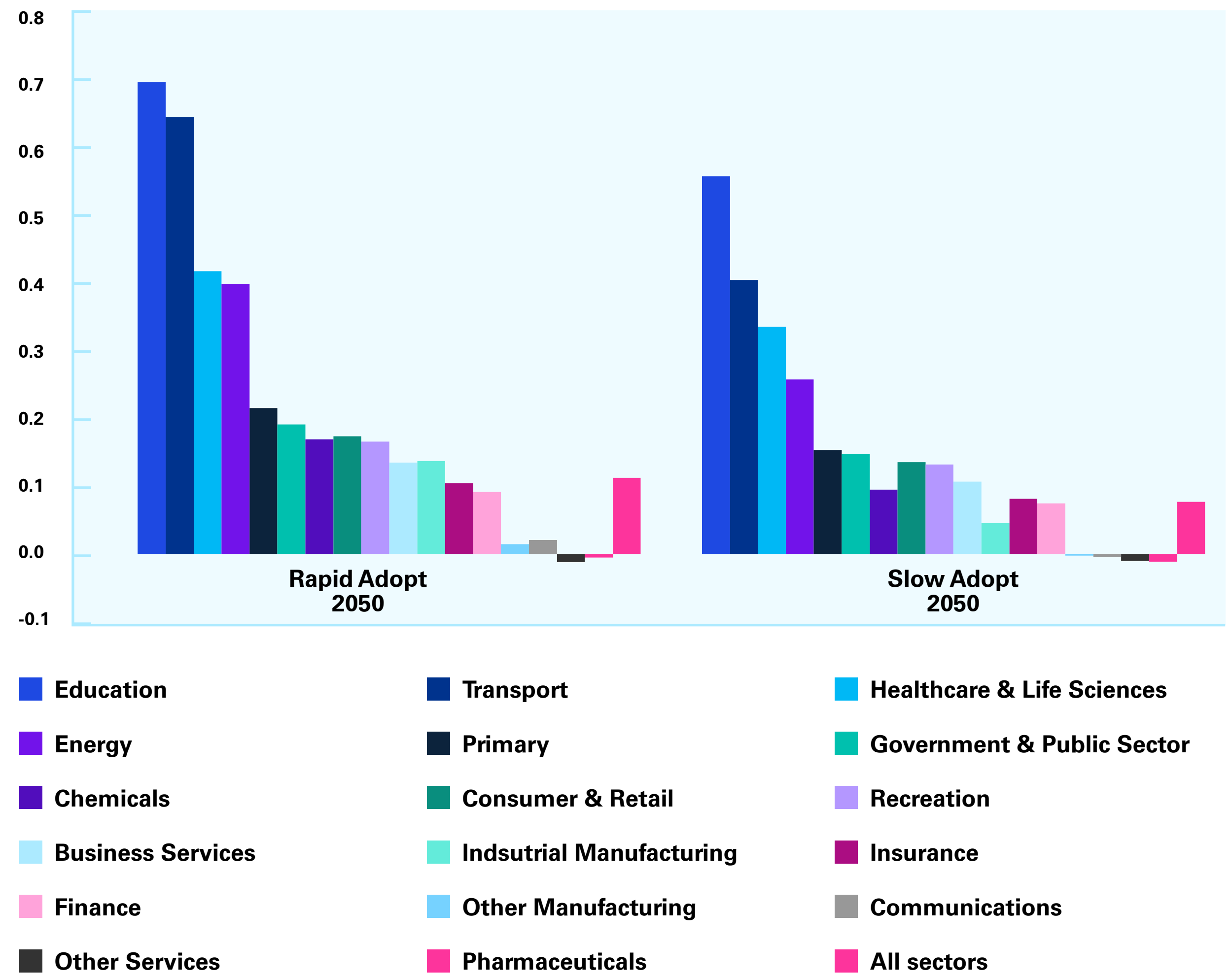
As seen from **Table 4.6**, the overall investment multiplier across when accounted for all the sectors in the economy, both rapid and slow adoption of GenAI create considerable investment opportunities for the stakeholders[42]. The rapid adoption scenario underscores the importance of proactive investment in GenAI infrastructure and training to maximize economic gains.

In **Figure 4.6**, incremental change in investment multiplier is compared across different sectors in the US Of the aggregated industries presented in this analysis, it is found that the education and transportation sectors will see the greatest gains in investment multiplier. Under the rapid adoption scenario, education, transport, healthcare, and energy industries are projected to produce an additional $0.70 and $0.40 in output per dollar of investment. These industries also lead in investment multiplier gains under the slow adoption scenario, which projects more muted investment multiplier increases of $0.56 and $0.41 per dollar of investment, respectively. Both the adoption scenarios project that only the Pharmaceuticals and Other Services will experience slight decrease in investment multipliers by 2050, with each decreasing by $0.01. The overall sectors indicated **$0.11** and **$0.08** additional returns of output under rapid and slow adoption, respectively.

As discussed above, the sectors such as Transport, Education, and Healthcare show the highest investment multiplier gains from early and extensive implementation of GenAI than slow adoption. In contrast, sectors such as Pharmaceuticals and Other Services exhibit minimal or decrease in investment multiplier, indicating limited benefits from GenAI adoption. The overall trend shows that rapid adoption consistently yields higher returns across most sectors compared to slow adoption, emphasizing the importance of early investment in GenAI technologies to maximize economic benefits. The Education sector's stand out with the highest investment multiplier, reflects the transformative potential of GenAI in enhancing educational outcomes and efficiencies.

Figures 4.6: Impact of GenAI adoption on Sectoral Investment Multiplier in the US

Net Change in Investment Multiplier across Sectors due to GenAI Adoption in 2050



[40] Moretti, E. (2004) "Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions." American Economic Review, 94 (3): 656–690.

[41] Luckin, R., W. Holmes, M. Griffiths, M., & L.B. Forcier (2016). "Intelligence Unleashed: An Argument for AI in Education." Pearson:London. Retrieved from: https://static.googleusercontent.com/media/edu.google.com/en//pdfs/Intelligence-Unleashed-Publication.pdf

[42] Please note that the investment multiplier presented here includes output from all sectors relative to the total investment in the entire economy. Therefore, it may not align with traditional financial interpretations of Return on Investment (ROI).

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

4.7 Impact of GenAI on the Global GDP

The model predicted impact on real GDP across ten global regions is presented in **Table 4.7.** The left panel compares the CAGR of GDP for the next decade (2023-2034) and the right panel provides the long-term annual growth rates for the period 2023-2050. The **baseline** CAGR of real GDP range from 0.68 percent in Japan to 3.91 percent in India. Under **rapid adoption**, the additional growth varies significantly, with the US reporting the highest incremental growth of 0.73 percent annually and that of China reporting the lowest incremental growth of 0.27 percent. **Slow adoption** results in more modest gains, such as 0.29 percent for the USA and 0.10 percent for China.

