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Expecting Job Replacement by GenAI: Effects on Workers' Economic Outlook and Behavior*

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Abstract

This paper examines the relationship between individuals' expectations of job replacement by generative AI (GenAI) and their macroeconomic outlooks and behaviors. Using online surveys combined with randomized experiments conducted in the U.S. and Japan, we derive the following findings about the effects of expecting greater job replacement due to GenAI. First, in both the U.S. and Japan, respondents revise their beliefs after receiving information about GenAI's job replacement ratios. Second, in Japan, such an expectation leads to an increase in inflation expectations driven by a rise in investment. Third, it increases respondents' willingness to use GenAI in workplaces in Japan. Fourth, in the U.S., expectations of greater job replacement amplify concerns about weaker short-term labor demand and reduced skill requirements, particularly among more educated respondents. In addition, these respondents anticipate lower investment, while less educated respondents expect higher investment.

Keywords: Generative Artificial intelligence, labor market, inflation, productivity.

JEL Classification codes: E24, E31, O30

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1 Introduction

"The best way to predict the future is to invent it."

— Alan Kay

The rapid advances in generative AI (GenAI) have sparked significant interest and prompted widespread speculation about its transformative potential. However, the high level of uncertainty surrounding GenAI has fueled ongoing debate about its economic impact. This discussion becomes especially heated when it concerns AI's effect on the labor market. This intense debate shapes public expectations about AI's impact on the economy. As recent studies on the role of expectations suggest, these perceptions can influence actual behavior, which in turn affects economic outlooks. For example, positive views on AI's impact can encourage its adoption, further boosting productivity and investment. Conversely, negative perspectives may hinder AI's use and learning, potentially resulting in smaller effects on the economy. As the importance of expectations about AI's impact is well recognized, many surveys have been conducted focusing on people's views regarding AI's impact on the labor market. However, to the best of our knowledge, there are no studies examining the role of expectations about AI in shaping people's economic outlook and behavior.

To address this gap, we conducted a survey on perceptions of AI's effect on the labor market, along with randomized experiments in the United States and Japan. Specifically, we divided respondents into two treatment groups. The first group was provided with information from an expert analysis that GenAI would replace 14% of current jobs, while the second group was informed that AI could replace 47% of jobs based on the estimates by Briggs and Kodnani (2023) and Frey and Osborne (2017).[1] We then asked participants about their expectations regarding the job replacement ratio before the treatment (referred to as "prior beliefs"), followed by their updated expectations after the treatment (referred to as "posterior beliefs"). In addition, respondents were asked to predict economic outcomes, such as real GDP growth rates over 1-, 3-, and 5-10-year horizons, as well as their intentions

[1] See Section 3.2 for more detailed discussion on the replacement ratio. We also collect responses from a third group that received unrelated astronomical information. However, in this paper, we focus on the two treatment groups, as these treatments reflect realistic situations that people may encounter.

to learn and use AI in the workplace. Using the responses about AI's impact on the labor market and views on macroeconomic variables, we identify the causal effect of individuals' expectations regarding the labor replacement ratio by GenAI on their economic outlooks and behavior. It is important to note that we do not aim to predict AI's impact on the economy or the labor market. Rather, we seek to uncover how changes in views on AI affect economic expectations and behavior.

Our study sheds light on ongoing debate about the impact of AI on macroeconomic variables beyond the labor market. In fact, Aldasoro et al. (2024) demonstrate that GenAI could exert inflationary pressure on the economy in the long run, while in the short run, it could result in either disinflationary or inflationary effects, depending on how economic agents form expectations regarding GenAI's impact. Specifically, if households and firms anticipate future productivity growth driven by AI, households may increase consumption, leading to inflationary pressure even in the short run. On the other hand, if an increase in productivity due to AI is unanticipated, consumption only increases gradually. Therefore, in the short run, it has a disinflationary impact as the production capacity expands. Our paper focuses on the impact of people's views regarding AI on inflation expectations, rather than assessing which prediction is more plausible.

Using the randomized experiment, we obtain the following findings. First, people's views on GenAI's labor market impact can be updated by expert opinion. In both the U.S. and Japan, respondents revise their beliefs after receiving information about GenAI's job replacement ratios. This updating behavior aligns with the previous literature on people's expectation about macroeconomic variables such as recession probabilities and is consistent with a Bayesian process.

Second, in Japan, higher posterior beliefs about the job replacement ratio lead to higher inflation expectations. In addition, a high replacement ratio is associated with positive real GDP growth, particularly among high-income individuals, though this estimate of the marginal effect is not statistically significant on average. Furthermore, a high replacement expectation leads to higher private investment growth among workers in creative occupations. We can infer that this result is partly due to their high reliance on many labor-intensive tasks such as writing text, which are likely to be replaced by GenAI. These results suggest that the investment demand associated with GenAI could contribute to rising inflation rates. Moreover, respondents in Japan show an increased intention to use GenAI in their workplace when they adjust their expectations regarding the replacement ratio to higher levels.

In contrast, in the U.S., we do not find any significant average effect of a higher replacement ratio on inflation expectations. However, the expectation of a higher replacement ratio leads to an expectation of weaker labor demand in the short term and a decline in the skills required for the respondent's current jobs. The impact on the outlook for labor demand is more pronounced among individuals with higher education levels. This suggests that people with higher education anticipate more negative effects of GenAI on the labor market, aligning with previous literature on the heterogeneous impacts of AI on labor. Finally, respondents in the U.S. do not increase their willingness to use or learn GenAI in their workplace, even though they have changed their views on its impact on their jobs.

The rest of the paper is organized as follows. Section 2 summarizes the literature related to this paper. Section 3 explains the data and the setting of the randomized control trial. Section 4 introduces econometric models by illustrating the identification strategy and then reports the survey and experiment results. Finally, Section 5 concludes.

2 Literature review

This study is related to four strands of literature. First, we build on the previous studies on the impact of AIs on labor market, especially when we implement the randomized experiment. Among many, Frey and Osborne (2017) is a seminal paper and analyzes the impact of automation on jobs using detailed job descriptions. They find that a large share of currents jobs are exposed to the automation by computers. Briggs and Kodnani (2023) discuss the potential of GenAI and their effects on economy, by showing different scenarios of AI developments and the subsequent impact on the labor market. We also use their estimates in the randomized experiments. Webb (2019) uses patent data to identify which task would be most affected by automation with AI. A growing number of studies analyze the relationship between labor market and AI including Manyika et al. (2017), Hui et al. (2023), Felten et al. (2021) and Acemoglu and Restrepo (2020).[2] Babina et al. (2023) find that companies with a larger initial proportion of more educated workers with expertise in science, technology, engineering, and mathematics tend to invest more in AI. In addition, they report that AI investments are associated with a flattening of organizational hierarchies, with a rise in junior-level employees and a decline in middle-management and senior positions. Cazzaniga et al. (2024) demonstrate that there are clear trends in AI exposure: women and college-educated individuals face higher exposure but are also better positioned to benefit from AI advancements, while older workers may struggle more to adapt to the new technology. Yang (2022) studies the impact of AI in Taiwan's electronics industry for the 2002–2018 period and finds that AI technology is positively associated with productivity and employment. Hering (2023) uses the online job posting data and finds that 20% of jobs faces the highest level of potential exposure.

Second, we extend the literature on expectation formations of economic variables.[3] In particular, we follow the experimental setting of Roth and Wohlfart (2020) that study the relationships between macroeconomic expectations and individual behavior. A growing body of research studies people's expectations. For example, Das et al. (2020) examine the heterogeneity in expectation formation across people with different socioeconomic statuses. They find that individuals with higher income or education levels tend to be more optimistic about future macroeconomic developments. Kuchler and Zafar (2019) explores the relationship between personal experiences and views on the macroeconomy, finding that individuals who experience unemployment personally become more pessimistic about future nationwide unemployment. The extent of this extrapolation is more pronounced among less sophisticated individuals. Malmendier and Nagel (2011) demonstrates that past individual experiences play a significant role in explaining risk-taking behavior. Regarding differences across age groups, Malmendier and Nagel (2016) finds that in response to inflation surprises, younger people update their expectations more strongly than older individuals, as recent experiences weigh more heavily in their accumulated lifetime history. However, household expectations about the economy may be

[2] BIS (2024) comprehensively discusses the impact of AI on the economy including labor market.
[3] Manski (2018) provides a comprehensive literature review on macroeconomic expectations.

biased. In fact, Mian et al. (2023) find that an individual's expectations for future economic growth are biased depending on whether her favorable political party controls the White House, and this bias is not necessarily linked to actual behaviors such as consumption. This result suggests that further intensive studies on household expectations are needed. The importance of individual beliefs in financial decision-making is highlighted by Bailey et al. (2019). We contribute to the literature by focusing on the relationship between views on AI's role and macroeconomic conditions.

Third, our study extends existing research on the impact of AI on the labor market through the use of surveys. Among others, Lane et al. (2023) provide a comprehensive view of AI's impact in workplaces, enabling international comparisons. McElheran et al. (2024) use a survey on businesses to study trends in AI adoption, finding that dynamic young firms with more educated, experienced, and younger owners have the highest rates of AI use. We extend this survey approach using a randomized controlled trial.

Finally, our paper sheds light on the differences in views regarding the impact of AI across countries. In terms of the impact of automation and robotics on the economy, a different landscape appears between Japan and the U.S. Many studies on the U.S. labor market, including Acemoglu and Restrepo (2020), demonstrate that robots replace human labor. On the other hand, Adachi et al. (2024) show that the increase in robot usage increases employment by raising the productivity and production scale of robot-adopting industries. Although the reasons for the differing impacts of robotics between the two countries remain debatable, such experiences may influence their expectations about the impact of AI, leading to different results. We contribute to this literature by conducting the same survey in both Japan and the U.S., uncovering differences in the causal effects of views on AI in shaping macroeconomic outlooks and individual behaviors between the two countries.

3 Data and setting of randomized experiment

This section describes the survey methodology, sampling strategy, data cleaning processes, and details of the randomized treatment groups.

3.1 Survey methodology

We collected 4,144 responses from both the U.S. and Japan through large-scale internet survey panels administered by Macromill, Inc., Japan's leading survey company. Only full-time employees between the ages of 20 and 59 were invited to participate in the survey and respondents who appropriately completed it could earn cash or a gift voucher. The survey was implemented to ensure that the number of respondents was equalized across gender, age, and job category. More specifically, respondents are categorized into 16 distinct demographic groups based on gender, age (20 to 39 years old and 40 to 59 years old), and job category (Sales and Administrative, Engineering, Planning and Specialist, and Creative). We should note that these four job categories are not comprehensive. However, we focus on them partly to ensure a sufficient number of responses within each category, and partly because workers in these categories are expected to be highly exposed to generative AI, according to existing studies such as Chui et al. (2023). The details of the job categories are summarized in Table A.1 in Appendix A. The survey was conducted from May 20 to June 3, 2024, for the U.S. participants and from May 20 to May 29, 2024, for Japanese participants.

3.2 Setting of randomized experiment

We randomly assigned respondents into three groups to evaluate the impact of GenAI on job replacement. The first group was presented with the following information: "A well-known study on AI estimates that 14% of current jobs could be replaced by GenAI in the future." The second group was informed that "A well-known study on AI estimates that 47% of current jobs could be replaced by GenAI in the future."

The replacement ratios of 14% and 47% are based on estimates provided by Briggs and Kodnani (2023). We should note that Briggs and Kodnani (2023) do not report the replacement ratio of the labor force by AI per se. Instead, they estimate the exposure of the labor force to AI-driven automation across various scenarios, assuming varying levels of AI development.[4] The 14% replacement ratio reflects the lowest estimate in

[4]Briggs and Kodnani (2023) refer to this estimate as the "share of full-time equivalent US employment exposed to automation by AI."

their scenarios, while the 47% figure is based on estimates from Frey and Osborne (2017), which also suggests that 47% of jobs are exposed to automation. We opted not to use the term “exposed” as in the original papers because it could be ambiguous and interpreted differently by respondents. However, we acknowledge certain limitations in our approach. Specifically, the term ”replaced” may evoke a negative perception of AI, even though its impact could be positive in many areas, such as increased productivity. Moreover, respondents familiar with the original research might notice the difference in terminology and become less engaged in answering subsequent questions. Despite these caveats, our approach reduces ambiguity and provides a finer understanding of the role of people’s views on AI. In addition, we did not mention the sources of these estimates in the survey. This decision was made to avoid introducing bias, as belief in the credibility of data sources can vary depending on individual characteristics, potentially introducing noise into their responses. Furthermore, we did not provide respondents with information on a forecast horizon for the professional estimates, given that the estimates do not specify a time horizon for AI’s labor market impact. This approach allows us to observe respondents’ own beliefs about when GenAI effects may materialize.

Respondents answered the questions introduced in Section 3.3 both before and after receiving the treatment information. This design allowed us to measure changes in responses resulting from the provided information. We focus on results from the two treatment groups with 14% and 47% job replacement ratio by GenAI, following the methodology of Roth and Wohlfart (2020).

3.3 Survey questions and definition of variables

We outline the question defining the treatment variable for the causal effect analysis, followed by the questions defining the outcome variables. Respondents answered each of these questions both prior to and following the treatment.

To construct the treatment variable, we ask respondents about the share of jobs being replaced by GenAI in 1, 5, and 10 years. The respondents enter values in percentages for each horizon. Details of this variable can be found in the first line of Table 1. As to the outcome variables in the randomized experiment, we ask questions regarding expectations for key macroeconomic variables over different time horizons (1 year, 3 years, and an average of 5-10 years). Respondents answered questions on Consumer Price Index (CPI), private investment growth, and real GDP growth both before and after treatment, with answer choices in 0.5% increments, as shown in rows 2 to 4 of Table 1.

Table 1: Details of the treatment variable and the outcome variables

Variable name	Question	Choices	Processing method
Share of jobs replaced by generative AI	What percentage of current jobs do you think will be replaced by generative AI in the future? Please answer about society in general, not about your own work specifically.	values: %	No processing
CPI	How do you think the following indicators in your country will change in the future? Consumer Price Index (YoY)	Choices 0.5 increments +0.5%, +1.0%, +1.5%, ...etc	Scaled between a minimum of 0 and a maximum of 1
Private investment	How do you think the following indicators in your country will change in the future? Private investment (YoY)	Choices 0.5 increments +0.5%, +1.0%, +1.5%, ...etc	Scaled between a minimum of 0 and a maximum of 1
Real GDP Growth	How do you think the following indicators in your country will change in the future? Real GDP (YoY)	Choices 0.5 increments +0.5%, +1.0%, +1.5%, ...etc	Scaled between a minimum of 0 and a maximum of 1

Notes: When asking about macroeconomic variables like CPI, private investment, real GDP, we provide the past values for 2022 and 2023 as reference points. The choices for the questions of macroeconomic variables are in increments of 0.5%, such as +0.5%, +1.0%, +1.5%, etc., with a maximum of +5.0%. If the respondent wants to choose a value greater than that, they should select the choice "Increase of more than 5.0%". Similarly, the minimum is -5.0, and if the respondent wants to choose a value less than that, they should select the choice "Decrease of more than 5.0%".

As additional outcome variables, we also survey respondents about their perspectives on their own jobs, specifically regarding wage growth, skills, labor demand, and productivity.[5] Details of these variables can be found in Table 2.

We also prepared variables for the intention for learning and using GenAI in the workplace. Details of these variables can be found in Table 3.

[5]They are asked about the projections of those variables over 1, 3, 5, and 10-year horizons. The 1-, 5-, and 10-year projections are used in this paper.

Table 2: Additional outcome variables: Wage growth, Skills, and Labor demand

Variable name	Question	Choices	Processing method
Wage growth	How do you think the spread of generative AI will impact wages for your current job in the future?	A1: 20% or greater increase A2: 10-19% increase A3: 5-9% increase A4: 1-4% increase A5: No change A6: 1-4% decrease A7: 5-9% decrease A8: 10-19% decrease A9: 20% or greater decrease A10: Other	Scaled between a minimum of 0 and a maximum of 1 Respondents with A10 are excluded from the sample for the estimation.
Skills	How do you think the spread of generative AI will change the skills required for your current job in the future?	A1: No change A2: Less skills will be required A3: More skills will be required A4: I don't know	Standardizing responses that indicate a decrease to a minimum value of 0 and those that indicate an increase to a maximum value of 1
Labor demand	How do you think the spread of generative AI will change the demand for your current job in the future?	A1: No change A2: Decreased demand A3: Increased demand A4: I don't know	Standardizing responses that indicate a decrease to a minimum value of 0 and those that indicate an increase to a maximum value of 1
Productivity	How do you think the spread of generative AI will change productivity in your current job in the future?	A1: No change A2: Decreased productivity A3: Increased productivity A4: I don't know	Standardizing responses that indicate a decrease to a minimum value of 0 and those that indicate an increase to a maximum value of 1

3.4 Representativeness and data cleaning

To ensure balanced demographic representation, our survey aimed for equal numbers of respondents across gender, age, and job category. Each group has nearly the same number of respondents across genders. For age, respondents were asked to specify their age in 5-year increments. We excluded respondents who were under 20 years old and those who were 60 years old or older. The sample includes an equal number of respondents aged 20–39 and 40–59, ensuring balanced representation across these age groups. Respondents were asked to choose one of 60 job categories, and we aimed to collect an equal number of valid responses across four consolidated groups: Sales and Administrative, Engineering, Planning and Specialist, and Creative. However, we obtained fewer valid responses from individuals in the Creative job category, resulting in a lower proportion of collected samples for this group.

We implemented a data cleaning process focused on the treatment variable, or the share of jobs replaced by GenAI. We exclude extreme responses of 0% or 100% from respondents'

Table 3: Additional outcome variables: GenAI learning / use intention

Variable name	Question	Choices	Processing method
Generative AI learning intention	Do you have the opportunity to learn about generative AI? Please select all that apply.	A1: I do not have the opportunity to learn it at present and do not plan to learn in the future A2: I do not have the opportunity to learn it at present, but I would like to learn in the future A3: I am learning it on my own during work hours A4: I am learning it through online courses, seminars, etc. during work hours A5: I am learning it at a graduate school, etc. A6: I am learning it on my own during my private time A7: I am learning it through online courses, seminars, etc. during my private time A8: Other	A1 and A2 are used Converting into binary A1 = 0 A2 = 1 A3 to A7 are not used See Notes
Generative AI use intention	Do you want to use generative AI in your work in the future? Select one only.	A1: I do not want to use it A2: I want to actively explore the possibility of using generative AI in work where its use is not currently permitted and put forward proposals for use in my company A3: I want to use it in my work if I am permitted to do so A4: I want to use it in my work if I am obliged to do so A5: I am currently using it and want to continue to use it in the future	All answers other than A5 are used Converting into binary A1 = 0 A2, A3, A4 = 1 A5 is not used See Notes

Notes: The question for ”Generative AI learning intention ” allows respondents to select more than one choice, but A1 and A2 cannot be selected at the same time. For the variable “GenAI learning intention ”, options A3 to A7 are not used. This is because these options indicate cases where respondents have already learned about generative AI. This variable is used to measure the intention to learn for respondents who have not yet learned about generative AI, so respondents who have already learned about generative AI are excluded. For the variable “GenAI use intention ”, option A5 is not used. This is because these options indicate cases where respondents have already learned about generative AI. This variable is used to measure the intention to use generative AI for respondents who have not yet used it, so respondents who have already used generative AI are excluded.

beliefs about the GenAI job replacement rates across all time horizons.[6] As discussed in Section 3.2, our analysis focuses on the two treatment groups who received prompts about a 14% and 47% GenAI job replacement ratio. After excluding outliers, the sample includes 2,399 observations in the U.S. and 1,726 in Japan. Figure 1 presents the final sample size and the job category share for analysis.