Table 4.7: Global Impact on GDP Growth due to GenAI Adoption

	2023-2034	Additional Growth due to GenAI		2023-2050	Additional Growth due to GenAI	
	Baseline	Rapid Adoption	Slow Adoption	Baseline	Rapid Adoption	Slow Adoption
USA	1.28%	0.73%	0.29%	1.39%	0.29%	0.27%
Canada	1.94%	1.19%	0.47%	1.92%	0.48%	0.42%
Mexico	2.44%	0.43%	0.17%	2.51%	0.15%	0.12%
China	2.10%	0.27%	0.10%	2.43%	0.10%	0.09%
India	3.91%	0.37%	0.15%	4.30%	0.16%	0.12%
Brazil	2.60%	0.47%	0.19%	2.54%	0.18%	0.18%
Japan	0.68%	0.46%	0.18%	0.74%	0.17%	0.14%
Korea	0.90%	0.51%	0.20%	1.05%	0.20%	0.17%
Europe	1.35%	0.75%	0.30%	1.40%	0.29%	0.27%
RoW	2.43%	0.43%	0.17%	2.57%	0.15%	0.12%
World	**1.89%**	**0.54%**	**0.22%**	**2.03%**	**0.20%**	**0.18%**

The longer-term projections to 2050, the baseline growth rates show slight increases, with India leading at 4.30 percent and Japan at the lower end with 0.74 percent. The impact of **rapid adoption** on additional growth diminishes slightly over the longer term, with the US seeing a 0.29 percent increase and India a 0.16 percent increase. Similarly, **slow adoption** results in even smaller gains, with the USA at 0.27 percent and India at 0.12 percent. Overall, the results suggest that while GenAI adoption can positively influence GDP growth, the extent of its impact varies by region and the speed of adoption, with rapid adoption generally providing more significant benefits. With the **rapid adoption**, the global economy is expected to grow an additional 0.54 percent per annum in the next decade, while the **slow adoption** yields an average 0.22 percent per annum, relative to the **baseline.**

The results on the projected incremental change in GDP due to the GenAI adoption relative to baseline, across global regions during 2023 through 2050 are presented in **Appendix Figures A1**. Under the **rapid adoption** scenario, the US and Europe are projected to gain $3.38 and $2.72 trillion by 2050, respectively. Other regions such as Canada, Mexico, China, India, Brazil, Japan, and Korea also show notable increases, though on a smaller scale. In the **slow adoption** scenario, the growth is more gradual, with the US GDP increasing to about $3.11 trillion and that of Europe to $2.53 trillion by 2050. The overall global GDP gain under rapid adoption is projected to be $11.04 trillion by 2050, while under slow adoption, it is expected to be $9.83 trillion.

Our estimates on impact on global GDP aligns with numerous studies that have quantified the impact of GenAI adoption. These studies, compiled by Roded (2024)[43] highlight the transformative potential of GenAI across various sectors. The consistency of our findings with these studies demonstrates that integrating GenAI, organizations can achieve significant economic gains, ultimately driving growth of the economy.

[43] Roded, T. (2024). "Putting the economic impact of GenAI into scale." FutureTech, MIT Computer Science and Artificial Intelligence Laboratory, Cambridge, MA. Retrieved from: https://futuretech.mit.edu/news/putting-the-economic-impact-of-genai-into-scale

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

4.8 How will adoption of GenAI Impact Global Labor Markets?

When GenAI is adopted across all regions, the model predicted varying impacts on employment across different regions, driven mainly by the intensity of labor and skill in the respective industries. Percent points change in employment relative to baseline employment, and impact on baseline unemployment rates in the respective regions for rapid and slow adoption of GenAI are presented **Table 4.8**.

In service-oriented economies such as the US and Europe, the net change in employment is generally positive under both rapid and slow adoption scenarios with expanded labor force due to upskilling. Canada is expected to show an exceptional growth in employment mainly driven by their health, education, business services, and other industries and services. The overall results for the rapid adoption scenario indicate that while GenAI adoption may initially create new job opportunities, the growth rate may stabilize over time. The impact on the unemployment rate is minimal, indicating that the labor market can absorb the changes brought by GenAI without significant disruptions. Our results indicate a small increase in unemployment rate in 2030 in the US (0.13 percent), Europe (0.08 percent), Japan (0.35 percent), and Brazil (0.10 percent) in the rapid adoption scenario. Developing countries such as Mexico, Brazil, and India exhibited more varied impacts. Mexico is projected to see a moderate increase in employment (5.91 percent by 2030 under rapid adoption) and a notable decrease in the unemployment rate, suggesting that GenAI could help alleviate some existing labor market pressures. The changes in employment in Brazil are expected to be more modest, with a 1.49 percent increase by 2030, and a mixed impact on unemployment, indicating potential challenges in leveraging GenAI effectively across its diverse economy. Although India is expected to experience a 2.05 percent increase in employment and 0.5 percent decline in unemployment rate in 2030, it is expected to experience a 1.91 percent points higher unemployment rate by 2050 relative to the baseline scenario. As Acemoglu and Restrepo (2018)[44] highlights, this may be attributed to potential mismatches between the skills required by the industries adopting GenAI and the existing workforce capabilities.

Table 4.8: Global Impact of GenAI Adoption on Employment

	Net Change in Employment relative to Baseline (percent points change)				Net change on Unemployment Rates relative to Baseline (percent points change)			
	Rapid Adoption		Slow Adoption		Rapid Adoption		Slow Adoption	
	2030	2050	2030	2050	2030	2050	2030	2050
USA	4.60%	4.21%	1.26%	3.02%	0.13%	0.15%	0.01%	0.04%
Canada	10.52%	10.29%	2.73%	7.56%	-0.41%	-0.50%	-0.11%	-0.33%
Mexico	5.91%	5.30%	1.55%	2.49%	-0.63%	-0.73%	-0.16%	-0.69%
China	0.41%	0.31%	0.25%	0.65%	-1.10%	-1.25%	-0.41%	-2.03%
India	2.05%	0.46%	0.55%	1.59%	-0.51%	1.91%	-0.14%	-0.19%
Brazil	1.49%	1.50%	0.43%	0.85%	0.10%	-0.08%	0.02%	-0.16%
Japan	1.92%	1.79%	0.52%	0.02%	0.35%	0.12%	0.09%	0.14%
Korea	1.90%	1.80%	0.53%	0.30%	-0.32%	-0.36%	-0.09%	-0.31%
Europe	5.90%	5.35%	1.57%	4.00%	0.08%	0.21%	0.02%	0.13%
RoW	2.20%	1.98%	0.63%	0.71%	-0.39%	-0.52%	-0.10%	-0.74%
World	**2.16%**	**1.72%**	**0.63%**	**1.21%**	**-0.49%**	**-0.03%**	**-0.16%**	**-0.72%**

Interestingly, China, being a rapidly industrializing economy, shows minimal net changes in employment but a significant decrease in the unemployment rate relative to the baseline scenario, especially by 2050 under the slow adoption scenario, which may be attributed to more efficient utilization of unemployed labor force in high-skill services (Liu and Qiang, 2024).[45] Similarly, Korea and Japan, with their advanced industrial bases, are expected to see modest employment gains and slight reductions in unemployment rates relative to the baseline scenario, indicating a smooth integration of GenAI into their high-tech industries. Government of Japan (2015) has long emphasized that integrating AI and other advanced technologies is crucial for Japan to address labor shortages and maintain its GDP, ensuring sustainable economic growth in the face of demographic challenges[46].

Globally, the overall impact of GenAI adoption on employment is positive but varies fairly by region. Developed countries with strong service sectors and technological infrastructures are likely to see more substantial employment gains and lower unemployment rates. While the developing countries may experience more mixed outcomes, with potential benefits tempered by challenges in workforce adaptation and economic integration, and the extent of its impact will depend heavily on regional economic structure and GenAI adoption rates.

[44] Acemoglu, D. & Restrepo, P. (2018). "Artificial Intelligence, Automation, and Work." NBER Working Paper No. 24196. Retrieved from: https://www.nber.org/system/files/working_papers/w24196/w24196.pdf

[45] Liu, Y. & C.Z. Qiang (2024). "Will Generative AI make Good Jobs Harder to Find?" The World Bank, Washington, DC. Retrieved from: https://blogs.worldbank.org/en/digital-development/will-generative-ai-make-good-jobs-harder-to-find-

[46] Government of Japan (2015). "Society 5.0." Cabinet Office, Retrieved from: https://www8.cao.go.jp/cstp/english/society5_0/index.html

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

5. Key Takeaways

This study on economic impact of Generative AI provides several critical insights and key takeaways. We employed an innovative approach of using KPMG proprietary tools for estimating company level GenAI productivity and integrated these estimates in a global economy-wide model. The study underscores the transformative potential of GenAI in driving economic growth, creating new job opportunities, and enhancing productivity. However, it also highlights the critical importance of upskilling the workforce to fully leverage the benefits of GenAI and ensure equitable distribution of its advantages.

Some of the key takeaways from this study are:

Economic Boost: The rapid adoption of GenAI could add up to $2.84 trillion to the US real GDP by 2030 and $3.37 trillion by 2050. The slower adoption too brings comparable gains by 2050. The global economy could see an additional growth of $11.04 trillion by 2050 under rapid adoption and $9.83 trillion under slow adoption. The US and Europe are projected to gain the most, with $3.38 trillion and $2.72 trillion respectively by 2050.

Investment Opportunities: Rapid adoption of GenAI offers higher investment multiplier effect across many sectors compared to slow adoption. Sectors such as Education, Transport, and Healthcare show the highest gains in investment multiplier from early and extensive implementation of GenAI.

Job Creation: Rapid GenAI adoption is expected to create a net gain of 8.06 million jobs by 2050, while slow adoption could result in 5.79 million new jobs. However, without upskilling, the net gain in jobs is significantly reduced to just 0.32 million.

Adoption Costs: High initial costs in labor and capital, but long-term benefits in productivity and economic growth outweigh expenses. The most substantial opportunities for returns and growth concentrated around the year 2030. Strategic investments in training workforce are crucial.

Industry Impact: Considerable job growth in most of the sectors and ROI, with education, healthcare, government, consumer and retail, finance, healthcare, being the top job gainers.

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Qualifications of the Study

Listed below are some of the qualifications highlight the need for careful interpretation and further validation of the study's findings.

- KPMG's GenAI Value Assessment analytic package uses outside-in data and KPMG proprietary techniques, which provide directional and illustrative insights based on third-party data. The productivity estimates used in this study are aggregated estimates at the industry/sectoral level, which may not capture the nuances of individual organizations or specific contexts.
- The study relies on various assumptions in its CGE model, such as the pace of GenAI adoption, the availability of upskilled labor, and the economic conditions. These assumptions on future in time may not hold true in all scenarios, potentially affecting the accuracy of the projections. As technology and the global economy evolve, the actual impacts of GenAI adoption may differ from the study's predictions.
- The study's results are based on aggregated data and may not fully account for the unique characteristics and conditions of different industries, regions, or organizations. This generalization could limit the applicability of the findings to specific cases.
- The findings in this study are based on specific assumptions and data sources, which may limit their generalizability to other contexts or regions not covered in the study.
- While the study provides valuable insights into economic growth, job creation, and productivity, it may not fully address other important aspects such as social, ethical, and environmental impacts of GenAI adoption. A more holistic approach would be needed to understand the broader implications of GenAI.

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Appendix—A: Labor Categories

The GTAP database includes detailed labor data that is categorized based on skill levels. The categorization follows the International Standard Classification of Occupations-1988 (ISCO-88) major groups and the ILO categories. Labor categories presented in **Table A1**, provide a framework for classifying jobs and occupations based on the skill level and type of work performed. The ILO classification helps in understanding the distribution of labor across different sectors and skill levels, facilitating more accurate economic modeling and analysis. By integrating this labor data, the model can analyze and predict economic outcomes with greater precision, considering the varying skill levels and occupational distributions within the labor market. This allows for more nuanced insights into labor dynamics and their impact on economic policies and trade scenarios

Table A1: Description of Labor Classification

Labor Category	ISCO-88 Major Group	ILO Descriptions
Managers	1, 2	Legislators and Senior Officials; Corporate Managers; General Managers; Physical, Mathematical and Engineering Science Professionals; Life Science and Health Professionals; Teaching Professionals; Other Professionals.
Technicians	3	Physical, Mathematical and Engineering Science Associate Professionals; Life Science and Health Associate Professionals; Teaching Associate Professionals; Other Associate Professionals.
Clerks	4	Office Clerks; Customer Services Clerks
Service Workers	5	Personal and Protective Services Workers; Models, Salespersons and Demonstrators
Low Skilled	6, 7, 8, 9	Skilled Agricultural and Fishery Workers; Plant and Machine Operators and Assemblers; Elementary Occupations;

Source: International Standard Classification of Occupations (ISCO), International Labor Organization (ILO), https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

In **Table A2**, we outline the employment distribution across various job categories in different regions for the year 2022. The employment data from ILO is mapped to GTAP sectors and regions aggregated for this study. The data reveals significant regional differences in employment distribution, with developed regions such as the USA, Canada, and Europe having higher shares of managers and technicians, while developing regions such as India, China, Mexico, and Brazil have larger proportions of low-skilled workers, reflecting the varying stages of economic development and industrial focus across these regions. Understanding employment distribution helps prepare the workforce for more advanced roles for effectively harnessing the impact of GenAI adoption.