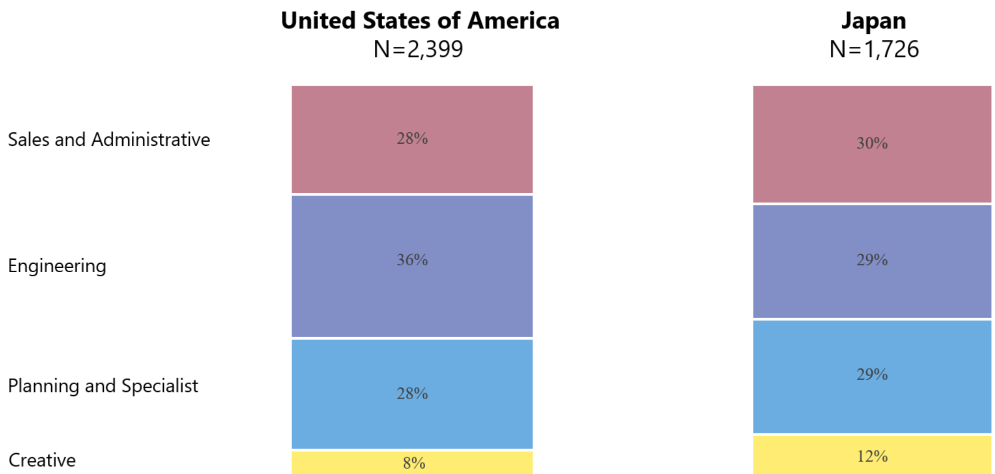


Figure 1: The actual number of samples per job category

Table 4 presents summary statistics for respondents' demographics and other characteristics across each treatment arm. The mean values and standard deviations for each variable show little variation between the treatment groups, suggesting that the randomization successfully achieved balance. The average age of respondents in both Japan and the U.S. was around 40 years old. This is because the survey was designed to include an equal number of people in the 20–39 age group and the 40–59 age group, and only included people aged 20–59. The actual number of employed people in Japan aged 40–59 is about 1.4 times higher than the number of people aged 20–39 in 2022 according to Labor Force Survey conducted by Ministry of Internal Affairs and Communications of Japan. On the other hand, the actual number of employed people in the U.S. aged 40–59 is about 95% of the number of people aged 20–39 in 2022 according to Labor Force Statistics (OECD).

[6]By excluding responses with 0% or 100%, the sample size decreased by approximately 500 for Japan and 200 for the U.S. in each treatment group. However, our main results remain consistent even when these outlier responses are included.

The average wages in the samples are higher than the average wage levels for the whole country in both Japan and the U.S., partly because the types of jobs in the respondents are limited.[7]

Table 4: Summary statistics by treatment group in Japan and the U.S.

Japan

	Treatment: 14% Low job replacement by GenAI						Treatment: 47% High job replacement by GenAI					
	Mean	SD	Median	Min.	Max.	Obs.	Mean	SD	Median	Min.	Max.	Obs.
Female	0.50	0.50	1	0	1	854	0.50	0.50	0	0	1	872
Age	39.41	10.08	37	22	57	854	39.56	9.86	37	22	57	872
At Least Bachelor's Degree	0.70	0.46	1	0	1	854	0.70	0.46	1	0	1	872
Income (Million yen)	5.91	3.80	5	2	30	768	6.08	4.03	5	2	30	789
Private Use of GenAI	0.33	0.47	0	0	1	854	0.30	0.46	0	0	1	872
Repetitive Work	0.44	0.50	0	0	1	835	0.43	0.49	0	0	1	850
Occupation Category: Sales & Admin	0.30	0.46	0	0	1	854	0.30	0.46	0	0	1	872
Occupation Category: Creative	0.11	0.32	0	0	1	854	0.12	0.32	0	0	1	872
Occupation Category: Engineering	0.29	0.45	0	0	1	854	0.29	0.46	0	0	1	872
Occupation Category: Planning & Profession	0.30	0.46	0	0	1	854	0.28	0.45	0	0	1	872

United States

	Treatment: 14% Low job replacement by GenAI						Treatment: 47% High job replacement by GenAI					
	Mean	SD	Median	Min.	Max.	Obs.	Mean	SD	Median	Min.	Max.	Obs.
Female	0.49	0.50	0.00	0.00	1.00	1183	0.49	0.50	0.00	0.00	1.00	1216
Age	39.27	8.45	37.00	22.00	57.00	1183	39.20	8.53	37.00	22.00	57.00	1216
At Least Bachelor's Degree	0.71	0.45	1.00	0.00	1.00	1183	0.69	0.46	1.00	0.00	1.00	1216
Income (thousands of dollars)	90	40	90	20	180	1177	100	40	90	20	180	1210
Private Use of GenAI	0.70	0.46	1.00	0.00	1.00	1183	0.68	0.47	1.00	0.00	1.00	1216
Repetitive Work	0.82	0.38	1.00	0.00	1.00	1179	0.83	0.38	1.00	0.00	1.00	1208
Occupation Category: Sales & Admin	0.28	0.45	0.00	0.00	1.00	1183	0.28	0.45	0.00	0.00	1.00	1216
Occupation Category: Creative	0.08	0.27	0.00	0.00	1.00	1183	0.07	0.26	0.00	0.00	1.00	1216
Occupation Category: Engineering	0.36	0.48	0.00	0.00	1.00	1183	0.37	0.48	0.00	0.00	1.00	1216
Occupation Category: Planning & Profession	0.29	0.45	0.00	0.00	1.00	1183	0.28	0.45	0.00	0.00	1.00	1216

Notes: This table shows summary statistics of respondent's demographic and other characteristics by treatment group. The upper panel indicates the summary statistics for respondents in Japan and the lower panel for the U.S. The unit of "Income (Million)" in million yen for Japan and million dollars for the U.S.

[7] The average annual wage in 2023 is 4.6 million yen in Japan and 65,000 U.S. dollar in the U.S., according to the National Tax Agency of Japan and the U.S. Bureau of Labor Statistics, respectively.

4 Results of randomized experiments

In this section, we first examine how respondents update their beliefs about the job replacement ratio after the treatment. We then present the results on the effect of this update on the outlook for macroeconomic indicators and their behavior.

4.1 Prior Beliefs

Before analyzing the updating of the job replacement ratio, we report basic statistics. In our sample, respondents' prior beliefs regarding the labor replacement ratio due to GenAI show significant variation, with many falling between the professional forecast values of 14% and 47%. The ratio tends to show higher values over a longer horizon. As Figure B.1 and Table B.1 in Appendix B show, the median values for 1-year, 5-year, 10-year ahead are 10%, 20% and 30%, respectively.

As Table B.2 shows, several factors explain the differences in respondents' prior beliefs, with education being particularly significant. Higher education is associated with lower expectations of job replacement by GenAI in both Japan and the U.S. However, income has a different impact between the two countries. In the U.S., higher income is associated with a more pessimistic outlook on job replacement, while in Japan, higher income is linked to lower job replacement beliefs.[8].

Another key factor would be the private use of GenAI. In the U.S., those using GenAI privately tend to have higher prior beliefs about the job replacement ratio, possibly perceiving it as a greater disruptor. In Japan, however, this correlation is not statistically significant. Age shows mixed results depending on the specification. In the U.S. multivariate regressions, age is positively correlated with job replacement expectations, while the age-squared term is negative, suggesting diminishing marginal effects as age increases. The marginal effect eventually turns negative when age exceeds approximately 40, based on the 1-year-ahead expectations. In Japan, the estimate for age is not statistically significant. Gender overall shows no significant correlation. However, it is noteworthy that

[8]Income and education are positively and highly correlated as shown in D.1. Therefore, we mainly focus on univariate regression results.

U.S. women tend to hold a more pessimistic outlook, anticipating higher replacement rates by GenAI as the time horizon stretches further into the future. Finally, people with subordinates expect higher replacement rates in 1- and 5-year horizons, though this correlation weakens over 10 years due to increased uncertainty. In Japan, respondents with repetitive jobs hold higher beliefs about replacement rates although there is no statistically significant estimate for the correlation with repetitive work in the U.S.

4.2 Updating of replacements by GenAI

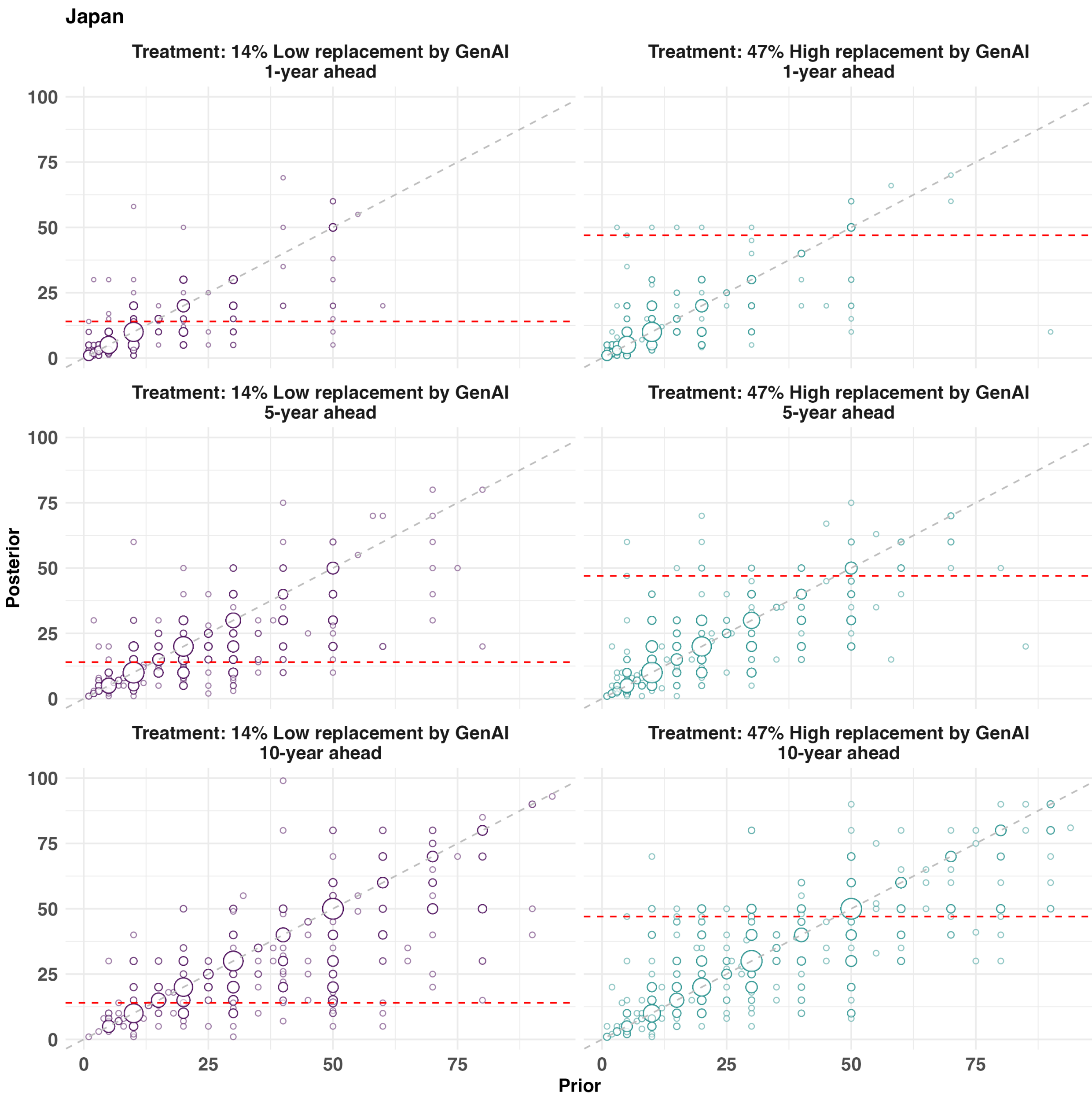
We examine whether the provided information leads to a significant shift in expectations toward the expert projections in the treatment groups. We test this updating process through visualizations and regression analysis.

Figure 2 and 3 display scatter plots of prior (X-axis) and posterior (Y-axis) beliefs in 1-year, 5-year and 10-year ahead horizon in Japan and the U.S.. Observations along the red dashed horizontal lines represent respondents who updated their beliefs towards the professional forecast, while those along the 45 degree line indicate respondents with no change. Responses of 0% or 100% labor replacement ratio by GenAI, specifically those with prior or posterior beliefs of 0 or 100, are excluded from the sample because they are regarded as outliers in this analysis.

The longer the forecast horizon, the more likely individuals are to update their beliefs. This suggests that as the uncertainty in personal responses increases, there is a greater tendency to rely on expert forecasts. Another possible explanation is that respondents interpret the professional forecasts as long-term estimates since the forecast do not mention any specific timeline. As illustrated in Table B.3, regarding 1-year ahead beliefs, about 70% of respondents in Japan and about 55% of respondents in the U.S. do not update their beliefs at all. A large portion of the remaining respondents adjust their beliefs toward the expert forecast—however, about 10% in Japan and 20% in the U.S. move in the opposite direction. The share of respondents who do not change the projection of the job replacement ratio in the 10-year forecast horizon is 59% in Japan and 46% in the U.S.

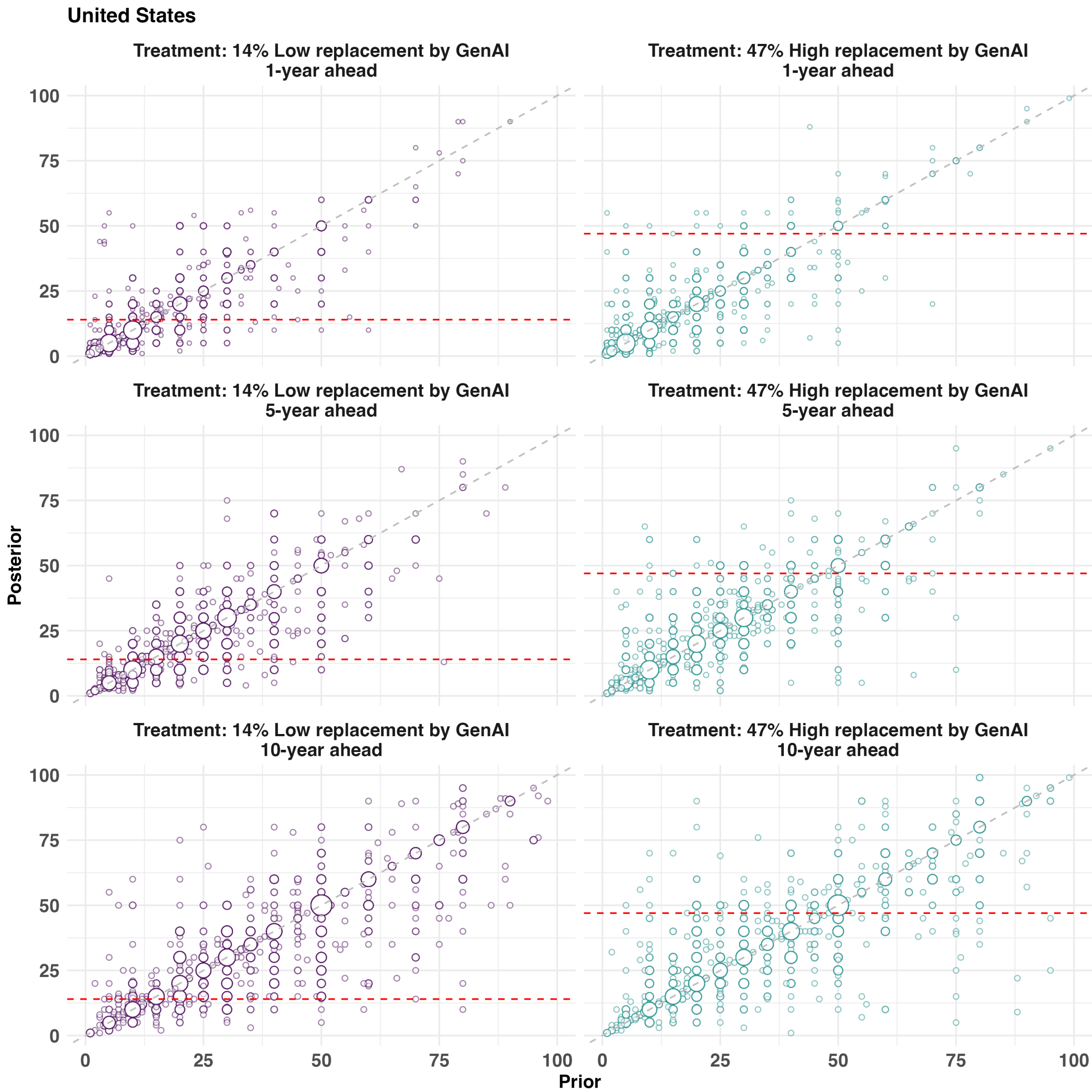
Another point worth mentioning is that the ratio of responses where the posterior is greater than the prior is higher for the high treatment group than that for the low treatment

Figure 2: Scatter plot of prior and posterior beliefs about the ratio of jobs replaced by GenAI - Japan



Notes: This scatter plot compares prior and posterior beliefs regarding the ratio of jobs replaced by GenAI in Japan. The size of the circles indicates the density of data points for each combination of prior and posterior beliefs. The gray dashed lines represent the 45 degree lines. The red dashed horizontal lines represent the job replacement ratios provided to respondents in each group as the professional forecast for the treatment.

Figure 3: Scatter plot of prior and posterior beliefs about the ratio of jobs replaced by GenAI - the U.S.



Notes: This scatter plot compares prior and posterior beliefs regarding the ratio of jobs replaced by GenAI in the U.S. The size of the circles indicates the density of data points for each combination of prior and posterior beliefs. The gray dashed lines represent the 45 degree lines. The red dashed horizontal lines represent the job replacement ratios provided to respondents in each group as the professional forecast for the treatment.

group. Put differently, respondents in the high treatment group are more likely to update their belief about the replacement upward compared to those in the low treatment group. For example, in Japan, 15.3% of respondents update their belief upward in the high treatment group while 9.1% of those update their belief upward in the low treatment as shown in Table B.3. The further into the future the belief pertains—such as five or ten years ahead—the larger the difference between the treatment groups in the proportion of respondents who update their beliefs upward. For the 10-year ahead horizon, 19% of respondents in the high treatment group update their belief upward, while 9.5% of those in the low treatment group do.

Finally, it is worth noting that the posterior beliefs do not exhibit increased variation compared to the prior beliefs. In fact, the inter-quartile range and the standard deviations remain relatively unchanged as seen in Table B.1. Moreover, this tendency holds true for both treatment groups.

We quantify to what extent respondents update the expected job replacement ratio by GenAI, regressing the updating (i.e. the difference in respondent's posterior and prior expectations) on the shock, which is defined as the difference between the professional forecast and the prior belief as follows:

$$\text{Shock}_i = \begin{cases} 47 - \text{Prior}_i & \text{if high replacement}_i = 1 \\ 14 - \text{Prior}_i & \text{if high replacement}_i = 0 \end{cases} \tag{1}$$

In addition, we control for respondent's prior belief to avoid mechanical correlation between the updating and the shock. Specifically, we estimate the following equation using OLS:

$$\text{Updating}_i = \beta_0 + \beta_1 \text{Shock}_i + \beta_2 \text{Prior}_i + \Pi \text{X}_i + \epsilon_i \tag{2}$$

where X_i is a set of control variables and ϵ_i is an idiosyncratic error. X_i includes age, age squared, a dummy for females, log of income, a dummy for respondents with at least a bachelor degree, a dummy for private use of generative AI, and dummies for having subordinates, routine/repetitive worker, region, occupation, industry, and firm size.

The estimation result in Table 5 shows that if prior beliefs are lower by 1 percentage point than professional forecasts—in other words, if the shock increases by 1 percentage points—this would, on average, result in a 3 percentage point update in 1-year ahead beliefs, a 7 percentage point update in 5-year beliefs, and a 10 percentage point update in 10-year beliefs. As uncertainty rises in the more distant future, it becomes clear that individuals rely more on professional forecast signals, resulting in a greater impact of shocks. This result implies the respondents may follow Bayesian updating; respondents who are less confident in their prior beliefs react more strongly to new signals.[9] To test this, we also include interaction terms with a dummy variable indicating whether respondents are confident in their responses (see Table B.4 in Appendix B). The results show that for some horizons, consistent with Bayesian updating, respondents who are confident in their prior beliefs exhibit significantly lower updating.

[9]One of the explanations is that respondents believe the impact of AI on the labor market will materialize in the long run and interpret the experts' projections as long-term outlooks.

Table 5: Updating belief

Japan						
	Updating (for 1-year ahead)		Updating (for 5-year ahead)		Updating (for 10-year ahead)	
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.03*** (0.009)	0.04*** (0.01)	0.07*** (0.01)	0.09*** (0.02)	0.11*** (0.02)	0.12*** (0.02)
Prior	-0.23*** (0.05)	-0.23*** (0.05)	-0.20*** (0.02)	-0.21*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)
Confident		1.1 (0.72)		1.2** (0.57)		-0.03 (0.60)
Shock x Confident		-0.03 (0.03)		-0.07*** (0.03)		-0.02 (0.03)
Adj. R2	0.16	0.16	0.20	0.20	0.17	0.17
Observations	1,505	1,505	1,505	1,505	1,505	1,505
F-test, stat.	7.7	7.5	9.5	9.5	8.1	7.7

United States						
	Updating (for 1-year ahead)		Updating (for 5-year ahead)		Updating (for 10-year ahead)	
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.02* (0.009)	0.05** (0.03)	0.05*** (0.01)	0.11*** (0.03)	0.07*** (0.01)	0.15*** (0.03)
Prior	-0.12*** (0.02)	-0.13*** (0.02)	-0.15*** (0.02)	-0.15*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)
Confident		0.31 (0.73)		0.44 (0.74)		-0.33 (0.66)
Shock x Confident		-0.04 (0.03)		-0.08** (0.03)		-0.10*** (0.03)
-----------------	---------------	---------------	---------------	---------------	---------------	---------------
Adj. R2	0.07	0.07	0.10	0.11	0.11	0.11
Observations	2,369	2,369	2,369	2,369	2,369	2,369
F-test, stat.	5.5	5.4	7.7	7.7	8.1	8.3

Notes: The table shows the OLS estimation results with Updating as a dependent variable. Updating is defined as the difference between the posterior and prior belief about the job replacement ratio of labor by GenAI. The upper panel indicates the result for respondents in Japan, and the lower panel for the U.S.. All specifications control for prior beliefs, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Robust standard errors are in parentheses. * denotes significance at 10%, ** at 5%, and *** at 1%. level.

We also find that heterogeneities influence the updating. In the U.S., individuals who privately use GenAI, with occupations in engineering, and with higher income levels tend to update less compared to other cohorts. We do not find significant differences based on other characteristics such as gender as seen in Table B.5.

One possible explanation for the differences in learning rules among individuals could be that ones with private use of GenAI, with occupations in engineering, and with higher income levels may have higher confidence in their prior beliefs. As shown in Table B.4, in the U.S., higher educational groups tend to have higher confidence, cancelling the positive effect of the shock on the updating while lower educational groups tends to prioritize new information.

4.3 The causal effect of job replacement expectations on personal behaviors

In this section, we examine whether updating beliefs about job replacement due to GenAI leads people to adjust their behavior. Specifically, we analyze whether the respondent's updatings affect their willingness to learn about and use GenAI in their workplace, referred to as "GenAI learning intention " and "GenAI use intention ," respectively.

GenAI learning intention is defined as a binary variable based on the responses to the question about learning opportunity as explained in Section 3.3. Similarly, GenAI use intention is defined as a binary variable based on responses to the question about the willingness to use GenAI in the workplace, as described in Section 3.3.

As illustrated in Figure C.2, Japan exhibits a higher share of respondents motivated to use GenAI across both treatment groups. In the higher job replacement treatment group, 75% of Japanese respondents indicated they were motivated, compared to 70% in the lower job replacement group. In contrast, 63% of respondents in the U.S. expressed intention to use GenAI across both treatment arms, with a notable portion stating they had "already used it in their workplace." Notably, Japan demonstrates an increase in intention in the higher job replacement group compared to the lower one. For learning intention , the overall rate is lower, partly because many respondents indicated they had "already started learning."

4.3.1 Empirical specification

We examine whether the updating of beliefs has an impact on GenAI learning intention and GenAI use intention, with the assumption that these intentions follow a logit formation. Our main independent variable in the estimation is updating: the difference between posterior and prior expectations. We exploit the exogenous variation created by the random treatment assignment by instrumenting the updating of expectations through equation (2). We also control for the people's prior belief as a respondent's shock is correlated with one's prior belief. To do so, we estimate the following equation using two-stage least squares:

$$\text{intention}_{\,i} = \frac{\exp(y_i)}{1 + \exp(y_i)} \tag{3}$$

where

$$y_i = \gamma_0 + \gamma_1 \widehat{\text{Updating}}_i + \gamma_2 \text{Prior}_i + \mathbf{\Pi' X_i} + e_i \tag{4}$$

$$\widehat{\text{Updating}}_i = \beta_0 + \beta_1 \text{Shock}_i + \beta_2 \text{Prior}_i + \Theta' \text{X}_i \tag{5}$$

intention $_i$ indicates the dummy variable for the usage or learning intention of individual i. $\widehat{\text{Updating}}_i$ is a fitted value of Updating based on equation (5). X_i is a vector of control variables including prior beliefs, age, age squared, a dummy for females, log of income, a dummy for respondents with at least a bachelor degree, a dummy for private use of generative AI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry and firm size.

4.3.2 Marginal effects and results

Table 6 presents the marginal effects of updating beliefs as derived from the IV estimation.[10] The results reveal that in Japan, belief updating significantly increases the intention to use GenAI, while no statistically significant estimate of the marginal effect is observed in the U.S. nor for GenAI learning intention.

When it comes to the willingness to learn GenAI, we do not find any statistically significant estimates for the relationship between the updating and the willingness to learn in either country. This may be attributable to the fact that many respondents have already engaged in learning, coupled with a significant reduction in the number of observations in the regression, which could have diminished the statistical power.

In Japan, a 1 percentage point update in beliefs with regard to the 1-year ahead job replacement rate by GenAI increases the probability of answering "willing to use GenAI" by 4.9 percentage points. Similarly, belief updates regarding the 5-year and 10-year ahead replacement rates increase the intention to use GenAI by 2.2 percentage points and 1.4

[10]In this paper, we report a marginal effect at the mean, which is calculated by setting the values of all covariates to their means in the sample.

percentage points, respectively.

One potential explanation for the stronger impact on usage intention in Japan is that, as shown in Table A.2, the relatively low adoption rate of GenAI at 31% leaves more room for individuals who perceive the risk of job replacement by GenAI to use the technology as a means of reducing this risk. As in Table C.3, among respondents who answered "motivated," there is a difference between Japan and the U.S.: the proportion of those using GenAI privately is low in Japan, whereas it is high in the U.S. People already using GenAI in their workplace tend to use it privately in both Japan and the U.S.

Table 6: IV estimates of marginal effects of updating on individual behavioral views

	Japan					
	GenAI Learning intention			GenAI Use intention		
	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Updating	0.0271 (0.0296)	0.0125 (0.0121)	0.0077 (0.0073)	0.0487** (0.0202)	0.0216* (0.0112)	0.0135*** (0.0047)
Observations	1,093	1,093	1,093	1,328	1,328	1,328
First stage F-stat	7.7	9.5	8.1	7.7	9.5	8.1
Mean Dep.var.	0.58	0.58	0.58	0.82	0.82	0.82
SD Dep.var.	0.49	0.49	0.49	0.38	0.38	0.38
	United States					
	GenAI Learning intention			GenAI Use intention		
	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Updating	-0.081 (0.0791)	-0.0285 (0.0294)	-0.0178 (0.0196)	-0.0041 (0.0228)	-0.0017 (0.0090)	-0.0012 (0.0060)
Observations	532	532	532	1,665	1,665	1,665
First stage F-stat	5.5	7.7	8.1	5.5	7.7	8.1
Mean Dep.var.	0.61	0.61	0.61	0.89	0.89	0.89
SD Dep.var.	0.49	0.49	0.49	0.31	0.31	0.31

Notes: This table shows IV estimation of marginal effects of updating on GenAI learning intention and use intention . The upper panel indicates the estimation result for respondents in Japan, the lower panel for respondents in the U.S..All specifications control for prior beliefs, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Robust standard errors are in parentheses.* denotes significance at 10%, ** at 5%, and *** at 1%. level.

4.4 The causal effect of job replacement expectations on macroeconomic outlook and perceptions on respondents' own jobs

4.4.1 Empirical specification

We examine how the posterior beliefs regarding GenAI replacement rates affect people's macroeconomic views. We employ the following variables to capture macroeconomic expectations: wage growth, real GDP growth, CPI, and the growth rate of capital investment. Additionally, we incorporate outcome variables pertaining to respondents' own labor demand, productivity, and required skill levels.

For wage growth, real GDP growth, CPI, and the growth rate of capital investment, respondents are asked to select specific expected values for the 1-year, and average 5- to 10-year horizons from a set of predefined options. We then scale each of these values between a minimum of 0 and a maximum of 1 for analysis, so that the finite nature of the minimum and maximum options is accounted for, allowing for consistent analysis of differences in respondents' selections across all variables.

For labor demand, productivity, and skills, we ask respondents to choose whether they expect an "increase," "decrease," or "no change" rather than selecting specific numerical values. We then standardize responses, with "decrease" set to a minimum value of 0 and "increase" set to a maximum value of 1, scaling these responses in the same manner as the other variables.

We assume these macroeconomic expectations are represented as a logistic function of the posterior and control variables as follows,

$$\text{Outcome}_i = \frac{\exp(y_i)}{1 + \exp(y_i)} \tag{6}$$

and

$$y_i = \gamma_0 + \gamma_1 \text{Posterior}_i + \gamma_2 \text{Prior}_i + \mathbf{\Pi}' \mathbf{X_i} + e_i \tag{7}$$

where Outcome $_i$ is a scaled response of individual i for expectation about a macroeconomic variable or respondent's job. We should note that we did not ask questions about expectations for macroeconomic variables at the 5-year horizon. Therefore, we use the following three different sets of outcome and instrumental variables. The first set matches expectations for the replacement ratio with macroeconomic outlooks 1 year ahead. The second set pairs average macroeconomic expectations for 5 to 10 year ahead with job replacement expectations 5 year ahead. Finally, the third set combines average macroeconomic expectations for 5- to 10 year ahead with job replacement expectations 10 year ahead. $\mathbf{X_i}$ is a vector of the same control variables as in our previous estimations. The variable of our interest is $Posterior_i$ and γ_1 indicates the effect of a job replacement ratio. However, the ordinary least squares (OLS) estimate of γ_1 cannot be interpreted as a causal effect. For example, people who are generally more optimistic may respond positively to the question about the job replacement ratio, as well as to questions regarding expectations about macroeconomic outcomes. It is also conceivable that there may exist reverse causality between posterior beliefs and macroeconomic expectations. To account for these endogenity issues, we instrument our respondent's posterior beliefs with the random assignment to the different forecasts regarding the job replacements by generative AI. In this respect, we specify the following equation and estimate with two-stage least squares:

$$y_i = \gamma_0 + \gamma_1 \widehat{\text{Posterior}}_i + \gamma_2 \text{Prior}_i + \mathbf{\Pi}'\mathbf{X_i} + e_i \tag{8}$$

$$\widehat{\text{Posterior}}_i = \hat{\beta}_0 + \hat{\beta}_1 \text{High Replacement}_i + \hat{\beta}_2 \text{Prior}_i + \Theta' \text{X}_i \tag{9}$$

where *High Replacement* indicates a dummy variable that takes the value of one if respondent i is assigned to the treatment group for the high job replacement ratio. Since we randomly assigned respondents to each group, the dummy variable provides exogenous variation to the posterior belief. We refer to this specification as the baseline.

Actual differences in generative AI exposure across groups should affect the extent to which people extrapolate from news about GenAI to their macroeconomic views. For instance, since heterogeneous effects on updating exist (Table B.5), conceivably these differences could lead to a difference in expectations about the macroeconomic outlooks. Individuals who are aware of news or research suggesting that generative AI is likely to replace jobs held by white-collar workers, or those working in related fields, may have pessimistic views on the macroeconomic impact of AI. Then, such individuals, when informed of a higher job replacement rate, may further reinforce their pessimistic view. Likewise, older cohorts, who may perceive a higher risk of job displacement, might also adopt a more pessimistic outlook.

We investigate heterogeneous effects based on age, gender, occupation, and education. To examine heterogeneous effects on the expectations about macroeconomic outcomes, we additionally interact the posterior belief with a dummy variable for heterogeneity as in the following equation.

$$\text{Outcome}_i = \frac{\exp(y_i)}{1+\exp(y_i)} \tag{10}$$

and

$$\begin{aligned} y_i = &\ \gamma_0 + \gamma_1 \widehat{\text{Posterior}}_i + \gamma_2 \widehat{\text{Posterior}_i \times \text{het}_i} \\ &+ \gamma_3 \text{Prior}_i + \mathbf{\Pi' X_i} + e_i \end{aligned} \tag{11}$$

where

$$\begin{aligned} \widehat{\text{Posterior}}_i = &\ \hat{\beta}_0 + \hat{\beta}_1 \text{High Replacement}_i \\ &+ \hat{\beta}_1 (\text{High Replacement}_i \times \text{het}_i) \\ &+ \hat{\beta}_3 \text{het}_i + \hat{\beta}_4 \text{Prior}_i + \Theta' \text{X}_i \end{aligned} \tag{12}$$

$$\begin{aligned} \widehat{\text{Posterior}_i \times \text{het}_i} = &\ \hat{\delta}_0 + \hat{\delta}_1 \text{High Replacement}_i \\ &+ \hat{\delta}_2 (\text{High Replacement}_i \times \text{het}_i) \\ &+ \hat{\delta}_3 \text{het}_i + \hat{\delta}_4 \text{Prior}_i + \Phi' \text{X}_i. \end{aligned} \tag{13}$$

where het_i denotes the dummy variable that takes the value of one if respondent i belongs to a specific group based on the characteristic such as gender. Equations (12) and (13) are estimated separately. The coefficients of interest are γ_1 and γ_2.

4.4.2 Marginal effects and results

While the details of the OLS and IV estimation results are provided in Tables D.2 and D.3 for reference, we focus on the marginal effects from the IV estimation in this section.

In Japan, the perceived job replacement ratio by GenAI has a marginally positive effect on CPI. A one percentage point increase in posterior belief will increase CPI by 0.26 percentage points 1 year ahead, by 0.17 percentage points 5 years ahead and by 0.10 percentage points 10 years ahead. Among different occupations, those working for "creative jobs" notably drive the overall inflation expectations through their updates on the generative AI job replacement ratio, with increases of 0.59 percentage points 1 year ahead, 0.25 percentage points 5 years ahead, and 0.19 percentage points 10 years ahead.

This positive effect on CPI may be attributed to expectations of increased demand for AI-related investment, as reflected in private investment or GDP forecasts. Although the average impact on private investment is positive, it is not statistically significant. However, the estimated marginal effect is significantly positive for respondents in creative jobs, indicating a 0.57 percentage point increase in 1 year. Regarding real GDP growth, while the baseline estimates are not statistically significant, a positive effect of 0.27 percentage points is observed for the high-income cohort.

While the job replacement ratio positively affects inflation expectation, it negatively affects expectations about labor market indicators, such as labor demand. The negative impact on labor demand is particularly pronounced among individuals not using generative AI privately, with a decrease of 2.52 percentage points 5 years ahead and 1.92 percentage points 10 years ahead. This implies that for those who do not use GenAI privately, updating their job replacement ratios upward leads to the view of weaker labor demand in the long term. Expectations for wage growth show weaker responses compared to other economic indicators. The insignificant response of wages could be due to two offsetting effects. On one hand, as Aldasoro et al. (2024) show, real wages may increase as labor productivity rises with the use of AI as a copilot tool. On the other hand, some segments of the labor force could be replaced by AI, reducing labor demand and exerting downward pressure on wages. However, as we look further into the long-term horizon, there is a discernible trend towards negative effects. This pattern parallels the expectations for labor demand, suggesting a consistent and coherent response regarding the anticipated impacts on the labor market.

In the U.S., beliefs about job replacement by GenAI do not have a causal relationship with expectations for CPI. In addition, the estimates for private investment growth and real GDP growth are, on average, not statistically significant. However, the job replacement ratio has negative effects on labor demand and required skill expectations. The labor demand indicator decreases by 3.4 percentage points and required skill by 3.0 percentage points in the one-year horizon when the job replacement ratio increases by one percentage point.[11] This pessimism toward labor demand and skills is particularly prevalent among

[11]Note that the labor demand indicator is constructed, based on the multiple choice responses, to take a

more educated and older respondents. The impact is economically significant; the expectation for labor demand among more educated respondents declines by 8.3 percentage points and required skill by 9.1 percentage points in one year ahead. The effect of the job replacement ratio on private investment also shows heterogeneity, particularly across respondents with different educational backgrounds. While respondents with lower educational attainment tend to have positive expectations, those with higher education exhibit a more negative outlook. One possible explanation for this difference is that respondents with higher educational levels in the U.S. expect generative AI to have a greater impact on their jobs, as a larger proportion of these respondents recognize that GenAI has been adopted in their workplaces.[12] The higher adoption rate of GenAI among those with higher educational levels is largely due to the fact that they are more likely to hold jobs that are relatively suited to the application of GenAI.

The negative impact of higher replacement risk on the labor demand outlook among respondents in creative jobs may also be explained for similar reasons. Workers in creative jobs have higher educational levels and are more likely to privately use GenAI, which leads to more recognition of the potential of GenAI in their workplaces.[13] In our survey, 75% of respondents in creative jobs use GenAI privately, compared to 52% of those in sales & administrative and 68% of those in planning and professional jobs.

value between 0 and 1.

[12]In our survey, 87% of respondents with higher education reported that GenAI has been adopted in their jobs, compared to 75% of those with lower educational levels. This pattern is consistent with other studies including Cazzaniga et al. (2024).

[13]Previous studies including Haase and Hanel (2023) find that GenAI is especially useful for creative tasks such as generating images.