Table A2: Employment by Skill across Regions

Employment in 2022 (million)	USA	Canada	Mexico	China	India	Brazil	Japan	Korea	Europe	RoW	World
Technicians	8.9	3.6	5.6	29.3	10.3	7.8	11.9	4.1	36.4	141.6	259.5
Clerks	22.4	3.5	4.2	29.5	15.6	9	10.9	5	24.9	143.3	268.2
Service Workers	31.6	3.5	10.1	113.5	41.2	32.6	6.4	9.4	34.2	184.3	466.7
Managers	60.9	6.6	5.7	36.8	19.2	12.2	12	4.5	50.6	216.7	425.2
Low skilled	39.7	3.1	32	593.2	438.6	43.7	24.8	4.5	51.7	808.1	2039.5
Total Labor	**163.6**	**20.3**	**57.6**	**802.4**	**525**	**105.3**	**65.8**	**27.5**	**197.8**	**1493.9**	**3459**

Employment share (%)	USA	Canada	Mexico	China	India	Brazil	Japan	Korea	Europe	RoW	World
Technicians	5.4%	17.7%	9.7%	3.7%	2.0%	7.4%	18.1%	14.9%	18.4%	9.5%	7.5%
Clerks	13.7%	17.2%	7.3%	3.7%	3.0%	8.5%	16.6%	18.2%	12.6%	9.6%	7.8%
Service Workers	19.3%	17.2%	17.5%	14.1%	7.8%	31.0%	9.7%	34.2%	17.3%	12.3%	13.5%
Managers	37.2%	32.5%	9.9%	4.6%	3.7%	11.6%	18.2%	16.4%	25.6%	14.5%	12.3%
Low skilled	24.3%	15.3%	55.6%	73.9%	83.5%	41.5%	37.7%	16.4%	26.1%	54.1%	59.0%
Total Labor	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Source: GTAP 11 Data Base (Aguiar et al. 2023) & International Labor Organization (ILO).

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Appendix—B: Tables and Figures

Table B1: Aggregation of Sectors in the CGE Model

No.	Aggregated Sectors	Model Sectors 48	Share of GDP	Technicians	Clerks	Service Workers	Managers	Low Skilled	All Labor
1	Primary	Agri	0.56%	0.08%	0.27%	0.22%	1.66%	1.70%	1.11%
2	Primary	Livestock	0.24%	0.04%	0.14%	0.12%	0.88%	0.90%	0.59%
3	Primary	Milk	0.04%	0.02%	0.06%	0.05%	0.35%	0.36%	0.24%
4	Primary	Forestry	0.14%	0.01%	0.03%	0.03%	0.20%	0.21%	0.14%
5	Primary	Fishing	0.02%	0.01%	0.01%	0.01%	0.08%	0.08%	0.05%
6	Energy	Coal	0.07%	0.04%	0.06%	0.01%	0.05%	0.25%	0.09%
7	Energy	Oil	0.53%	0.12%	0.20%	0.04%	0.19%	0.84%	0.31%
8	Energy	Natural Gas	0.46%	0.09%	0.12%	0.02%	0.08%	0.25%	0.12%
9	Industrial Manufacturing	Energy Intensive Industries	0.43%	0.04%	0.06%	0.01%	0.05%	0.25%	0.09%
10	Other Manufacturing	Processed Food	0.93%	0.34%	0.73%	0.27%	0.79%	2.45%	1.06%
11	Other Manufacturing	Dairy Products	0.11%	0.04%	0.08%	0.03%	0.09%	0.28%	0.12%
12	Other Manufacturing	Beverages & Tobacco	0.36%	0.06%	0.13%	0.05%	0.14%	0.43%	0.19%
13	Other Manufacturing	Textiles	0.09%	0.11%	0.25%	0.09%	0.27%	0.83%	0.36%
14	Other Manufacturing	Apparel	0.07%	0.06%	0.14%	0.05%	0.15%	0.46%	0.20%

Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

No.	Aggregated Sectors	Model Sectors 48	Share of GDP	Technicians	Clerks	Service Workers	Managers	Low Skilled	All Labor
15	Other Manufacturing	Leather	0.03%	0.01%	0.02%	0.01%	0.03%	0.08%	0.04%
16	Other Manufacturing	Wood Products	0.17%	0.29%	0.62%	0.23%	0.67%	2.07%	0.90%
17	Other Manufacturing	Paper Products	0.49%	0.32%	0.68%	0.25%	0.75%	2.30%	1.00%
18	Energy	Petroleum Products	0.13%	0.02%	0.04%	0.01%	0.04%	0.12%	0.05%
19	Chemicals	Chemicals	0.89%	0.24%	0.52%	0.19%	0.56%	1.73%	0.75%
20	Pharmaceuticals	Pharmaceutical Products	0.52%	0.09%	0.20%	0.07%	0.22%	0.67%	0.29%
21	Chemicals	Rubber & Plastic	0.39%	0.29%	0.63%	0.23%	0.68%	2.10%	0.91%
22	Other Manufacturing	Minerals	0.26%	0.14%	0.31%	0.12%	0.34%	1.05%	0.45%
23	Industrial Manufacturing	Iron & Steel	0.22%	0.14%	0.30%	0.11%	0.33%	1.01%	0.44%
24	Industrial Manufacturing	Non-Ferrous Metals	0.21%	0.09%	0.18%	0.07%	0.20%	0.62%	0.27%
25	Industrial Manufacturing	Fabricated Metals	0.88%	0.36%	0.77%	0.29%	0.84%	2.60%	1.13%
26	Other Manufacturing	Electronics	1.41%	0.25%	0.53%	0.20%	0.58%	1.79%	0.78%
27	Industrial Manufacturing	Electric Equipment	0.39%	0.20%	0.44%	0.16%	0.48%	1.49%	0.64%
28	Industrial Manufacturing	Machinery	0.86%	0.55%	1.19%	0.44%	1.30%	4.01%	1.74%
29	Industrial Manufacturing	Motor Vehicles	0.70%	0.30%	0.64%	0.24%	0.70%	2.15%	0.93%
30	Industrial Manufacturing	Transportation Equipment	0.43%	0.26%	0.57%	0.21%	0.62%	1.91%	0.83%
31	Other Manufacturing	Other Industries & Services	9.17%	1.02%	1.56%	0.45%	0.92%	3.29%	1.50%
32	Energy	Electricity	1.15%	0.28%	0.35%	0.04%	0.21%	0.51%	0.27%
33	Other Services	Water	0.65%	0.73%	0.91%	0.11%	0.54%	1.33%	0.71%
34	Other Services	Construction	4.86%	1.54%	4.01%	0.72%	3.84%	30.33%	9.57%
35	Consumer & Retail	Trade	9.80%	21.89%	9.14%	21.58%	4.28%	5.85%	9.63%
36	Other Services	Hospitality	3.64%	7.74%	3.23%	7.62%	1.51%	2.07%	3.40%
37	Transport	Road Transportation	1.73%	1.80%	2.29%	0.38%	0.35%	2.94%	1.33%