Table 7: IV estimates of marginal effects of posterior beliefs on macroeconomic expectations by group (Japan, in percentage points)

	Japan								
	CPI (%)			**Private Investment (%)**			**Real GDP Growth (%)**		
	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Baseline:	0.26* (0.14)	0.17** (0.07)	0.10** (0.05)	0.15 (0.15)	0.09 (0.07)	0.06 (0.05)	0.19 (0.13)	0.07 (0.07)	0.04 (0.04)
Gender:									
Male	0.00 (0.23)	0.12 (0.15)	0.11 (0.10)	0.04 (0.24)	0.03 (0.15)	0.04 (0.10)	0.11 (0.20)	0.08 (0.14)	0.07 (0.09)
Female	0.65 (0.46)	0.20 (0.25)	0.10 (0.15)	0.33 (0.51)	0.13 (0.26)	0.07 (0.16)	0.32 (0.44)	0.06 (0.24)	0.03 (0.14)
Age Group:									
Age>44	0.23 (0.14)	0.14* (0.07)	0.09* (0.04)	0.09 (0.15)	0.06 (0.07)	0.04 (0.04)	0.15 (0.13)	0.03 (0.07)	0.02 (0.04)
Age<=44	0.29* (0.15)	0.19** (0.08)	0.12** (0.05)	0.21 (0.16)	0.12 (0.08)	0.08 (0.05)	0.23 (0.14)	0.10 (0.08)	0.06 (0.05)
Education:									
Below College	0.14 (0.25)	0.15 (0.11)	0.09 (0.05)	0.34 (0.27)	0.12 (0.11)	0.06 (0.06)	0.33 (0.25)	0.11 (0.11)	0.06 (0.05)
College	0.33 (0.45)	0.18 (0.19)	0.12 (0.10)	0.05 (0.48)	0.08 (0.20)	0.06 (0.10)	0.12 (0.43)	0.04 (0.19)	0.03 (0.10)
Income:									
Low	0.26* (0.14)	0.17** (0.07)	0.11** (0.04)	0.15 (0.15)	0.09 (0.08)	0.06 (0.05)	0.19 (0.12)	0.06 (0.07)	0.04 (0.04)
High	0.28* (0.15)	0.15* (0.08)	0.09* (0.05)	0.21 (0.16)	0.09 (0.08)	0.06 (0.05)	0.27** (0.13)	0.08 (0.07)	0.05 (0.05)
Private Use of GenAI:									
No	0.24 (0.15)	0.08 (0.09)	0.06 (0.05)	0.17 (0.21)	0.06 (0.10)	0.04 (0.06)	0.27 (0.26)	0.03 (0.09)	0.02 (0.05)
Yes	0.54 (1.55)	0.44 (0.41)	0.23 (0.18)	-0.02 (1.55)	0.20 (0.31)	0.10 (0.16)	-0.68 (2.68)	0.19 (0.26)	0.10 (0.13)
Occupation:									
Sales Admin	0.69 (0.45)	-0.84 (0.60)	-0.09 (0.13)	0.02 (0.50)	0.20 (0.71)	0.07 (0.16)	-0.02 (0.42)	-0.08 (0.66)	0.01 (0.15)
Creative	0.59* (0.32)	0.25 (0.16)	0.19* (0.11)	0.57* (0.34)	0.22 (0.16)	0.17 (0.11)	0.46 (0.29)	0.17 (0.14)	0.13 (0.10)
Engineering	-0.00 (0.51)	0.03 (0.37)	-0.01 (0.17)	0.02 (0.48)	-0.17 (0.30)	-0.09 (0.15)	0.10 (0.40)	-0.06 (0.27)	-0.04 (0.13)
Planning Profession	0.58 (0.41)	0.25 (0.17)	0.21** (0.10)	0.09 (0.40)	0.09 (0.17)	0.08 (0.11)	0.12 (0.35)	0.07 (0.16)	0.06 (0.10)

Notes: This table shows IV estimation of the marginal effects of posterior beliefs on expectations for CPI, private investment, and real GDP. All estimates are reported in percentage points. That is, a coefficient of 0.19 corresponds to a change of 0.19 percentage points in the outcome variable. Both baseline and heterogeneous effects are estimated. All specifications control for prior beliefs, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Robust standard errors are in parentheses. * denotes significance at 10%, ** at 5%, and *** at 1%.

Table 8: IV estimates of marginal effects of posterior beliefs on macroeconomic expectations by group (the U.S., in percentage points)

	United States								
	CPI (%)			**Private Investment (%)**			**Real GDP Growth (%)**		
	1-year	5-year	10-year	1-year	5-year	10-year	1-year	5-year	10-year
Baseline:	-0.07 (0.17)	-0.03 (0.07)	-0.02 (0.05)	-0.11 (0.18)	0.02 (0.08)	0.01 (0.06)	-0.06 (0.17)	-0.03 (0.08)	-0.02 (0.05)
Gender:									
Male	-0.01 (0.23)	-0.03 (0.08)	-0.03 (0.06)	-0.10 (0.26)	-0.00 (0.09)	-0.02 (0.07)	-0.09 (0.23)	-0.04 (0.09)	-0.04 (0.06)
Female	-0.18 (0.32)	-0.00 (0.12)	-0.00 (0.09)	-0.15 (0.36)	0.09 (0.15)	0.06 (0.11)	0.01 (0.34)	0.00 (0.14)	-0.00 (0.10)
Age Group:									
Age>44	-0.07 (0.17)	-0.01 (0.08)	-0.01 (0.05)	-0.08 (0.18)	0.05 (0.09)	0.03 (0.06)	-0.05 (0.17)	-0.00 (0.09)	-0.01 (0.06)
Age≤44	-0.07 (0.17)	-0.02 (0.08)	-0.02 (0.06)	-0.10 (0.18)	0.02 (0.10)	0.01 (0.07)	-0.06 (0.17)	-0.03 (0.09)	-0.02 (0.06)
Education:									
Below College	0.23 (0.15)	0.11 (0.09)	0.07 (0.07)	0.37 (0.26)	0.21* (0.12)	0.14* (0.08)	0.21 (0.17)	0.15 (0.11)	0.09 (0.08)
College	-0.37 (0.31)	-0.09 (0.14)	-0.06 (0.10)	-0.66** (0.32)	-0.08 (0.16)	-0.06 (0.11)	-0.34 (0.28)	-0.12 (0.15)	-0.08 (0.10)
Income:									
Low	-0.05 (0.18)	-0.02 (0.07)	-0.02 (0.05)	-0.12 (0.19)	0.02 (0.09)	0.01 (0.06)	-0.06 (0.18)	-0.03 (0.08)	-0.02 (0.05)
High	-0.06 (0.18)	-0.03 (0.07)	-0.02 (0.05)	-0.11 (0.19)	0.02 (0.09)	0.01 (0.06)	-0.06 (0.18)	-0.03 (0.08)	-0.03 (0.05)
Private Use of GenAI:									
No	-0.27 (0.33)	-0.03 (0.09)	-0.01 (0.05)	0.12 (0.33)	0.14 (0.10)	0.09 (0.06)	0.12 (0.30)	0.06 (0.09)	0.04 (0.05)
Yes	-0.08 (0.50)	-0.03 (0.14)	-0.02 (0.10)	-0.11 (0.47)	-0.04 (0.14)	-0.04 (0.09)	-0.05 (0.44)	-0.08 (0.13)	-0.07 (0.09)
Occupation:									
Sales Admin	0.08 (0.64)	-0.00 (0.13)	0.00 (0.09)	0.64 (1.22)	0.09 (0.15)	0.06 (0.10)	0.73 (1.05)	0.03 (0.14)	0.02 (0.10)
Creative	-0.14 (0.24)	-0.04 (0.15)	-0.05 (0.15)	-0.15 (0.27)	-0.08 (0.19)	-0.10 (0.19)	-0.04 (0.24)	-0.03 (0.17)	-0.05 (0.17)
Engineering	-0.33 (0.63)	-0.30 (0.21)	-0.17 (0.13)	-0.82 (0.73)	-0.09 (0.24)	-0.06 (0.15)	-0.56 (0.65)	-0.18 (0.23)	-0.12 (0.15)
Planning Profession	-0.01 (0.36)	0.06 (0.13)	0.04 (0.11)	-0.06 (0.35)	0.03 (0.16)	0.02 (0.13)	-0.05 (0.39)	-0.03 (0.15)	-0.02 (0.12)

Notes: This table shows IV estimation of the marginal effects of posterior beliefs on expectations for CPI, private investment, and real GDP in the U.S. All estimates are in percentage points. That is, a coefficient of 0.19 implies a 0.19pp change in the expected macroeconomic variable. All models control for prior beliefs, age, age squared, gender, income, education, GenAI use, managerial responsibility, task routine level, region, occupation, industry, and firm size. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: IV estimates of marginal effects of posterior beliefs on views on respondent's jobs by group (Japan, % points)

	Labor Demand (%)			**Labor Productivity (%)**		
	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Baseline:	0.47 (2.04)	-1.32 (1.09)	-0.94 (0.69)	4.82 (3.92)	0.81 (1.22)	0.21 (0.61)
Gender:						
Male	-1.74 (3.60)	-2.02 (2.31)	-1.48 (1.62)	5.70 (6.09)	-0.76 (2.04)	0.18 (1.37)
Female	3.60 (7.06)	-0.91 (3.83)	-0.72 (2.41)	3.31 (9.24)	1.69 (4.00)	0.22 (2.04)
Age Group:						
Age>44	0.59 (2.07)	-1.19 (1.07)	-0.87 (0.67)	4.64 (3.77)	0.33 (0.93)	-0.18 (0.59)
Age<=44	0.37 (2.23)	-1.42 (1.20)	-1.00 (0.74)	5.04 (3.86)	1.18 (1.42)	0.60 (1.11)
Education:						
Below College	4.43 (3.24)	0.52 (1.53)	-0.43 (0.73)	4.61 (3.76)	0.05 (1.20)	0.18 (0.62)
College	-1.82 (6.44)	-2.67 (3.03)	-1.45 (1.54)	5.00 (6.33)	1.43 (3.14)	0.24 (1.27)
Private Use of GenAI:						
No	1.14 (2.09)	-2.52** (1.16)	-1.92** (0.84)	5.38 (47.00)	0.87 (2.24)	0.01 (0.69)
Yes	-7.20 (28.85)	2.17 (4.06)	2.02 (1.72)	-3.60 (56.24)	0.58 (3.81)	0.89 (3.68)
Occupation:						
Sales Admin	4.28 (6.67)	-2.63 (9.48)	-0.32 (2.21)	-7.38 (8.68)	9.85 (26.42)	0.28 (1.96)
Creative	6.64 (5.11)	0.21 (2.30)	-0.38 (1.57)	9.01 (7.16)	-0.15 (2.50)	0.77 (1.65)
Engineering	0.44 (6.95)	-0.56 (5.21)	-1.60 (2.14)	-0.62 (20.41)	-3.94 (18.69)	-2.31 (7.12)
Planning Profession	-1.69 (5.85)	-2.11 (2.65)	-1.23 (1.60)	3.79 (6.41)	1.30 (2.63)	1.16 (2.41)
	Skill Requirements (%)			**Wage Growth (%)**		
	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Baseline:	-0.90 (2.30)	-1.23 (1.21)	-0.50 (0.71)	0.33 (0.25)	-0.04 (0.15)	-0.03 (0.09)
Gender:						
Male	-2.80 (3.82)	-3.28 (2.41)	-1.44 (1.58)	0.22 (0.46)	-0.14 (0.32)	-0.10 (0.22)
Female	1.53 (7.11)	-0.16 (3.88)	-0.13 (2.36)	0.50 (0.92)	0.01 (0.52)	0.00 (0.32)
Age Group:						
Age>44	-1.59 (2.46)	-1.31 (1.22)	-0.44 (0.69)	0.33 (0.26)	-0.04 (0.15)	-0.02 (0.09)
Age<=44	-0.40 (2.69)	-1.19 (1.34)	-0.55 (0.76)	0.34 (0.28)	-0.05 (0.17)	-0.03 (0.10)
Education:						
Below College	4.37 (3.00)	-0.72 (1.69)	-0.30 (0.84)	0.78* (0.44)	0.35 (0.21)	0.15 (0.11)
College	-4.45 (5.62)	-1.62 (2.86)	-0.71 (1.53)	0.07 (0.80)	-0.35 (0.38)	-0.21 (0.20)
Private Use of GenAI:						
No	-2.06 (10.33)	-0.22 (1.59)	0.08 (0.81)	0.37 (0.25)	-0.09 (0.20)	-0.05 (0.11)
Yes	11.78 (122.20)	-4.41* (2.53)	-2.39 (1.67)	-0.15 (2.55)	0.10 (0.64)	0.05 (0.32)
Occupation:						
Sales Admin	2.94 (6.58)	-4.30 (7.29)	-1.75 (1.90)	-1.76** (0.87)	2.57 (1.63)	0.44 (0.33)
Creative	0.01 (5.18)	0.43 (2.71)	0.17 (1.67)	0.53 (0.64)	0.00 (0.30)	0.01 (0.21)
Engineering	0.16 (5.69)	-4.00 (7.34)	-1.33 (2.67)	0.07 (0.92)	-0.29 (0.67)	-0.12 (0.31)
Planning Profession	-1.76 (5.83)	-1.09 (2.69)	0.21 (1.72)	-0.11 (0.68)	-0.27 (0.34)	-0.24 (0.21)

Notes: This table shows IV estimation of the marginal effects of posterior beliefs on respondent's job expectations for labor demand, labor productivity, skills and wage growth. All estimates are reported in percentage points. That is, a coefficient of 0.19 corresponds to a change of 0.19 percentage points in the outcome variable. Both baseline and heterogeneous effects are estimated. All specifications control for prior beliefs, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Robust standard errors are in parentheses.

Table 10: IV estimates of marginal effects of posterior beliefs on views on respondent's jobs by group (United States, % points)

	Labor Demand (%)			Labor Productivity (%)		
	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Baseline:	-3.44* (1.83)	-0.82 (1.11)	-0.36 (0.83)	-3.54* (2.03)	-0.34 (0.89)	-0.89 (0.79)
Gender:						
Male	-4.72 (4.12)	-1.09 (1.26)	-0.28 (0.97)	-5.45 (6.70)	-0.64 (1.15)	-1.30 (1.44)
Female	-1.35 (6.28)	-0.01 (2.09)	-0.48 (1.48)	-1.17 (9.90)	0.60 (2.53)	-0.34 (2.15)
Age Group:						
Age>44	-4.38*** (1.68)	-0.89 (1.18)	-0.28 (0.89)	-4.76 (3.32)	-0.59 (0.98)	-1.31 (1.15)
Age<=44	-3.72** (1.81)	-0.82 (1.23)	-0.36 (0.92)	-3.95 (3.53)	-0.38 (1.05)	-0.94 (1.22)
Education:						
Below College	0.60 (2.21)	0.39 (1.49)	0.01 (1.19)	-0.27 (1.91)	1.96 (2.66)	-0.72 (1.35)
College	-8.26*** (3.15)	-1.40 (2.22)	-0.53 (1.67)	-7.69 (9.56)	-1.93 (4.31)	-0.98 (1.62)
Private Use of GenAI:						
No	-5.31 (7.71)	-1.13 (1.32)	0.98 (0.68)	-5.55 (14.50)	-0.69 (1.65)	-0.33 (0.91)
Yes	-3.39 (10.58)	-0.66 (2.42)	-1.32 (1.30)	-3.48 (17.34)	-0.14 (2.95)	-1.31 (1.12)
Occupation:						
Sales Admin	12.50 (34.66)	-1.97 (2.05)	-0.55 (1.54)	-2.30 (12.86)	-1.60 (2.85)	-1.73 (1.72)
Creative	-4.85 (3.68)	0.43 (2.53)	-5.45** (2.60)	-3.11 (2.92)	1.72 (2.76)	-0.55 (2.22)
Engineering	-1.85 (10.97)	0.13 (3.89)	1.38 (2.27)	-10.90 (7.34)	3.34 (8.35)	-0.09 (2.70)
Planning Profession	-4.32 (7.61)	-0.39 (2.17)	-0.17 (1.83)	-3.11 (5.22)	-1.37 (2.92)	-0.61 (1.56)

	Skill Requirements (%)			Wage Growth (%)		
	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Baseline:	-3.02 (2.12)	0.32 (1.27)	0.69 (0.91)	-0.16 (0.46)	-0.24 (0.23)	-0.17 (0.17)
Gender:						
Male	-4.34 (4.28)	-0.15 (1.35)	0.54 (0.98)	-0.26 (0.63)	-0.23 (0.26)	-0.14 (0.20)
Female	-0.87 (6.60)	1.68 (2.31)	0.92 (1.56)	0.02 (0.91)	-0.27 (0.41)	-0.20 (0.30)
Age Group:						
Age>44	-4.05** (1.91)	0.45 (1.36)	1.14 (0.99)	-0.17 (0.44)	-0.17 (0.25)	-0.12 (0.18)
Age<=44	-3.34 (2.04)	0.33 (1.40)	0.70 (1.01)	-0.16 (0.45)	-0.24 (0.26)	-0.17 (0.18)
Education:						
Below College	1.95 (3.01)	0.64 (1.49)	0.94 (1.13)	0.36 (0.36)	0.11 (0.30)	0.02 (0.24)
College	-9.14** (3.78)	0.15 (2.38)	0.57 (1.64)	-0.73 (0.79)	-0.41 (0.45)	-0.26 (0.33)
Private Use of GenAI:						
No	-0.27 (4.97)	0.91 (1.27)	0.40 (0.71)	1.05* (0.62)	0.17 (0.25)	0.13 (0.14)
Yes	-3.00 (6.55)	-0.02 (2.14)	0.92 (1.91)	-0.17 (1.04)	-0.48 (0.41)	-0.40 (0.29)
Occupation:						
Sales Admin	-10.60** (4.99)	-1.54 (2.32)	-0.21 (1.65)	-1.45 (1.30)	-0.31 (0.43)	-0.21 (0.31)
Creative	-4.51 (4.06)	0.60 (2.73)	-1.17 (2.70)	0.20 (0.59)	-0.00 (0.50)	-0.05 (0.52)
Engineering	-9.70 (11.08)	1.73 (4.23)	1.70 (2.52)	-1.81 (1.82)	-0.16 (0.81)	-0.13 (0.50)
Planning Profession	-1.42 (5.04)	1.54 (2.18)	1.33 (1.84)	0.02 (0.94)	-0.27 (0.46)	-0.16 (0.37)

Notes: This table shows IV estimation of the marginal effects of posterior beliefs on respondent's job expectations for labor demand, labor productivity, skills and wage growth. All estimates are reported in percentage points. That is, a coefficient of 0.19 corresponds to a change of 0.19 percentage points in the outcome variable. Both baseline and heterogeneous effects are estimated. All specifications control for prior beliefs, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Robust standard errors are in parentheses.

5 Conclusion

We conduct a randomized experiment in which participants in the U.S. and Japan are provided with two different assessments from professional forecasters regarding the ratio of jobs replaced by GenAI. Using the exogenous variation, we investigate the causal impact of job replacement expectations on macroeconomic expectations and individual behavioral views.

We obtain the following findings. First, individuals in both countries adjust their perceptions of the job replacement ratio by GenAI in response to the information provided by professional forecasters. This adjustment is more pronounced as the time horizon extends and uncertainty about the future increases.

Second, in Japan, higher post-treatment beliefs about the job replacement ratio lead to higher inflation expectations. In addition, the belief in a higher job replacement ratio leads to positive real GDP growth expectations, particularly among higher-income groups, while this effect is not statistically significant on average. Furthermore, among individuals in creative professions, an expectation of a higher job replacement ratio is causally related to an increase in private investment growth. These findings imply that the demand for investment in new industries spurred by generative AI could be a driver of the higher inflation expectation. Moreover, respondents in Japan tend to show greater intention to adopt generative AI in their workplaces as their beliefs about job replacement evolve.

On the other hand, in the U.S., higher expectations of job replacement are associated with short-term reductions in labor demand and a decrease in the skills required for existing jobs. This negative effect on labor demand expectations is more evident among individuals with higher levels of education. This suggests that those with higher education levels anticipate a stronger negative impact of GenAI on the labor market and their jobs, aligning with previous studies that point to the varied impacts of GenAI on different labor groups (e.g. Babina et al. (2023)).[14]

The differences observed between the U.S. and Japan may be tied to the level of public

[14]This result is also consistent with findings from the survey on economists' predictions conducted by Chicago Booth Kent A. Clark Center for Global Markets (https://www.kentclarkcenter.org/surveys/ai-and-the-labor-market/), which suggests that AI may have a negative impact on the earning potential of substantial numbers of high-skilled workers in advanced economies.

discourse and familiarity with GenAI's potential impact on the labor market. In Japan, where the adoption rate of GenAI is lower and public awareness may be less developed, there is a greater tendency to update beliefs, perceiving more potential for growth driven by GenAI.

A growing number of studies analyze the role of news and public attention in the economy, particularly as social media increasingly permeates every aspect of our daily lives. Opinions on AI's impact vary widely—some are moderate, while others are extreme. Policymakers may sometimes dismiss extreme views as hype. However, even if these views have an almost zero probability of coming to fruition, they can still influence individuals' macroeconomic outlook and behavior. Further research on expectation formation and its development is required for a better understanding of the economic impact.

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Appendices

A Definition and Summary Statistics

Table A.1: Job Categories

Job categories	Sub categories	Detailed categories
Sales and Administrative	Sales	Planning and sales, corporate sales, individual sales, MR and other sales related work Telemarketing, call center Career counselor, agency recruiter
	Clerical/administrative	General clerical work, assistant, receptionist, secretary and other clerical work Treasury, financial planning, accounting General affairs, human resources, legal, intellectual property, public relations, IR Logistics, materials purchasing, trading
Engineering	IT engineer (system development, system engineer, infrastructure)	System consultant / systems analyst / pre-sales Web, open-source, and mobile software development Mainframe system development Embedded system / firmware / control system development Packaged software / middleware development Network and server engineering (LAN, WAN, Web-based systems) Telecommunications infrastructure design and implementation (carrier/ISP services) Operations, maintenance, monitoring, and technical support Internal systems engineer, information systems management Research, patent development, and technical marketing Quality assurance
	Engineer (mechanical, electrical, electronic, semiconductor, control)	Circuit and system design Semiconductor design Control design Machinery, mechanical design, mold design Optical technology and optical design Production technology, process development Quality assurance, product evaluation, quality assurance, production control, manufacturing control Sales engineer, field application engineer (FAE) Service engineer, support engineer Research, patent development, and technical marketing Evaluation, inspection, experimentation
	Material, chemical, food and pharmaceutical engineering	Material, chemical, food and pharmaceutical engineering Cosmetics, food product and fragrance Pharmaceutical Medical equipment
Planning and Specialist	Planning, marketing, management	Product planning, sales planning, marketing, promotion Management planning, business management, new business development Managerial position, executive Fashion merchandiser, buyer, retail sales planning, franchise owner
	Professional (consultant, licensed professional, finance, real estate)	Business consultant, think tank Licensed professional, expert consultant Financial professional Real estate and property management
Creative	Creative work (media, apparel, design)	Advertising and graphics Publishing and printing Video, audio, events, entertainment, television and broadcasting Fashion, interior, space and product design
	Web, the Internet, gaming	Website, Internet services Gaming and multimedia

Table A.2: Summary statistics in Japan and the U.S. - Explanatory/Dependent variables

	Japan						United States					
	Mean	SD	Median	Min.	Max.	Obs.	Mean	SD	Median	Min.	Max.	Obs.
Female	0.50	0.50	1.00	0.00	1.00	1726	0.49	0.50	0.00	0.00	1.00	2399
Age	39.49	9.97	37.00	22.00	57.00	1726	39.23	8.49	37.00	22.00	57.00	2399
At Least Bachelor's Degree	0.70	0.46	1.00	0.00	1.00	1726	0.70	0.46	1.00	0.00	1.00	2399
Income (Million)	6.00	3.92	5.00	2.00	30.00	1557	0.09	0.04	0.09	0.02	0.18	2387
Private Use of GenAI	0.31	0.46	0.00	0.00	1.00	1726	0.69	0.46	1.00	0.00	1.00	2399
High Job Replacement (by GenAI) Indicator	0.51	0.50	1.00	0.00	1.00	1726	0.51	0.50	1.00	0.00	1.00	2399
Repetitive Work	0.43	0.50	0.00	0.00	1.00	1685	0.83	0.38	1.00	0.00	1.00	2387
Prior: 1-Year Ahead	11.14	9.94	10.00	1.00	90.00	1726	16.15	14.07	10.00	1.00	99.00	2399
Prior: 5-Year Ahead	20.76	14.01	20.00	1.00	85.00	1726	24.84	15.38	20.00	1.00	95.00	2399
Prior: 10-Year Ahead	33.56	20.14	30.00	1.00	94.00	1726	36.41	21.38	33.00	1.00	99.00	2399
Posterior: 1-Year Ahead	10.76	9.62	10.00	1.00	70.00	1726	16.20	14.43	10.00	1.00	99.00	2399
Posterior: 5-Year Ahead	19.30	13.12	20.00	1.00	80.00	1726	24.22	15.60	20.00	1.00	95.00	2399
Posterior: 10-Year Ahead	31.17	19.24	30.00	1.00	99.00	1726	35.30	21.29	30.00	1.00	99.00	2399
Updating: 1-Year Ahead	-0.38	6.31	0.00	-80.00	48.00	1726	0.05	7.80	0.00	-50.00	54.00	2399
Updating: 5-Year Ahead	-1.46	8.80	0.00	-65.00	55.00	1726	-0.63	9.56	0.00	-65.00	56.00	2399
Updating: 10-Year Ahead	-2.39	11.73	0.00	-65.00	60.00	1726	-1.11	12.53	0.00	-79.00	70.00	2399
Confident: 1-Year Ahead	0.35	0.48	0.00	0.00	1.00	1726	0.82	0.39	1.00	0.00	1.00	2399
Confident: 5-Year Ahead	0.35	0.48	0.00	0.00	1.00	1726	0.83	0.37	1.00	0.00	1.00	2399
Confident: 10-Year Ahead	0.32	0.46	0.00	0.00	1.00	1726	0.78	0.42	1.00	0.00	1.00	2399
Age Below 44	0.67	0.47	1.00	0.00	1.00	1726	0.75	0.43	1.00	0.00	1.00	2399
Income Over 10 Mil	0.08	0.27	0.00	0.00	1.00	1726	0.41	0.49	0.00	0.00	1.00	2399
Occupation Category: Sales & Admin	0.30	0.46	0.00	0.00	1.00	1726	0.28	0.45	0.00	0.00	1.00	2399
Occupation Category: Creative	0.12	0.32	0.00	0.00	1.00	1726	0.08	0.26	0.00	0.00	1.00	2399
Occupation Category: Engineering	0.29	0.45	0.00	0.00	1.00	1726	0.36	0.48	0.00	0.00	1.00	2399
Occupation Category: Planning & Profession	0.29	0.46	0.00	0.00	1.00	1726	0.28	0.45	0.00	0.00	1.00	2399
Firm Established Below 20 Years	0.24	0.42	0.00	0.00	1.00	1540	0.55	0.50	1.00	0.00	1.00	2347
Experience Below 10 Years	0.54	0.50	1.00	0.00	1.00	1656	0.73	0.44	1.00	0.00	1.00	2397
GenAI Learning Intention	0.58	0.49	1.00	0.0	1.0	1255	0.61	0.49	1.00	0.00	1.00	547
GenAI Use Imtemtion	0.82	0.38	1.00	0.0	1.0	1536	0.89	0.31	1.00	0.00	1.00	1702
Wage Growth: 1-Year Ahead	1.12	4.79	0.00	-20.0	20.0	1657	2.07	6.84	0.00	-20.00	20.00	2377
Wage Growth: 5-Year Ahead	0.82	6.02	0.00	-20.0	20.0	1653	2.32	9.33	2.50	-20.00	20.00	2380
Wage Growth: 10-Year Ahead	0.82	6.02	0.00	-20.0	20.0	1653	2.32	9.33	2.50	-20.00	20.00	2380
Real GDP Growth: 1-Year Ahead	-0.43	2.08	0.00	-5.5	5.0	1280	0.76	2.51	1.00	-5.50	5.50	2210
Real GDP Growth: 5-Year Ahead	-0.47	2.53	0.00	-5.5	5.5	1274	1.01	2.90	1.50	-5.50	5.50	2198
Real GDP Growth: 10-Year Ahead	-0.47	2.53	0.00	-5.5	5.5	1274	1.01	2.90	1.50	-5.50	5.50	2198
CPI: 1-Year Ahead	0.19	2.38	0.50	-5.5	5.5	1301	0.42	2.45	0.50	-5.50	5.50	2227
CPI: 5-Year Ahead	0.44	2.72	1.00	-5.5	5.5	1290	0.67	2.63	1.00	-5.50	5.50	2216
CPI: 10-Year Ahead	0.44	2.72	1.00	-5.5	5.5	1290	0.67	2.63	1.00	-5.50	5.50	2216
Private Investment: 1-Year Ahead	-0.22	2.42	0.25	-5.5	5.5	1272	0.98	2.78	1.50	-5.50	5.50	2199
Private Investment: 5-Year Ahead	-0.19	2.80	0.00	-5.5	5.5	1253	1.18	3.01	1.50	-5.50	5.50	2179
Private Investment: 10-Year Ahead	-0.19	2.80	0.00	-5.5	5.5	1253	1.18	3.01	1.50	-5.50	5.50	2179
Labor Demand: 1-Year Ahead	0.01	0.72	0.00	-1.0	1.0	1391	0.25	0.80	0.00	-1.00	1.00	2305
Labor Demand: 5-Year Ahead	-0.09	0.82	0.00	-1.0	1.0	1311	0.12	0.90	0.00	-1.00	1.00	2274
Labor Demand: 10-Year Ahead	-0.14	0.82	0.00	-1.0	1.0	1296	0.10	0.90	0.00	-1.00	1.00	2211
Productivity: 1-Year Ahead	0.38	0.67	0.00	-1.0	1.0	1392	0.51	0.72	1.00	-1.00	1.00	2310
Productivity: 5-Year Ahead	0.52	0.70	1.00	-1.0	1.0	1340	0.52	0.77	1.00	-1.00	1.00	2276
Productivity: 10-Year Ahead	0.50	0.72	1.00	-1.0	1.0	1314	0.51	0.78	1.00	-1.00	1.00	2211
Skill: 1-Year Ahead	0.23	0.77	0.00	-1.0	1.0	1424	0.23	0.84	0.00	-1.00	1.00	2327
Skill: 5-Year Ahead	0.19	0.86	0.00	-1.0	1.0	1424	0.13	0.93	1.00	-1.00	1.00	2301
Skill: 10-Year Ahead	0.17	0.87	0.00	-1.0	1.0	1385	0.15	0.91	1.00	-1.00	1.00	2256

Notes: This table shows summary statistics. The dependent variables are displayed up to to two decimal places. Prior, posterior, wage growth, real GDP growth, CPI, and private investment growth are displayed in percentage units. Note that the unit of 'Income (Million)' differs between Japan and the U.S.: in Japan, it is in million yen, while in the U.S., it is in million dollars. include those from treatment groups at 14% (low job replacement ratio) and 47% (high job replacement ratio).

Table A.3: Summary statistics in Japan and the U.S. - Variables for fixed-effects

	Japan						United States					
	Mean	SD	Median	Min.	Max.	Obs.	Mean	SD	Median	Min.	Max.	Obs.
Occupation: Admin	0.21	0.40	0.00	0.00	1.00	1726	0.19	0.39	0.00	0.00	1.00	2399
Occupation: Chemical	0.06	0.23	0.00	0.00	1.00	1726	0.01	0.12	0.00	0.00	1.00	2399
Occupation: Creative	0.06	0.24	0.00	0.00	1.00	1726	0.04	0.19	0.00	0.00	1.00	2399
Occupation: Engineer	0.08	0.27	0.00	0.00	1.00	1726	0.05	0.23	0.00	0.00	1.00	2399
Occupation: IT Engineer	0.15	0.36	0.00	0.00	1.00	1726	0.29	0.46	0.00	0.00	1.00	2399
Occupation: Management/Marketing	0.23	0.42	0.00	0.00	1.00	1726	0.13	0.33	0.00	0.00	1.00	2399
Occupation: Profession	0.06	0.25	0.00	0.00	1.00	1726	0.16	0.37	0.00	0.00	1.00	2399
Occupation: Sales	0.10	0.29	0.00	0.00	1.00	1726	0.09	0.29	0.00	0.00	1.00	2399
Occupation: Web/Internet/Game	0.05	0.22	0.00	0.00	1.00	1726	0.04	0.19	0.00	0.00	1.00	2399
Industry: Agriculture/Forestry/Fisheries	0.00	0.02	0.00	0.00	1.00	1726	0.01	0.11	0.00	0.00	1.00	2399
Industry: Construction	0.04	0.21	0.00	0.00	1.00	1726	0.06	0.23	0.00	0.00	1.00	2399
Industry: Education	0.01	0.11	0.00	0.00	1.00	1726	0.04	0.20	0.00	0.00	1.00	2399
Industry: Electricity/Gas	0.02	0.14	0.00	0.00	1.00	1726	0.02	0.14	0.00	0.00	1.00	2399
Industry: Finance/Insurance	0.08	0.27	0.00	0.00	1.00	1726	0.16	0.37	0.00	0.00	1.00	2399
Industry: Food Services	0.00	0.05	0.00	0.00	1.00	1726	0.01	0.10	0.00	0.00	1.00	2399
Industry: Information/Communications	0.07	0.25	0.00	0.00	1.00	1726	0.05	0.21	0.00	0.00	1.00	2399
Industry: Manufacturing	0.30	0.46	0.00	0.00	1.00	1726	0.13	0.33	0.00	0.00	1.00	2399
Industry: Medical/Welfare	0.02	0.15	0.00	0.00	1.00	1726	0.04	0.18	0.00	0.00	1.00	2399
Industry: Mining	0.00	0.03	0.00	0.00	1.00	1726	0.00	0.07	0.00	0.00	1.00	2399
Industry: Postal Services	0.00	0.03	0.00	0.00	1.00	1726	0.00	0.06	0.00	0.00	1.00	2399
Industry: Real Estate Services	0.02	0.15	0.00	0.00	1.00	1726	0.04	0.19	0.00	0.00	1.00	2399
Industry: Software/Information Services	0.16	0.37	0.00	0.00	1.00	1726	0.20	0.40	0.00	0.00	1.00	2399
Industry: Transportation	0.03	0.17	0.00	0.00	1.00	1726	0.03	0.16	0.00	0.00	1.00	2399
Industry: Travel/Accommodation	0.01	0.09	0.00	0.00	1.00	1726	0.01	0.10	0.00	0.00	1.00	2399
Industry: Wholesale/Retail	0.10	0.30	0.00	0.00	1.00	1726	0.09	0.29	0.00	0.00	1.00	2399
Industry: Other Services	0.10	0.30	0.00	0.00	1.00	1726	0.02	0.13	0.00	0.00	1.00	2399
Industry: Others	0.03	0.16	0.00	0.00	1.00	1726	0.10	0.30	0.00	0.00	1.00	2399
JP Region: Hokkaido	0.02	0.16	0.00	0.00	1.00	1726	0.00	0.00	0.00	0.00	0.00	2399
JP Region: Tohoku	0.04	0.19	0.00	0.00	1.00	1726	0.00	0.00	0.00	0.00	0.00	2399
JP Region: Kanto	0.51	0.50	1.00	0.00	1.00	1726	0.00	0.00	0.00	0.00	0.00	2399
JP Region: Chubu	0.14	0.35	0.00	0.00	1.00	1726	0.00	0.00	0.00	0.00	0.00	2399
JP Region: Kansai	0.16	0.37	0.00	0.00	1.00	1726	0.00	0.00	0.00	0.00	0.00	2399
JP Region: Chugoku	0.04	0.18	0.00	0.00	1.00	1726	0.00	0.00	0.00	0.00	0.00	2399
JP Region: Shikoku	0.02	0.13	0.00	0.00	1.00	1726	0.00	0.00	0.00	0.00	0.00	2399
JP Region: Kyushu/Okinawa	0.07	0.25	0.00	0.00	1.00	1726	0.00	0.00	0.00	0.00	0.00	2399
U.S. Region: Midwest	0.00	0.00	0.00	0.00	0.00	1726	0.16	0.37	0.00	0.00	1.00	2399
U.S. Region: Northeast	0.00	0.00	0.00	0.00	0.00	1726	0.22	0.42	0.00	0.00	1.00	2399
U.S. Region: South	0.00	0.00	0.00	0.00	0.00	1726	0.40	0.49	0.00	0.00	1.00	2399
U.S. Region: West	0.00	0.00	0.00	0.00	0.00	1726	0.21	0.41	0.00	0.00	1.00	2399
Firm (Working Place) Size: Large	0.40	0.49	0.00	0.00	1.00	1726	0.28	0.45	0.00	0.00	1.00	2399
Firm (Working Place) Size: Medium	0.32	0.47	0.00	0.00	1.00	1726	0.52	0.50	1.00	0.00	1.00	2399
Firm (Working Place) Size: Small	0.27	0.44	0.00	0.00	1.00	1726	0.20	0.40	0.00	0.00	1.00	2399

Notes: This table shows summary statistics of variables used as fixed effects of the regressions. Observations include those from treatment groups at 14% and 47%.

B Prior, Posterior, and Updating

Table B.1: Summary statistics for prior and posterior beliefs about the GenAI job replacement ratio

	Japan							United States						
	Mean	SD	Med	IQR	Min	Max	Obs	Mean	SD	Med	IQR	Min	Max	Obs
1-year ahead														
Prior: replacement	11.1	9.94	10	5	1	90	1726	16.2	14.1	10	15	1	99	2399
Posterior: Low replacement	10.4	9.26	10	5	1	69	854	15.6	14.0	10	15	1	90	1183
Posterior: High replacement	11.1	9.95	10	5	1	70	872	16.7	14.8	10	16	1	99	1216
5-year ahead														
Prior: replacement	20.8	14.0	20	20	1	85	1726	24.8	15.4	20	18	1	95	2399
Posterior: Low replacement	18.5	12.9	15	10	1	80	854	23.0	15.2	20	20	1	90	1183
Posterior: High replacement	20.1	13.3	20	20	1	75	872	25.4	15.9	24	23	1	95	1216
10-year ahead														
Prior: replacement	33.6	20.1	30	30	1	94	1726	36.4	21.4	33	30	1	99	2399
Posterior: Low replacement	29.6	19.0	25	30	1	99	854	33.7	21.5	30	35	1	95	1183
Posterior: High replacement	32.7	19.3	30	30	1	90	872	36.9	20.9	35	30	1	99	1216

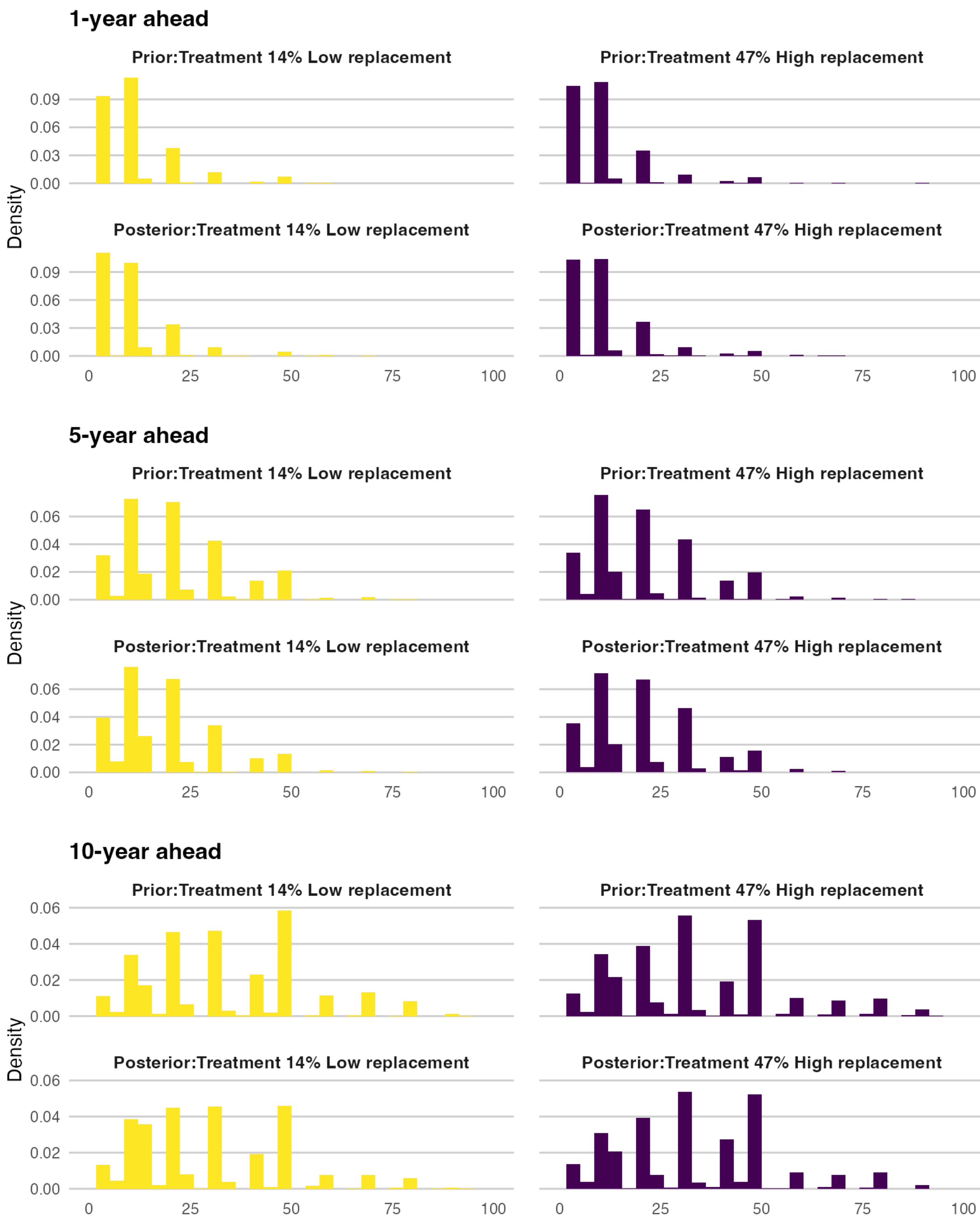
Notes: The table shows the summary statistics for prior and posterior beliefts in terms of the GenAI job replacement ratio. Observations for the posterior are distributed in each treatment (low replacement:14%, high replacement:47%) .