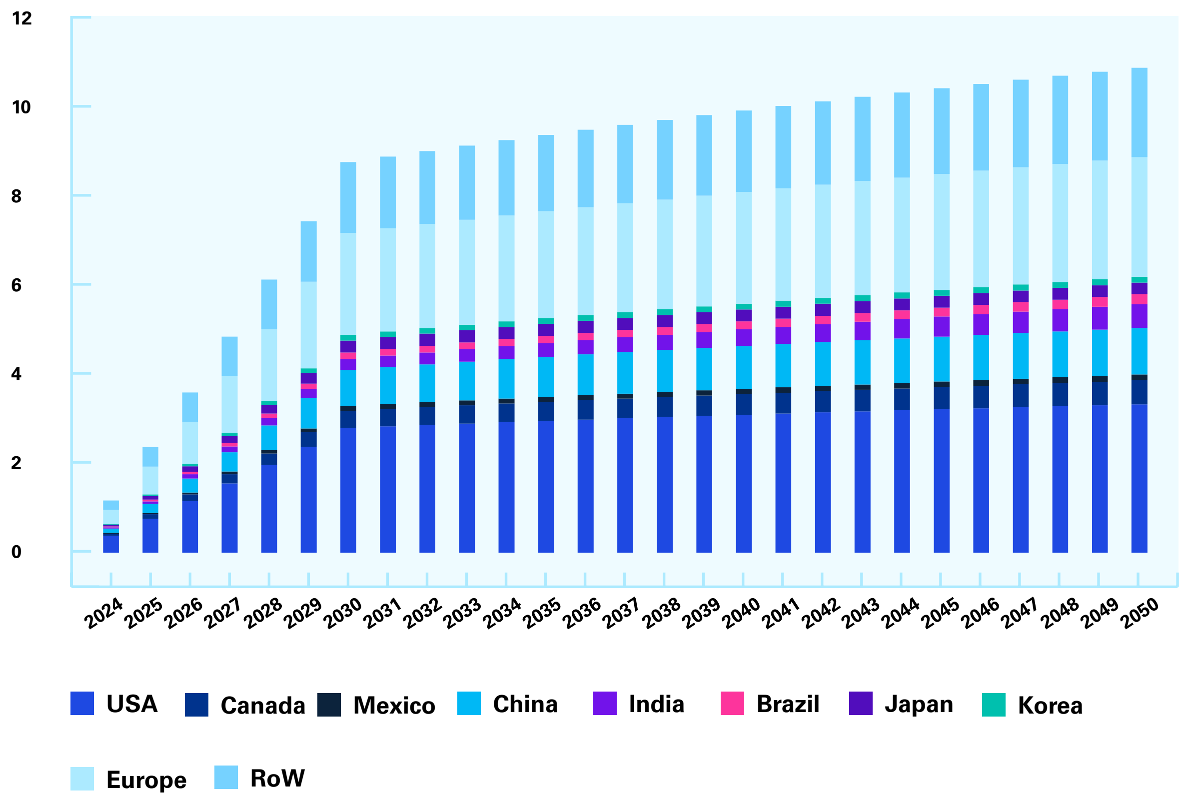
Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

No.	Aggregated Sectors	Model Sectors 48	Share of GDP	Technicians	Clerks	Service Workers	Managers	Low Skilled	All Labor
38	Transport	Water Transportation	0.06%	0.22%	0.27%	0.05%	0.04%	0.35%	0.16%
39	Transport	Air Transportation	0.42%	0.53%	0.67%	0.11%	0.10%	0.86%	0.39%
40	Communications	Communications	4.30%	4.44%	5.65%	0.94%	0.86%	7.24%	3.28%
41	Finance	Finance	4.51%	15.35%	12.40%	10.66%	10.98%	2.25%	9.23%
42	Insurance	Insurance	2.70%	4.05%	3.27%	2.81%	2.89%	0.59%	2.43%
43	Other Services	Real Estate	5.16%	2.60%	3.03%	2.60%	2.68%	0.55%	2.19%
44	Business Services	Business Services	17.65%	10.28%	11.97%	10.29%	10.60%	2.17%	8.66%
45	Recreation	Recreation	2.93%	0.08%	3.79%	4.58%	5.68%	0.57%	3.66%
46	Government & Public Sector	Public Administration	6.78%	5.06%	6.09%	7.36%	9.12%	0.91%	6.15%
47	Education	Education	4.34%	7.42%	8.93%	10.79%	13.37%	1.33%	9.02%
48	Healthcare & Life Sciences	Health	8.10%	10.39%	12.50%	15.10%	18.71%	1.87%	12.62%
	GDP (2024 $ trillion)		**26.87**						
	Employment (million)			8.9	22.4	31.6	60.9	39.7	**163.6**

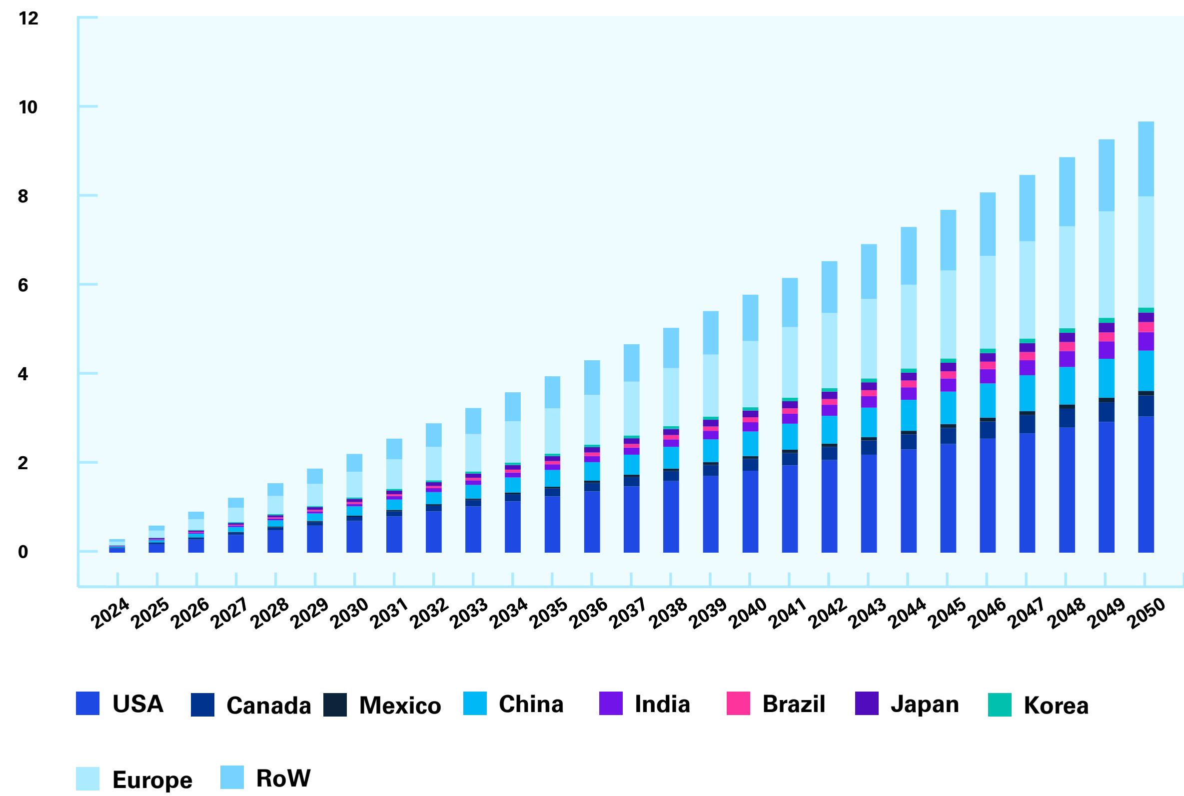
Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Figures B1: Impact of GenAI Adoption on Global GDP