Table B.2: Correlates of prior beliefs about a job replacement by GenAI - Japan and the U.S.

	Prior beliefs (Probability of job replacements by GenAI) 1-year ahead		5-year ahead		10-year ahead	
	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Japan						
Age	-0.004* (0.002)	-0.01 (0.02)	-0.002 (0.002)	-0.01 (0.02)	-0.002 (0.002)	-0.01 (0.02)
Age squared	-5.2e-5* (3e-5)	0.0001 (0.0003)	-2.6e-5 (2.5e-5)	0.0001 (0.0002)	-2.2e-5 (2.7e-5)	0.0001 (0.0002)
Female	0.10** (0.05)	0.04 (0.06)	0.10** (0.04)	0.06 (0.04)	0.03 (0.04)	-0.02 (0.05)
High Education (at least bachelor)	-0.18*** (0.05)	-0.20*** (0.06)	-0.18*** (0.04)	-0.19*** (0.05)	-0.17*** (0.05)	-0.16*** (0.05)
Log income	-0.15** (0.06)	-0.09 (0.07)	-0.10** (0.04)	-0.04 (0.05)	-0.10** (0.05)	-0.06 (0.06)
Private use of GenAI	0.02 (0.05)	0.05 (0.05)	0.01 (0.04)	0.03 (0.05)	0.02 (0.05)	0.05 (0.05)
Having subordinates	0.14*** (0.05)	0.20*** (0.05)	0.07* (0.04)	0.10** (0.04)	0.03 (0.04)	0.03 (0.05)
Repetition Work	0.20*** (0.05)	0.12** (0.06)	0.13*** (0.04)	0.07 (0.05)	0.10** (0.04)	0.05 (0.05)
Observations	1,726	1,505	1,726	1,505	1,726	1,505
United States						
Age	-0.009*** (0.002)	0.05*** (0.02)	-0.005*** (0.002)	0.03** (0.02)	-0.003 (0.002)	0.03* (0.02)
Age squared	-0.0001*** (2.9e-5)	-0.0007*** (0.0002)	-7.6e-5*** (2.4e-5)	-0.0005** (0.0002)	-4.7e-5* (2.7e-5)	-0.0004* (0.0002)
Female	-0.03 (0.04)	0.02 (0.04)	0.05 (0.03)	0.07** (0.03)	0.08** (0.04)	0.08** (0.04)
High Education (at least bachelor)	0.10** (0.04)	-0.04 (0.05)	-0.03 (0.04)	-0.11*** (0.04)	-0.15*** (0.04)	-0.19*** (0.04)
Log income	0.33*** (0.04)	0.22*** (0.05)	0.17*** (0.04)	0.15*** (0.04)	0.05 (0.04)	0.08* (0.04)
Private use of GenAI	0.50*** (0.04)	0.36*** (0.05)	0.25*** (0.04)	0.21*** (0.04)	0.14*** (0.04)	0.14*** (0.04)
Having subordinates	0.47*** (0.06)	0.17** (0.07)	0.17*** (0.05)	0.03 (0.06)	0.03 (0.06)	-0.03 (0.07)
Repetition Work	0.11* (0.06)	0.07 (0.06)	0.01 (0.05)	-0.01 (0.05)	-0.01 (0.05)	-0.03 (0.05)
Observations	2,399	2,369	2,399	2,369	2,399	2,369

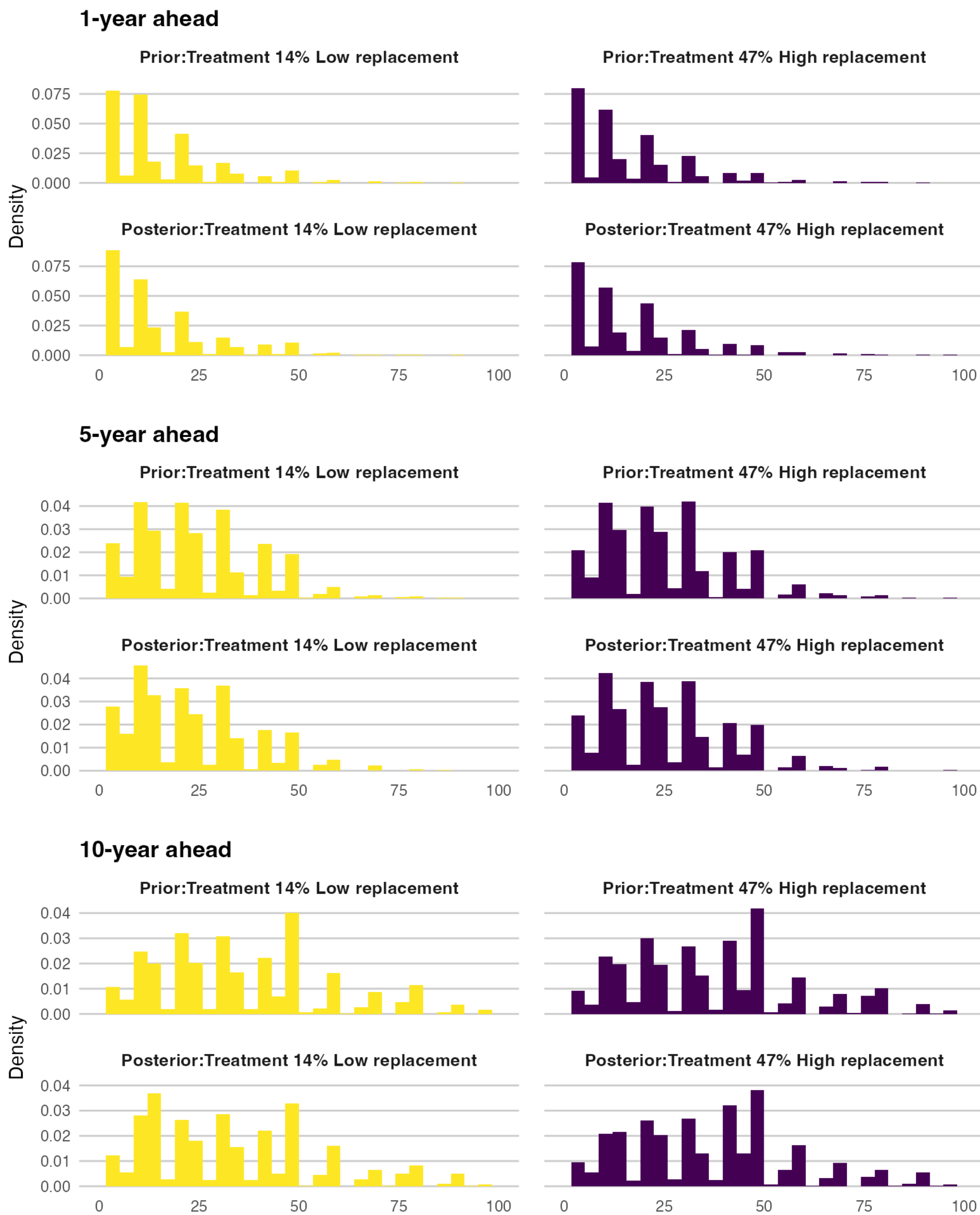
Notes: This table shows the regression results on the prior beliefs about the GenAI job replacement. It implies what demographic factors can be correlated with the prior beliefs. The unit of income differs between Japan and the U.S.: in Japan, it is in yen, while in the U.S., it is in dollars. Univariate shows regression coefficients from separate univariate regression for the different covariates. Multivariate shows regression coefficients from a multivariate regression. Robust standard errors are in parentheses. Data are from 2 treatment arms. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Figure B.1: Prior and posterior beliefs about the GenAI job replacement ratio - Japan



Notes: This figure shows the distribution of prior and posterior beliefs about the GenAI job replacement ratios across treatment arms in Japan. (Left) Yellow : Low replacement by GenAI (14%), (Right) Violet: High replacement by GenAI (47%).

Figure B.2: Prior and posterior beliefs about the GenAI job replacement ratio - the U.S.



Notes: This figure shows the distribution of prior and posterior beliefs about the GenAI job replacement ratios across treatment arms in the U.S.(Left) Yellow : Low replacement by GenAI (14%), (Right) Violet: High replacement by GenAI (47%).

Table B.3: Distribution of ratios between posterior and prior (greater = posterior is larger than prior)

	Japan			United States		
	Greater	Same	Smaller	Greater	Same	Smaller
1-year ahead						
Treatment: 14% Low job replacement by GenAI	9.13%	72.25%	18.62%	20.37%	54.95%	24.68%
Treatment: 47% High job replacement by GenAI	15.25%	70.76%	13.99%	24.42%	54.28%	21.30%
5-year ahead						
Treatment: 14% Low job replacement by GenAI	10.89%	60.07%	29.04%	22.49%	47.00%	30.52%
Treatment: 47% High job replacement by GenAI	17.55%	61.70%	20.76%	25.74%	47.53%	26.73%
10-year ahead						
Treatment: 14% Low job replacement by GenAI	9.48%	59.13%	31.38%	21.13%	45.90%	32.97%
Treatment: 47% High job replacement by GenAI	19.04%	58.37%	22.59%	27.06%	45.97%	26.97%

Notes: The table shows distributions of transitions from prior to posterior. 'Greater' represents the percentage of respondents whose posterior belief is higher than their prior belief. 'Same' represents the percentage of respondents whose posterior belief is the same as their prior belief. 'Smaller' represents the percentage of respondents whose posterior belief is lower than their prior belief.

Table B.4: Confidence heterogeneity by education level

Japan	**Low Educ 1-year**	**High Educ 1-year**	**Low Educ 5-year**	**High Educ 5-year**	**Low Educ 10-year**	**High Educ 10-year**
Shock	0.07*** (0.03)	0.02 (0.01)	0.08*** (0.03)	0.04** (0.02)	0.11*** (0.04)	0.07*** (0.02)
Confident	3.4** (1.4)	-0.17 (0.76)	3.3** (1.3)	1.4 (0.95)	-0.005 (1.9)	1.2 (1.1)
Shock x Confident	-0.10** (0.05)	0.01 (0.03)	-0.11** (0.05)	-0.07** (0.03)	-0.05 (0.07)	-0.06 (0.04)
Prior	-0.29*** (0.11)	-0.20*** (0.04)	-0.24*** (0.04)	-0.27*** (0.03)	-0.20*** (0.03)	-0.22*** (0.02)
Adj. R2	0.21	0.13	0.17	0.19	0.16	0.16
Observations	434	1,071	434	1,071	434	1,071
F-test, Stat.	3.7	4.8	3.2	6.8	2.9	5.5
United States	**Low Educ 1-year**	**High Educ 1-year**	**Low Educ 5-year**	**High Educ 5-year**	**Low Educ 10-year**	**High Educ 10-year**
Shock	0.10** (0.04)	0.03 (0.03)	0.06 (0.06)	0.06 (0.04)	0.08 (0.06)	0.07* (0.04)
Confident	0.97 (1.3)	-0.08 (0.89)	0.24 (1.6)	1.3 (1.2)	2.5 (1.7)	0.84 (1.2)
Shock x Confident	-0.08 (0.05)	-0.03 (0.03)	-0.03 (0.06)	-0.09* (0.04)	-0.09 (0.07)	-0.08** (0.04)
Prior	-0.13*** (0.04)	-0.12*** (0.02)	-0.21*** (0.03)	-0.19*** (0.02)	-0.20*** (0.03)	-0.17*** (0.02)
Adj. R2	0.09	0.07	0.13	0.09	0.10	0.10
Observations	709	1,660	709	1,660	709	1,660
F-test, Stat.	2.6	4.1	3.5	4.8	3.0	5.6

Notes: The table describes OLS estimates of the shock and the interaction with the respondent's confidence on the updating by educational attainment level. All specifications control for the respondent's prior belief, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

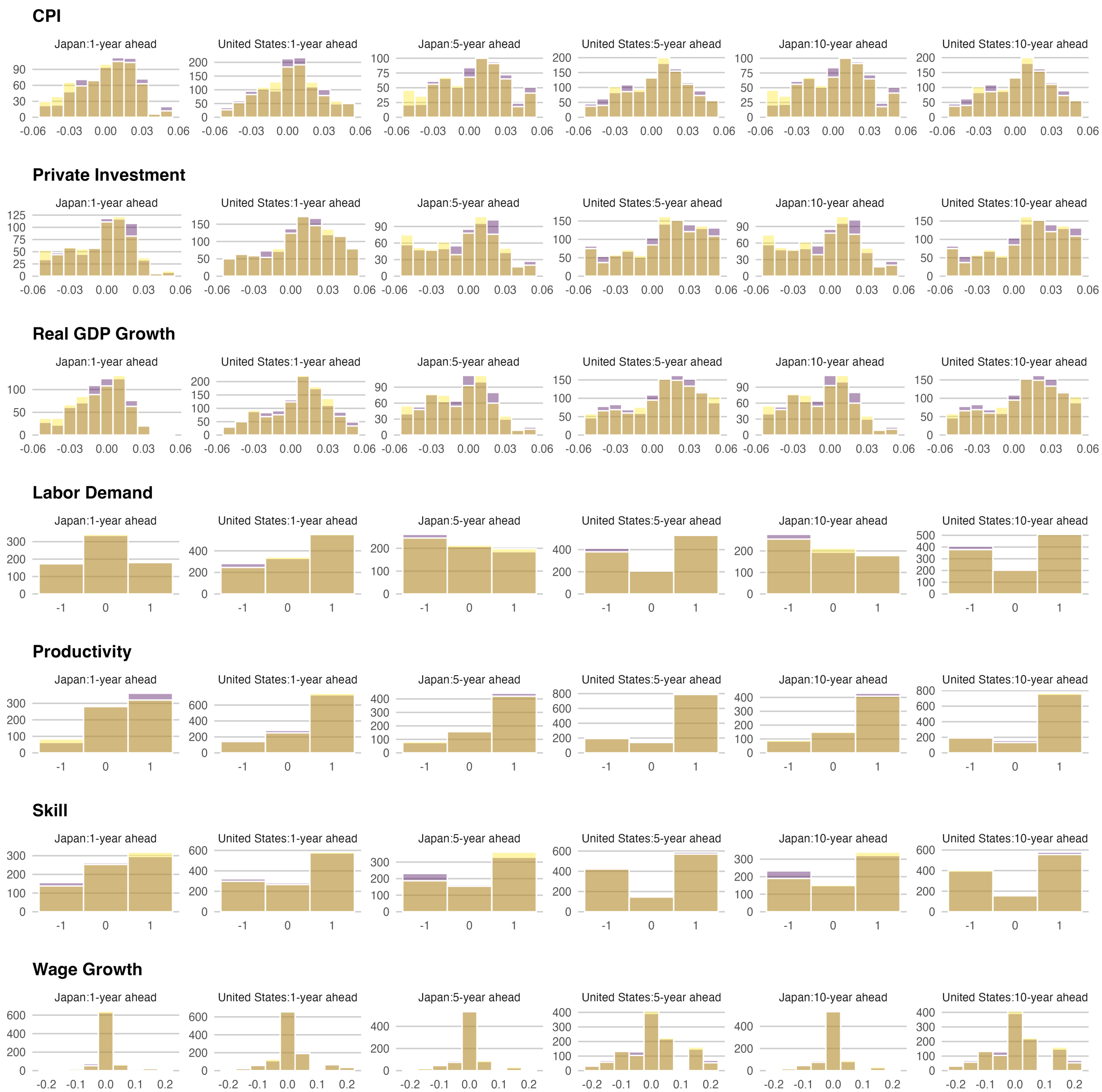
Table B.5: Updating belief: heterogeneity across groups

Shock Variable	Japan			United States		
	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Shock	0.03** (0.01)	0.06*** (0.02)	0.08*** (0.02)	0.006 (0.01)	0.04*** (0.02)	0.07*** (0.02)
Shock x Female	0.006 (0.02)	0.010 (0.02)	0.05 (0.03)	0.02 (0.02)	0.01 (0.02)	-0.001 (0.03)
Shock	0.03** (0.01)	0.08*** (0.02)	0.14*** (0.03)	0.02 (0.02)	0.04* (0.02)	0.07** (0.03)
Shock x Age < 44	-0.002 (0.02)	-0.02 (0.03)	-0.04 (0.04)	-0.0004 (0.02)	0.010 (0.03)	-0.008 (0.04)
Shock	0.04* (0.02)	0.09*** (0.03)	0.16*** (0.03)	0.04** (0.02)	0.07*** (0.02)	0.07** (0.03)
Shock x High Educ	-0.01 (0.02)	-0.03 (0.03)	-0.07* (0.04)	-0.03 (0.02)	-0.03 (0.03)	-0.0007 (0.03)
Shock	0.03*** (0.01)	0.07*** (0.01)	0.11*** (0.02)	0.03** (0.01)	0.06*** (0.01)	0.09*** (0.02)
Shock x High Income	-0.03 (0.03)	0.003 (0.04)	-0.05 (0.05)	0.009 (0.02)	-0.02 (0.02)	-0.06* (0.03)
Shock	0.03*** (0.01)	0.07*** (0.01)	0.10*** (0.02)	0.03** (0.01)	0.08*** (0.02)	0.15*** (0.03)
Shock x Private Use of GenAI	0.0008 (0.02)	-0.01 (0.03)	-0.02 (0.04)	-0.02 (0.02)	-0.05** (0.03)	-0.12*** (0.03)
Shock	0.04*** (0.01)	0.07*** (0.01)	0.10*** (0.02)	0.02 (0.01)	0.04*** (0.02)	0.05*** (0.02)
Shock x Occupation (Sales & Admin)	-0.02 (0.02)	-0.0010 (0.03)	0.02 (0.04)	0.002 (0.02)	0.03 (0.03)	0.05 (0.03)
Shock	0.03*** (0.01)	0.06*** (0.02)	0.10*** (0.02)	0.02* (0.01)	0.04*** (0.02)	0.07*** (0.01)
Shock x Occupation (Creative)	-0.006 (0.03)	0.06 (0.04)	0.06 (0.06)	0.02 (0.04)	0.03 (0.04)	-0.04 (0.05)
Shock	0.02* (0.01)	0.07*** (0.01)	0.11*** (0.02)	0.03*** (0.01)	0.07*** (0.01)	0.10*** (0.02)
Shock x Occupation (Engineering)	0.03 (0.02)	-0.03 (0.03)	0.010 (0.04)	-0.03* (0.02)	-0.07*** (0.02)	-0.10*** (0.03)
Shock	0.03*** (0.01)	0.07*** (0.02)	0.13*** (0.02)	0.009 (0.01)	0.04*** (0.02)	0.04** (0.02)
Shock x Occupation (Planning & Profession)	-0.006 (0.02)	0.001 (0.03)	-0.06 (0.04)	0.03 (0.02)	0.04 (0.02)	0.08** (0.03)
Observations	1,505	1,505	1,505	2,369	2,369	2,369

Notes: The table describes OLS estimates for the updating for different groups. All specifications control for the respondent's prior belief, interactions of the prior with the dimension of heterogeneity and dummies for the dimension of heterogeneity, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

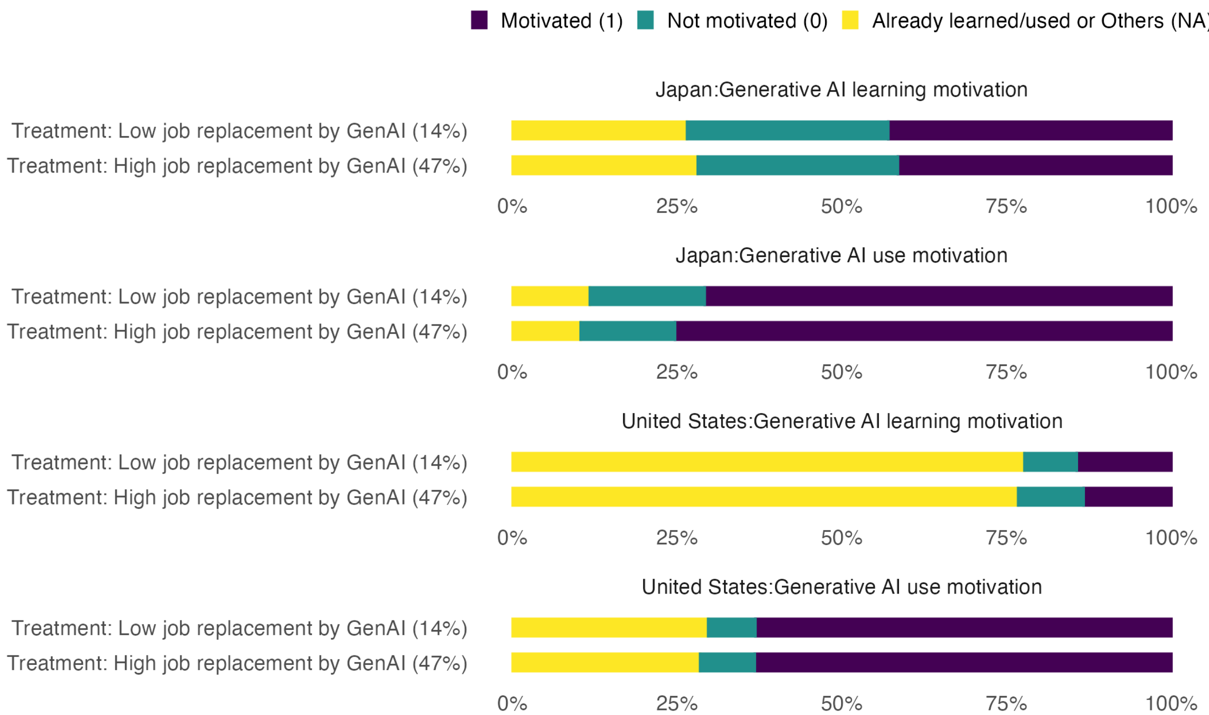
C Distribution of macroeconomic outlooks and behavioral views

Figure C.1: Distributions of the respondent's views regarding macroeconomy and their jobs across treatment arms (higher treatment: violet, lower treatment: yellow)



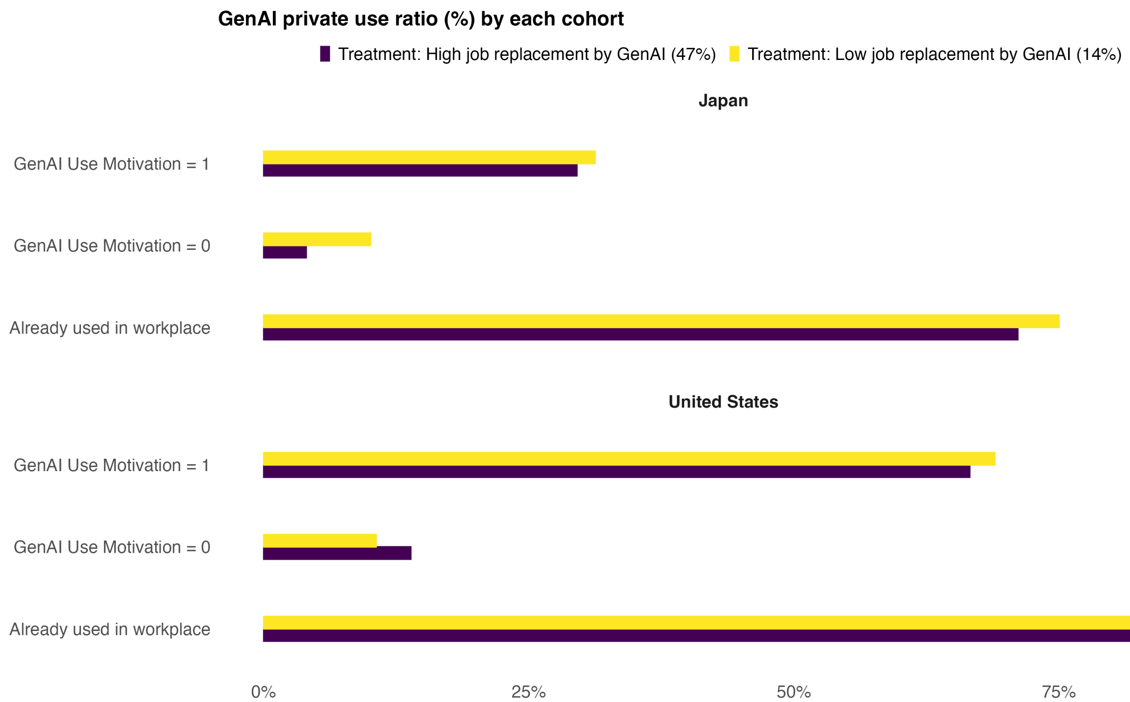
Notes: This figure shows the distributions of responses regarding macroeconomic views in each treatment group. The x-axis values are based on the original values(e.g. CPI ranges from -0.055 (5.5% decrease) to 0.055 (5.5% increase)). Violet bars describe high job replacement by GenAI (47%) while yellow bars do low job replacement by GenAI (14%).

Figure C.2: Distributions of the behavioral views for GenAI across treatment arms



Notes: This figure displays distributions of responses regarding learning intentions and using intentions of GenAI in each treatment group. Responses are classified into three types: "motivated", "not motivated", and "already learned/used or others". We defined a dummy variable that takes 1 if the respondent is categorized as 'motivated' and 0 if categorized as 'not motivated'. The question for learning intention is "Q51.Do you have the opportunity to learn about generative AI ? Please select all that apply.". Then we regard the answer "1. I do not have the opportunity to learn it at present and do not plan to learn in the future" as "not motivated", the answer "2. I do not have the opportunity to learn it at present. but I would like to learn in the future" as "motivated", and the rest of the answers (3 to 7) as "already learned/used or others". Likewise, The question for use intention is "Q53.Do you want to use generative AI in your work in the future ? (Select one only)". Then we regard the answer "1. I do not want to use it" as "not motivated", the answer "2. I want to actively explore the possibility of using generative AI in work where its use is not currently permitted and put forward proposals for use in my company" to "4. I want to use it in my work if I am obliged to do so" as "motivated", and the rest of the answers (5) as "already learned/used or others".

Figure C.3: GenAI private use ratio by motivation responses to use in working place across treatment arms



Notes: This figure displays GenAI private use ratio by responses regarding use intentions in the working place in each treatment group. Responses are classified into three types: "motivated", "not motivated", and "already used in workplace". Yellow bars show GenAI use ratio of higher job replacement treatment group while violet bars show GenAI use ratio of lower job replacement treatment group.

D Additional figures and tables for benchmark and heterogeneity

Table D.1: Coefficients of updating on behavioral views

	GenAI Learning Intention			GenAI Use Intention		
Japan	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Updating	0.13 (0.14)	0.06 (0.06)	0.04 (0.04)	0.40** (0.17)	0.18** (0.07)	0.11** (0.05)
Observations	1,093	1,093	1,093	1,328	1,328	1,328
First stage F-stat	7.7	9.5	8.1	7.7	9.5	8.1
Mean Dep.var.	0.58	0.58	0.58	0.82	0.82	0.82
SD Dep.var.	0.49	0.49	0.49	0.38	0.38	0.38
	GenAI Learning Intention			GenAI Use Intention		
United States	1-year ahead	5-year ahead	10-year ahead	1-year ahead	5-year ahead	10-year ahead
Updating	-0.39 (0.35)	-0.14 (0.13)	-0.08 (0.09)	-0.06 (0.32)	-0.02 (0.12)	-0.02 (0.09)
Observations	532	532	532	1,665	1,665	1,665
First stage F-stat	5.5	7.7	8.1	5.5	7.7	8.1
Mean Dep.var.	0.61	0.61	0.61	0.89	0.89	0.89
SD Dep.var.	0.49	0.49	0.49	0.31	0.31	0.31

Notes: This table shows the IV estimates of the coefficients for the belief updating on GenAI learning intention and GenAI use intention, corresponding to the marginal effects displayed in Table 6. All dependent variables are scaled. All specifications control for prior belief, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor's degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table D.2: Coefficients of posterior beliefs on macroeconomic views - Japan

1-year ahead	**Wage growth**	**Real GDP growth**	**CPI**	**Investment growth**	**Labor Demand**	**Productivity**	**Skill**
Panel A: OLS							
posterior	0.009*** (0.003)	-0.002 (0.004)	-0.01*** (0.004)	-0.010* (0.005)	0.008 (0.008)	-0.01* (0.008)	-0.007 (0.009)
Panel B: IV							
posterior	0.03 (0.03)	0.07 (0.05)	0.10* (0.05)	0.06 (0.05)	0.02 (0.09)	0.25*** (0.09)	-0.04 (0.10)
Observations	1,465	1,170	1,189	1,162	1,255	1,255	1,280
First stage F-stat	56.6	56.6	56.6	56.6	56.6	56.6	56.6
Mean Dep.var.	0.53	0.46	0.52	0.48	0.51	0.69	0.61
SD Dep.var.	0.12	0.19	0.22	0.22	0.36	0.33	0.38
5 year ahead	**Wage growth**	**Real GDP growth**	**CPI**	**Investment growth**	**Labor Demand**	**Productivity**	**Skill**
Panel A: OLS							
posterior	0.007*** (0.003)	-0.003 (0.004)	-0.006 (0.004)	-0.007* (0.004)	-0.002 (0.007)	-0.01 (0.008)	-0.004 (0.006)
Panel B: IV							
posterior	-0.004 (0.01)	0.03 (0.03)	0.06** (0.03)	0.04 (0.03)	-0.06 (0.05)	0.05 (0.05)	-0.05 (0.05)
Observations	1,459	1,163	1,179	1,145	1,187	1,204	1,276
First stage F-stat	60.4	60.4	60.4	60.4	60.4	60.4	60.4
Mean Dep.var.	0.52	0.46	0.54	0.48	0.45	0.76	0.60
SD Dep.var.	0.15	0.23	0.25	0.25	0.41	0.35	0.43
10 year ahead	**Wage growth**	**Real GDP growth**	**CPI**	**Investment growth**	**Labor Demand**	**Productivity**	**Skill**
Panel A: OLS							
posterior	0.003* (0.002)	-0.003 (0.003)	-0.003 (0.003)	-0.003 (0.003)	0.0006 (0.005)	-0.002 (0.006)	-0.0009 (0.005)
Panel B: IV							
posterior	-0.003 (0.009)	0.02 (0.01)	0.04** (0.02)	0.02 (0.02)	-0.04 (0.03)	0.01 (0.03)	-0.02 (0.03)
Observations	1,459	1,163	1,179	1,145	1,170	1,179	1,241
First stage F-stat	74.7	74.7	74.7	74.7	74.7	74.7	74.7
Mean Dep.var.	0.52	0.46	0.54	0.48	0.43	0.75	0.59
SD Dep.var.	0.15	0.23	0.25	0.25	0.41	0.36	0.43

Notes: This table shows the OLS and IV estimates of the coefficients for posterior beliefs on views regarding the macroeconomy and the respondent's job in Japan, forming the basis of the marginal effect's result reported in Table **??** and Table **??**. All dependent variables are scaled. All specifications control for prior beliefs, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor's degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Posterior beliefs regarding the GenAI job replacement ratio are used for the same period of time as the dependent variable. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table D.3: Coefficients of posterior beliefs on macroeconomic views - the U.S.

1 year ahead	**Wage growth**	**Real GDP growth**	**CPI**	**Investment growth**	**Labor Demand**	**Productivity**	**Skill**
Panel A: OLS							
posterior	-0.003 (0.002)	0.003 (0.003)	0.008*** (0.003)	0.004 (0.003)	0.002 (0.006)	-0.0007 (0.007)	0.009 (0.006)
Panel B: IV							
posterior	-0.02 (0.05)	-0.02 (0.07)	-0.02 (0.06)	-0.04 (0.07)	-0.16 (0.13)	-0.19 (0.14)	-0.13 (0.13)
Observations	2,351	2,190	2,206	2,181	2,282	2,287	2,304
First stage F-stat	161.1	161.1	161.1	161.1	161.1	161.1	161.1
Mean Dep.var.	0.55	0.57	0.54	0.59	0.62	0.75	0.62
SD Dep.var.	0.17	0.23	0.22	0.25	0.40	0.36	0.42
5 year ahead	**Wage growth**	**Real GDP growth**	**CPI**	**Investment growth**	**Labor Demand**	**Productivity**	**Skill**
Panel A: OLS							
posterior	-0.0002 (0.002)	0.009*** (0.003)	0.007*** (0.002)	0.008*** (0.003)	0.004 (0.004)	0.007 (0.005)	0.007 (0.005)
Panel B: IV							
posterior	-0.03 (0.03)	-0.01 (0.03)	-0.010 (0.03)	0.007 (0.03)	-0.04 (0.05)	-0.02 (0.06)	0.01 (0.05)
Observations	2,353	2,179	2,196	2,160	2,252	2,253	2,277
First stage F-stat	118.9	118.9	118.9	118.9	118.9	118.9	118.9
Mean Dep.var.	0.56	0.59	0.56	0.61	0.56	0.76	0.57
SD Dep.var.	0.23	0.26	0.24	0.27	0.45	0.39	0.46
10 year ahead	**Wage growth**	**Real GDP growth**	**CPI**	**Investment growth**	**Labor Demand**	**Productivity**	**Skill**
Panel A: OLS							
posterior	0.001 (0.002)	0.005** (0.002)	0.004* (0.002)	0.006*** (0.002)	0.0007 (0.004)	0.003 (0.004)	0.004 (0.003)
Panel B: IV							
posterior	-0.02 (0.02)	-0.009 (0.02)	-0.007 (0.02)	0.003 (0.02)	-0.02 (0.04)	-0.05 (0.04)	0.03 (0.04)
Observations	2,353	2,179	2,196	2,160	2,191	2,189	2,233
First stage F-stat	134.3	134.3	134.3	134.3	134.3	134.3	134.3
Mean Dep.var.	0.56	0.59	0.56	0.61	0.55	0.75	0.57
SD Dep.var.	0.23	0.26	0.24	0.27	0.45	0.39	0.46

Notes: This table shows the OLS and IV estimates of the coefficients for posterior beliefs on views regarding the macroeconomy and the respondent's job in the U.S., forming the basis of the marginal effect's result reported in Table **??** and Table **??**. All dependent variables are scaled. All specifications control for prior beliefs, age, age squared, a dummy for females, log income, a dummy for respondents with at least a bachelor's degree, a dummy for private use of GenAI, a dummy for having subordinates, a dummy for routine/repetitive work, region, occupation, industry, and firm size. Posterior beliefs regarding the GenAI job replacement ratio are used for the same period of time as the dependent variable. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

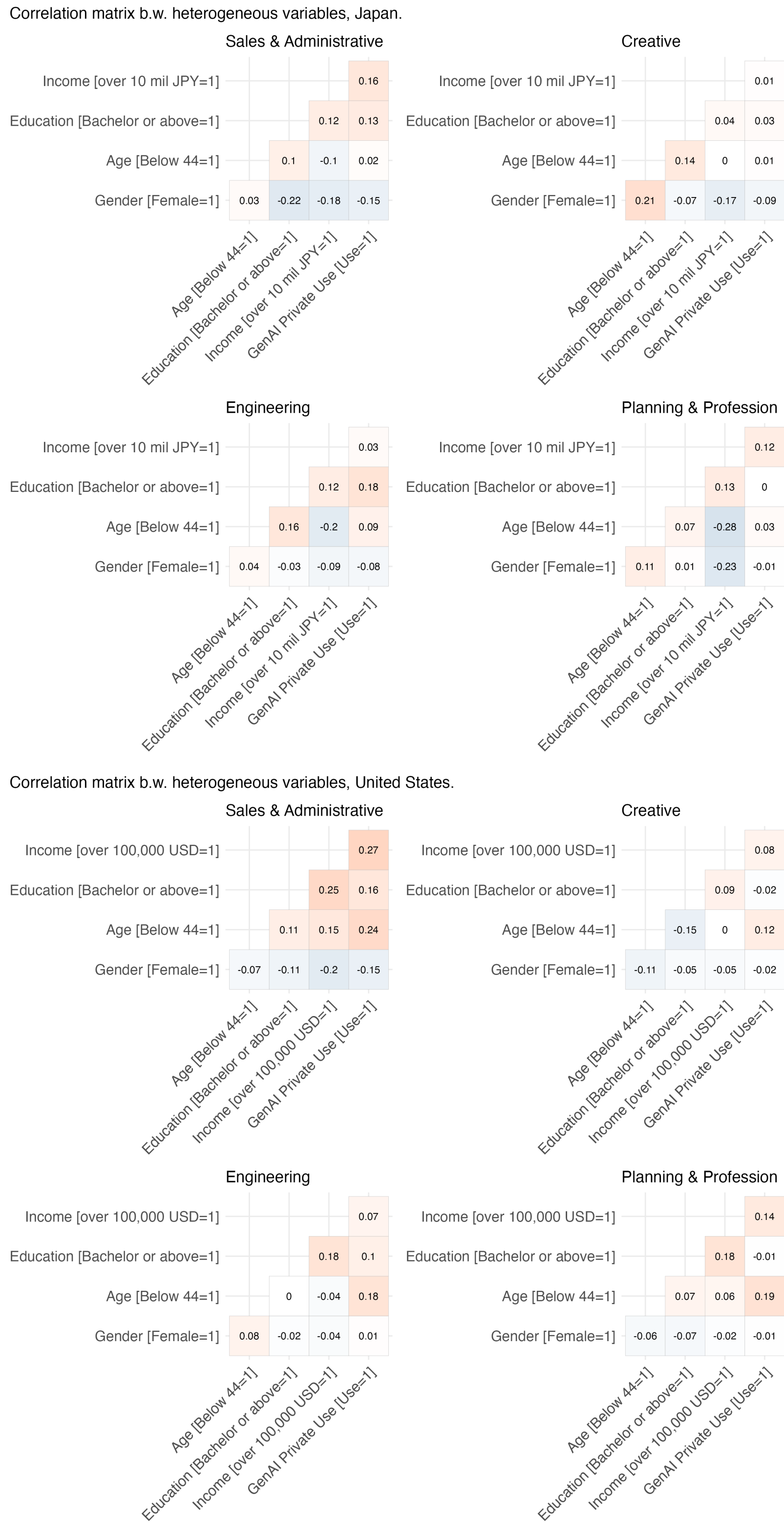
Table D.4: Summary statistics by occupational categories