Net Change in Global GDP (2024 $ trillion) due to Rapid Adoption



Net Change in Global GDP (2024 $ trillion) due to Slow Adoption of GenAI



Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Table B2. A Summary of Employment changes by Industry in the US

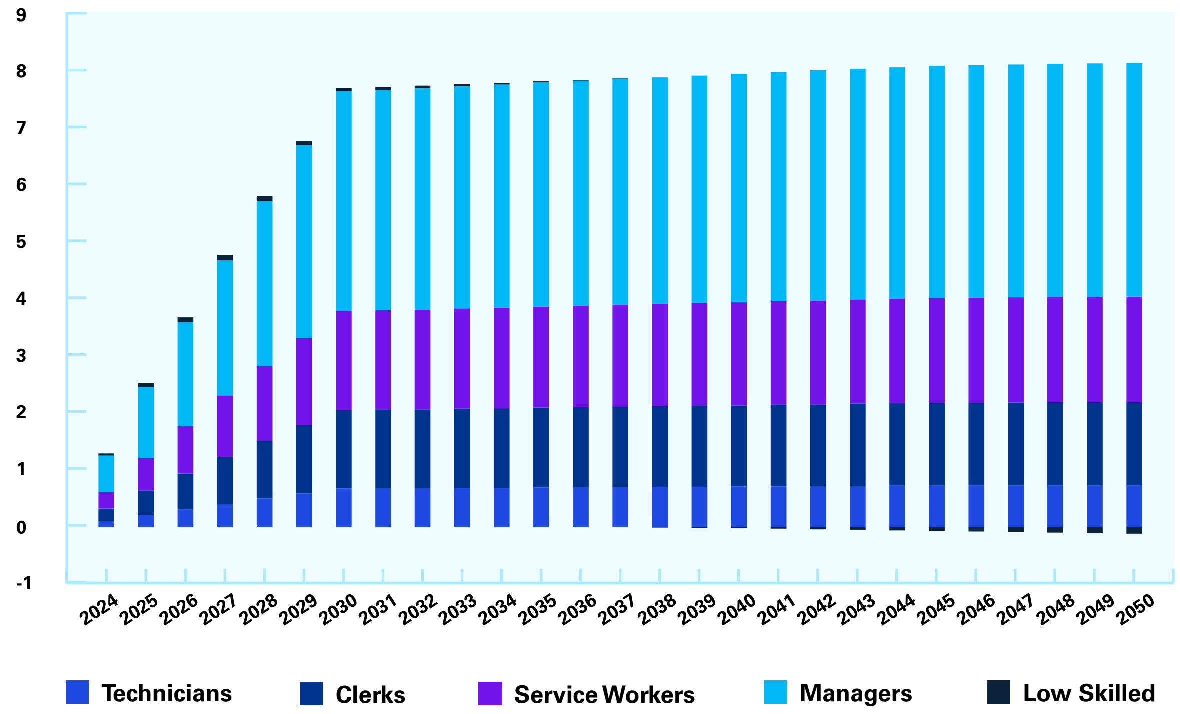
Rapid Gen AI Adoption			
Industries Gaining the Most Jobs		Industries Gaining the Least Jobs	
Industry	Jobs added by 2050 (Thousand)	Industry	Jobs added by 2050 (Thousand)
Education	1525.8	Pharmaceuticals	69.7
Government & Public Sector	1482.8	Energy	53.2
Consumer & Retail	722.3	Industrial Manufacturing	13.2
Healthcare & Life Sciences	547.9	Business Services	-43.9
Finance	510.7	Other Services	-984.2

Slow Gen AI Adoption			
Industries Gaining the Most Jobs		Industries Gaining the Least Jobs	
Industry	Jobs added by 2050 (Thousand)	Industry	Jobs added by 2050 (Thousand)
Education	1525.8	Chemicals	46.4
Government & Public Sector	1482.8	Pharmaceuticals	28.3
Consumer & Retail	722.3	Business Services	-35.3
Healthcare & Life Sciences	547.9	Other Services	-154.4
Finance	510.7	Industrial Manufacturing	-199.0

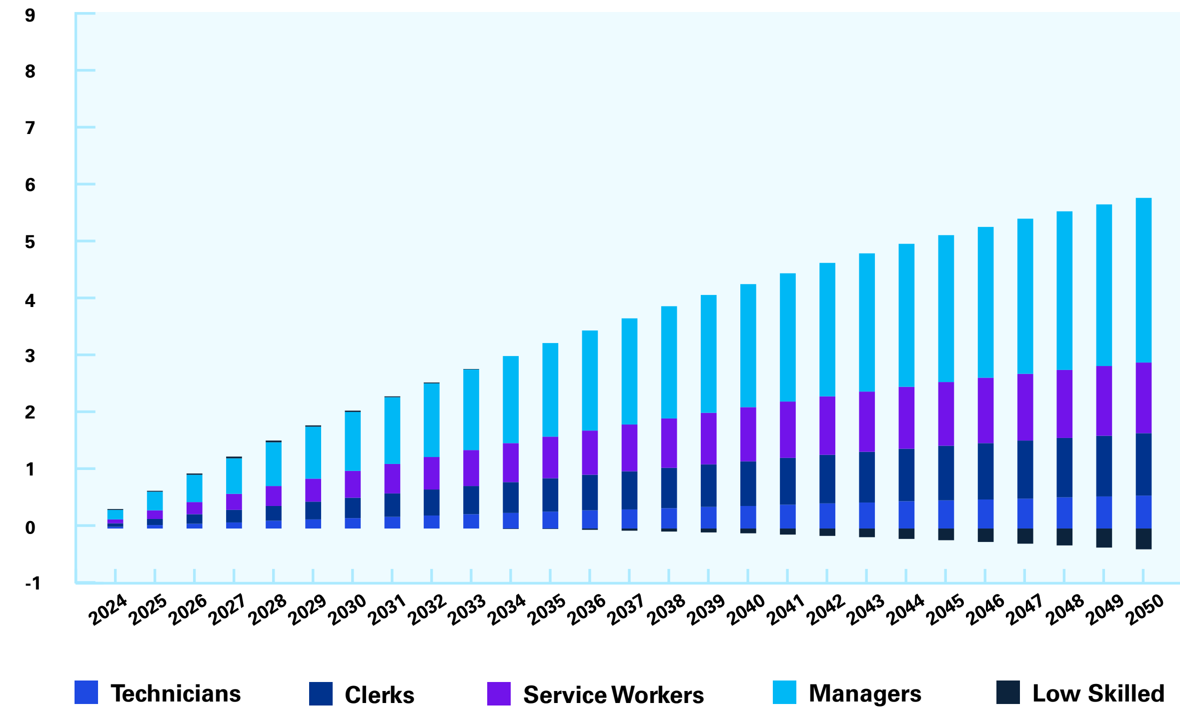
Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Figures B2: Change in US Employment by Labor Type (million)

Change in Employment by Labor Type in the US (Million)
Rapid Adoption vs. Baseline



Change in Employment by Labor Type in the US (Million)
Slow Adoption vs. Baseline

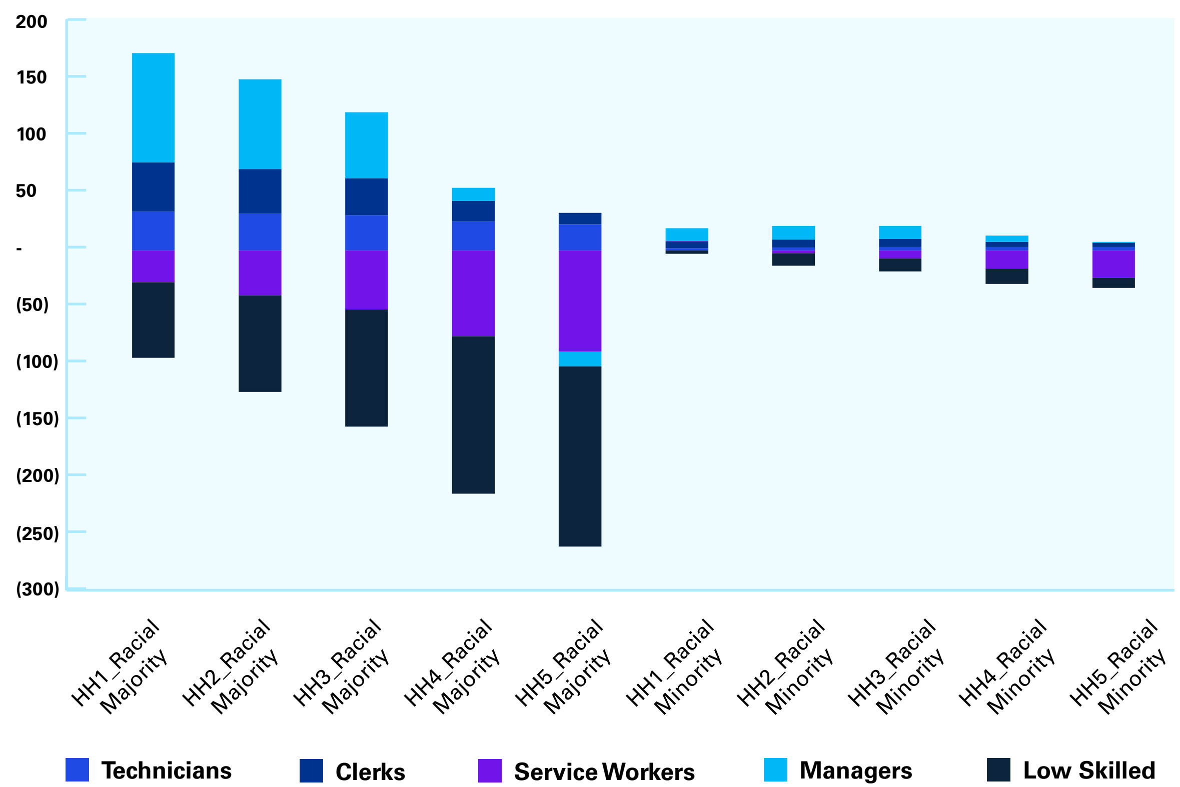


Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Figures B3: Employment Change across US Households due to Rapid Adoption with No Upskilling

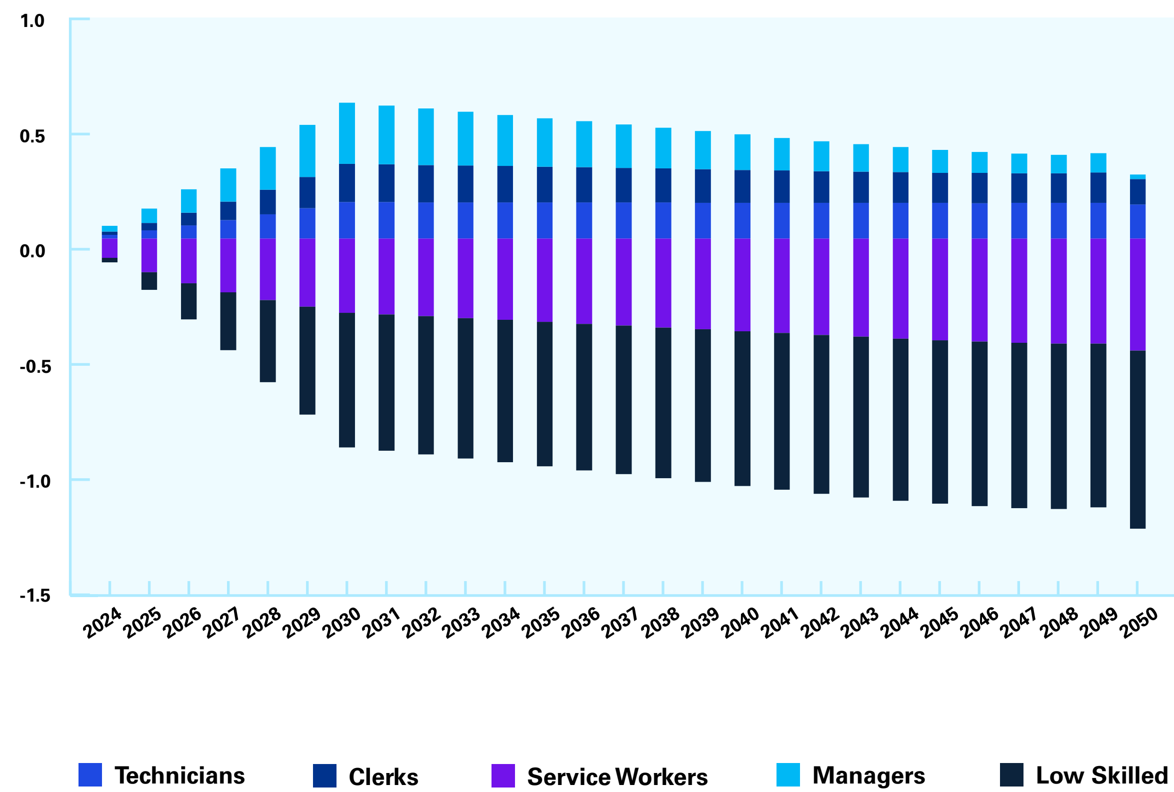
Rapid GenAI Adoption:

Net Change in US Employment (thousand) in 2030 relative to Baseline without Upskilling the Labor Force



Change in Employment by Labor Type in the US (Million)

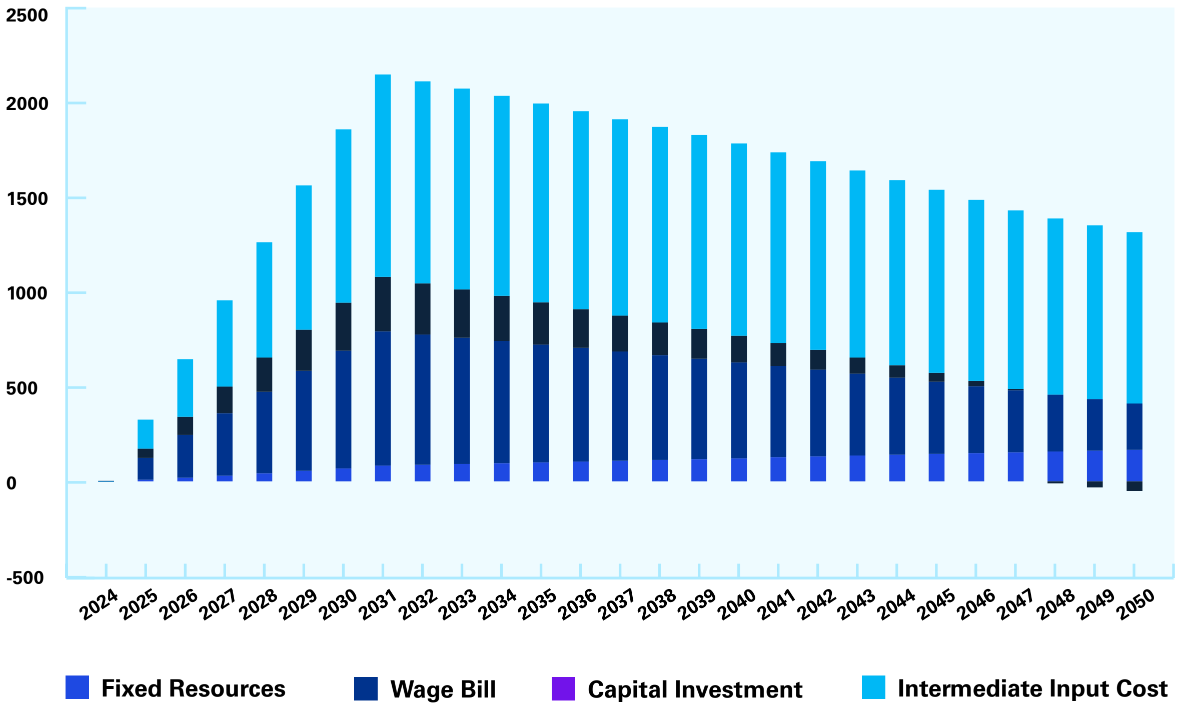
Rapid Adoption (No-Upskilling) vs. Baseline



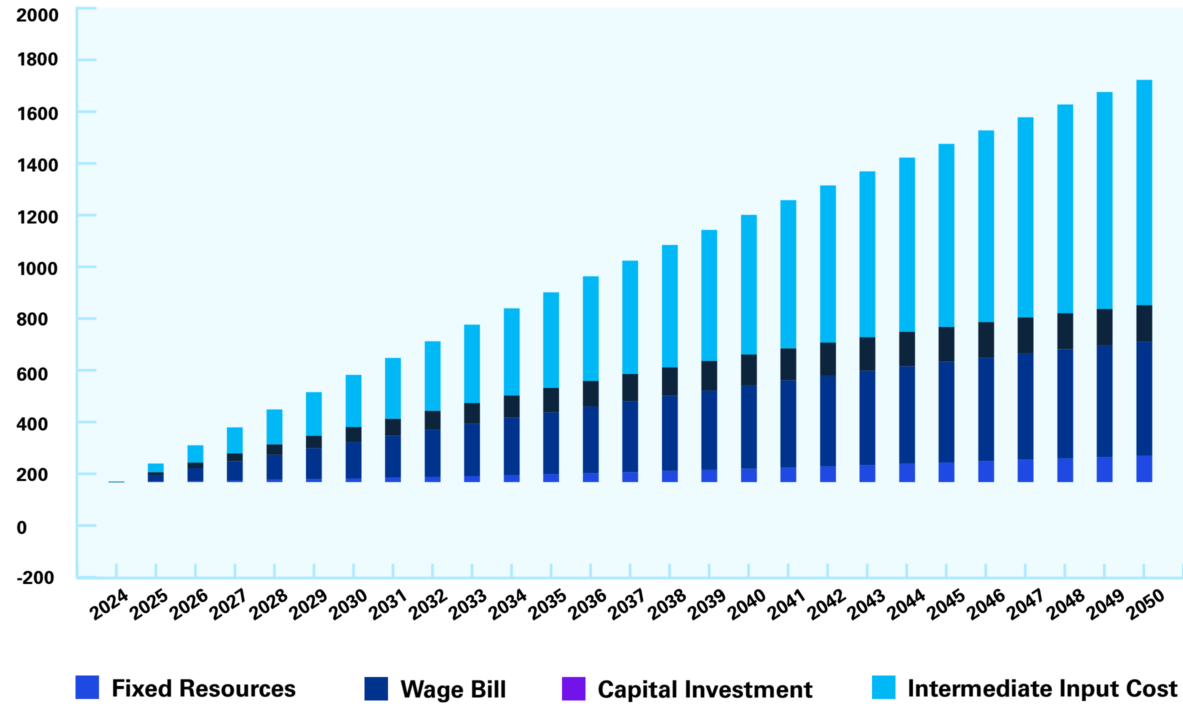
Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

Figures B4: Change in Total Costs of adopting GenAI

Rapid Adoption Costs ($ Bill)



Slow Adoption Costs ($ Bill)



Note, findings reflect productivity estimates that continue to be updated as generative AI and agentic AI use expand.

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