	Sales & Admin					Creative					Engineering					Planning & Profession				
Japan	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs
Variables for Heterogeneity																				
Gender [Female=1]	0.54	0.50	0.00	1.00	521	0.49	0.50	0.00	1.00	199	0.48	0.50	0.00	1.00	501	0.49	0.50	0.00	1.00	505
Age [Below 44=1]	0.67	0.47	0.00	1.00	521	0.67	0.47	0.00	1.00	199	0.69	0.46	0.00	1.00	501	0.67	0.47	0.00	1.00	505
Education [Bachelor or above=1]	0.63	0.48	0.00	1.00	521	0.56	0.50	0.00	1.00	199	0.68	0.47	0.00	1.00	501	0.85	0.35	0.00	1.00	505
High Income [over 10 mil JPY=1]	0.04	0.20	0.00	1.00	521	0.03	0.17	0.00	1.00	199	0.04	0.20	0.00	1.00	501	0.18	0.38	0.00	1.00	505
GenAI Private Use [Use=1]	0.21	0.41	0.00	1.00	521	0.30	0.46	0.00	1.00	199	0.33	0.47	0.00	1.00	501	0.41	0.49	0.00	1.00	505
Key Dependent Variables																				
Updating (1-year ahead)	-0.25	6.40	-45.00	48.00	521	-0.45	8.01	-80.00	30.00	199	-0.41	5.89	-40.00	47.00	501	-0.45	5.88	-40.00	30.00	505
Updating (5-year ahead)	-1.71	8.62	-60.00	50.00	521	-1.92	9.87	-65.00	50.00	199	-1.29	8.95	-43.00	55.00	501	-1.19	8.38	-40.00	40.00	505
Updating (10-year ahead)	-2.22	11.38	-65.00	50.00	521	-3.13	14.35	-50.00	59.00	199	-2.07	11.21	-45.00	60.00	501	-2.60	11.44	-50.00	50.00	505
Posterior (1-year ahead)	11.50	9.81	1.00	60.00	521	11.40	10.13	1.00	60.00	199	10.38	9.67	1.00	66.00	501	10.13	9.11	1.00	70.00	505
Posterior (5-year ahead)	20.32	13.80	1.00	80.00	521	19.93	13.08	1.00	70.00	199	18.73	13.04	1.00	70.00	501	18.55	12.42	1.00	75.00	505
Posterior (10-year ahead)	32.00	19.82	1.00	90.00	521	32.24	18.64	3.00	99.00	199	30.69	19.41	1.00	90.00	501	30.37	18.69	2.00	93.00	505
Wage Growth (1-year ahead)	0.89	5.10	-20.0	20.0	492	1.19	5.85	-20.0	20.0	194	1.11	4.39	-20.0	20.0	478	1.34	4.38	-20.0	20.0	493
Wage Growth (5-year ahead)	0.50	6.19	-20.0	20.0	494	-0.32	6.66	-20.0	20.0	195	1.10	5.74	-20.0	20.0	475	1.32	5.78	-20.0	20.0	489
Wage Growth (10-year ahead)	0.50	6.19	-20.0	20.0	494	-0.32	6.66	-20.0	20.0	195	1.10	5.74	-20.0	20.0	475	1.32	5.78	-20.0	20.0	489
Real GDP Growth (1-year ahead)	-0.43	2.20	-5.5	5.0	357	-0.70	2.32	-5.5	4.5	141	-0.50	2.03	-5.5	3.5	374	-0.26	1.94	-5.5	4.5	408
Real GDP Growth (5-year ahead)	-0.61	2.61	-5.5	5.5	354	-0.65	2.69	-5.5	5.5	141	-0.53	2.51	-5.5	5.5	370	-0.24	2.40	-5.5	5.5	409
Real GDP Growth (10-year ahead)	-0.61	2.61	-5.5	5.5	354	-0.65	2.69	-5.5	5.5	141	-0.53	2.51	-5.5	5.5	370	-0.24	2.40	-5.5	5.5	409
CPI (1-year ahead)	-0.01	2.42	-5.5	5.5	360	-0.06	2.64	-5.5	5.5	145	0.10	2.42	-5.5	5.5	378	0.53	2.17	-5.5	5.5	418
CPI (5-year ahead)	0.17	2.77	-5.5	5.5	354	0.27	2.92	-5.5	5.5	143	0.42	2.78	-5.5	5.5	377	0.75	2.53	-5.5	5.5	416
CPI (10-year ahead)	0.17	2.77	-5.5	5.5	354	0.27	2.92	-5.5	5.5	143	0.42	2.78	-5.5	5.5	377	0.75	2.53	-5.5	5.5	416
Private Investment (1-year ahead)	-0.40	2.64	-5.5	5.5	359	-0.37	2.63	-5.5	5.5	141	-0.23	2.34	-5.5	5.0	368	-0.01	2.20	-5.5	5.5	404
Private Investment (5-year ahead)	-0.48	2.90	-5.5	5.5	346	-0.39	2.99	-5.5	5.5	141	-0.15	2.80	-5.5	5.5	362	0.10	2.63	-5.5	5.5	404
Private Investment (10-year ahead)	-0.48	2.90	-5.5	5.5	346	-0.39	2.99	-5.5	5.5	141	-0.15	2.80	-5.5	5.5	362	0.10	2.63	-5.5	5.5	404
Labor Demand (1-year ahead)	-0.16	0.67	-1.00	1.00	395	-0.01	0.75	-1.00	1.00	159	0.10	0.71	-1.00	1.00	408	0.10	0.72	-1.00	1.00	429
Labor Demand (5-year ahead)	-0.23	0.75	-1.00	1.00	372	-0.21	0.87	-1.00	1.00	154	-0.03	0.83	-1.00	1.00	382	0.02	0.82	-1.00	1.00	403
Labor Demand (10-year ahead)	-0.25	0.77	-1.00	1.00	372	-0.20	0.87	-1.00	1.00	154	-0.12	0.82	-1.00	1.00	372	-0.02	0.82	-1.00	1.00	398
Productivity (1-year ahead)	0.24	0.67	-1.00	1.00	390	0.47	0.70	-1.00	1.00	160	0.39	0.66	-1.00	1.00	405	0.48	0.64	-1.00	1.00	437
Productivity (5-year ahead)	0.40	0.71	-1.00	1.00	376	0.47	0.78	-1.00	1.00	154	0.56	0.69	-1.00	1.00	392	0.62	0.65	-1.00	1.00	418
Productivity (10-year ahead)	0.35	0.75	-1.00	1.00	369	0.47	0.79	-1.00	1.00	152	0.54	0.71	-1.00	1.00	381	0.62	0.65	-1.00	1.00	412
Skill (1-year ahead)	0.06	0.76	-1.00	1.00	407	0.32	0.78	-1.00	1.00	170	0.27	0.76	-1.00	1.00	407	0.30	0.75	-1.00	1.00	440
Skill (5-year ahead)	0.00	0.83	-1.00	1.00	408	0.25	0.90	-1.00	1.00	169	0.20	0.87	-1.00	1.00	408	0.33	0.83	-1.00	1.00	439
Skill (10-year ahead)	-0.04	0.83	-1.00	1.00	390	0.28	0.90	-1.00	1.00	165	0.17	0.88	-1.00	1.00	400	0.32	0.84	-1.00	1.00	430

	Sales & Admin					Creative					Engineering					Planning & Profession				
United States	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs
Variables for Heterogeneity																				
Gender [Female=1]	0.54	0.50	0.00	1.00	665	0.44	0.50	0.00	1.00	182	0.46	0.50	0.00	1.00	871	0.50	0.50	0.00	1.00	681
Age [Below 44=1]	0.72	0.45	0.00	1.00	665	0.86	0.35	0.00	1.00	182	0.77	0.42	0.00	1.00	871	0.74	0.44	0.00	1.00	681
Education [Bachelor or above=1]	0.54	0.50	0.00	1.00	665	0.73	0.45	0.00	1.00	182	0.78	0.41	0.00	1.00	871	0.74	0.44	0.00	1.00	681
High Income [over 0.1 mil USD=1]	0.26	0.44	0.00	1.00	665	0.35	0.48	0.00	1.00	182	0.50	0.50	0.00	1.00	871	0.47	0.50	0.00	1.00	681
GenAI Private Use [Use=1]	0.52	0.50	0.00	1.00	665	0.75	0.44	0.00	1.00	182	0.82	0.39	0.00	1.00	871	0.68	0.47	0.00	1.00	681
Key Dependent Variables																				
Updating (1-year ahead)	0.12	8.04	-50.00	46.00	665	0.91	9.02	-30.00	54.00	182	-0.12	7.75	-50.00	45.00	871	-0.05	7.27	-45.00	44.00	681
Updating (5-year ahead)	-0.75	10.64	-65.00	50.00	665	-0.29	10.38	-35.00	40.00	182	-0.74	8.84	-45.00	56.00	871	-0.45	9.10	-50.00	50.00	681
Updating (10-year ahead)	-1.10	12.42	-66.00	60.00	665	0.12	12.21	-45.00	50.00	182	-1.16	12.51	-79.00	70.00	871	-1.37	12.77	-70.00	60.00	681
Posterior (1-year ahead)	15.18	14.34	1.00	90.00	665	16.15	13.67	1.00	80.00	182	17.74	15.38	1.00	99.00	871	15.22	13.27	1.00	88.00	681
Posterior (5-year ahead)	24.57	17.13	1.00	95.00	665	22.72	12.69	1.00	80.00	182	24.26	15.28	1.00	95.00	871	24.20	15.14	1.00	80.00	681
Posterior (10-year ahead)	37.18	23.55	1.00	99.00	665	34.98	17.95	1.00	80.00	182	33.89	20.18	1.00	95.00	871	35.35	21.06	1.00	99.00	681
Wage Growth (1-year ahead)	1.56	6.63	-20.0	20.0	654	3.60	5.60	-7.5	20.0	182	2.34	7.49	-20.0	20.0	865	1.81	6.39	-20.0	20.0	676
Wage Growth (5-year ahead)	1.10	9.21	-20.0	20.0	655	4.41	8.67	-20.0	20.0	182	3.04	9.64	-20.0	20.0	867	2.04	9.07	-20.0	20.0	676
Wage Growth (10-year ahead)	1.10	9.21	-20.0	20.0	655	4.41	8.67	-20.0	20.0	182	3.04	9.64	-20.0	20.0	867	2.04	9.07	-20.0	20.0	676
Real GDP Growth (1-year ahead)	0.48	2.64	-5.5	5.5	565	0.51	2.59	-5.5	5.5	175	1.10	2.45	-5.5	5.5	831	0.65	2.38	-5.5	5.5	639
Real GDP Growth (5-year ahead)	0.57	3.10	-5.5	5.5	564	0.71	2.93	-5.5	5.5	173	1.37	2.76	-5.5	5.5	828	1.02	2.83	-5.5	5.5	633
Real GDP Growth (10-year ahead)	0.57	3.10	-5.5	5.5	564	0.71	2.93	-5.5	5.5	173	1.37	2.76	-5.5	5.5	828	1.02	2.83	-5.5	5.5	633
CPI (1-year ahead)	0.33	2.59	-5.5	5.5	566	0.17	2.45	-5.0	5.0	175	0.59	2.44	-5.5	5.5	840	0.37	2.33	-5.5	5.5	646
CPI (5-year ahead)	0.52	2.74	-5.5	5.5	564	0.27	2.56	-5.5	5.0	174	0.89	2.54	-5.5	5.5	837	0.62	2.64	-5.5	5.5	641
CPI (10-year ahead)	0.52	2.74	-5.5	5.5	564	0.27	2.56	-5.5	5.0	174	0.89	2.54	-5.5	5.5	837	0.62	2.64	-5.5	5.5	641
Private Investment (1-year ahead)	0.59	2.95	-5.5	5.5	558	0.51	3.02	-5.5	5.5	174	1.44	2.66	-5.5	5.5	832	0.85	2.64	-5.5	5.5	635
Private Investment (5-year ahead)	0.85	3.18	-5.5	5.5	550	0.76	3.25	-5.5	5.5	172	1.54	2.84	-5.5	5.5	827	1.10	2.96	-5.5	5.5	630
Private Investment (10-year ahead)	0.85	3.18	-5.5	5.5	550	0.76	3.25	-5.5	5.5	172	1.54	2.84	-5.5	5.5	827	1.10	2.96	-5.5	5.5	630
Labor Demand (1-year ahead)	0.05	0.80	-1.00	1.00	625	0.34	0.81	-1.00	1.00	175	0.40	0.79	-1.00	1.00	847	0.22	0.79	-1.00	1.00	658
Labor Demand (5-year ahead)	-0.08	0.88	-1.00	1.00	605	0.16	0.90	-1.00	1.00	173	0.29	0.87	-1.00	1.00	842	0.08	0.90	-1.00	1.00	654
Labor Demand (10-year ahead)	-0.08	0.88	-1.00	1.00	596	-0.01	0.92	-1.00	1.00	165	0.27	0.88	-1.00	1.00	823	0.09	0.90	-1.00	1.00	627
Productivity (1-year ahead)	0.37	0.73	-1.00	1.00	615	0.56	0.72	-1.00	1.00	176	0.58	0.70	-1.00	1.00	857	0.53	0.71	-1.00	1.00	662
Productivity (5-year ahead)	0.44	0.79	-1.00	1.00	612	0.31	0.90	-1.00	1.00	172	0.58	0.75	-1.00	1.00	843	0.58	0.74	-1.00	1.00	649
Productivity (10-year ahead)	0.47	0.78	-1.00	1.00	590	0.18	0.89	-1.00	1.00	161	0.57	0.76	-1.00	1.00	828	0.54	0.77	-1.00	1.00	632
Skill (1-year ahead)	0.12	0.84	-1.00	1.00	632	0.23	0.89	-1.00	1.00	179	0.34	0.83	-1.00	1.00	854	0.20	0.84	-1.00	1.00	662
Skill (5-year ahead)	0.05	0.90	-1.00	1.00	622	0.02	0.95	-1.00	1.00	176	0.21	0.92	-1.00	1.00	846	0.15	0.93	-1.00	1.00	657
Skill (10-year ahead)	0.02	0.91	-1.00	1.00	607	-0.02	0.92	-1.00	1.00	171	0.24	0.91	-1.00	1.00	836	0.20	0.91	-1.00	1.00	642

Notes: The table describes summary statistics by occupational categories: Sales & Admin, Creative, Engineering, and Planning & Profession. Both treatment groups are pooled. Posterior, wage growth, real GDP growth, CPI, and private investment (growth) are displayed in percentage units. Two types of variables are displayed: one for heterogeneity, such as gender, age, education, income, and GenAI private usage, while the other for key dependent variables like macroeconomic perspectives as well as updating and posterior beliefs. 'High income' is defined as a dummy variable that takes the value of 1 if the income exceeds 10 million yen in Japan or 100,000 U.S. dollars in the U.S.

Figure D.1: Correlation matrix between main heterogeneous variables

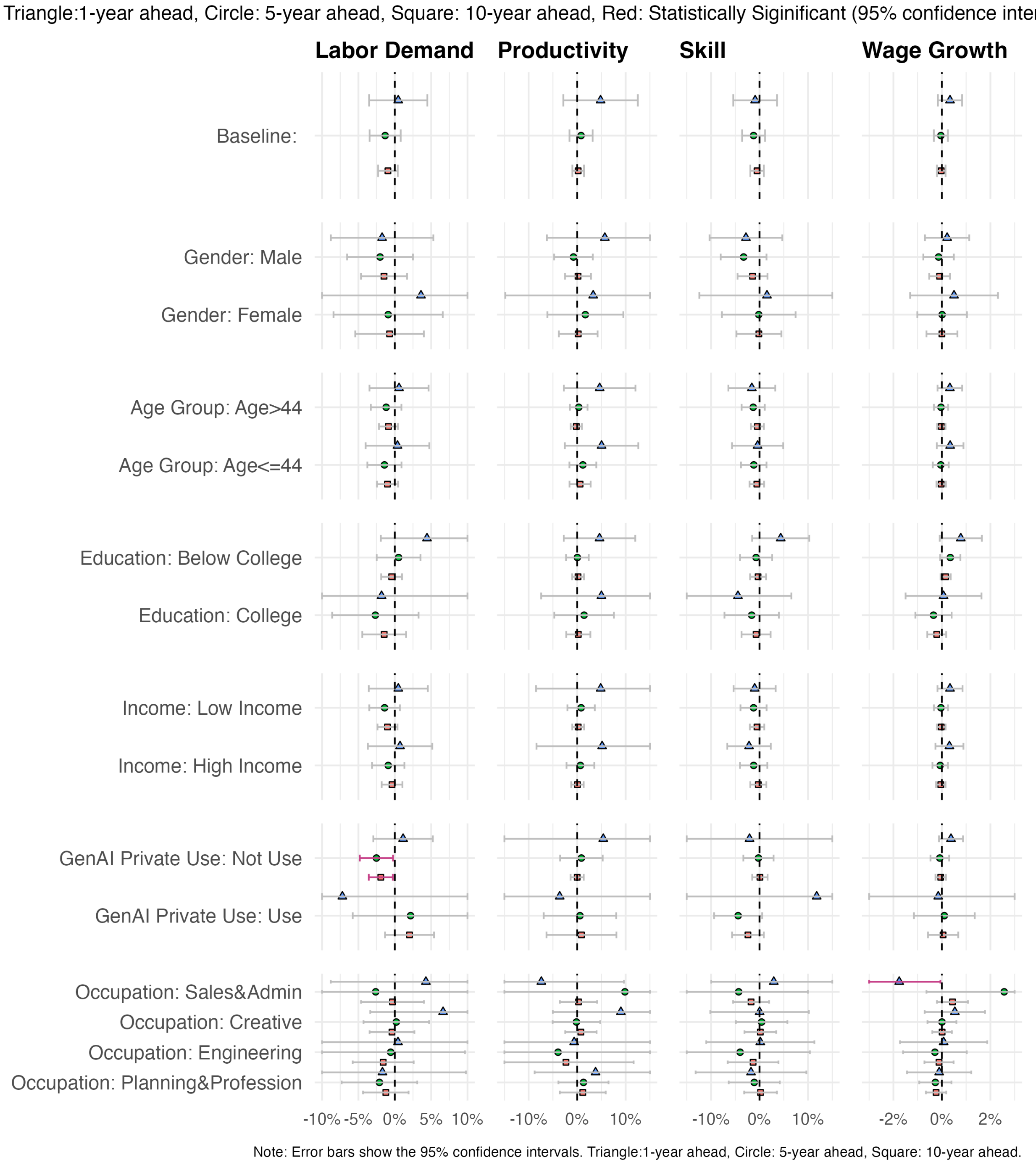


Notes: This figure displays a correlation matrix between main heterogeneous variables with pooled data including both treatment groups. Correlation values are calculated by pair-wise complete observations. The red areas indicate positive correlation values while the blue areas indicate negative ones.

Figure D.2: Marginal effects of the posterior beliefs on macroeconomic views - Japan, 95% CI

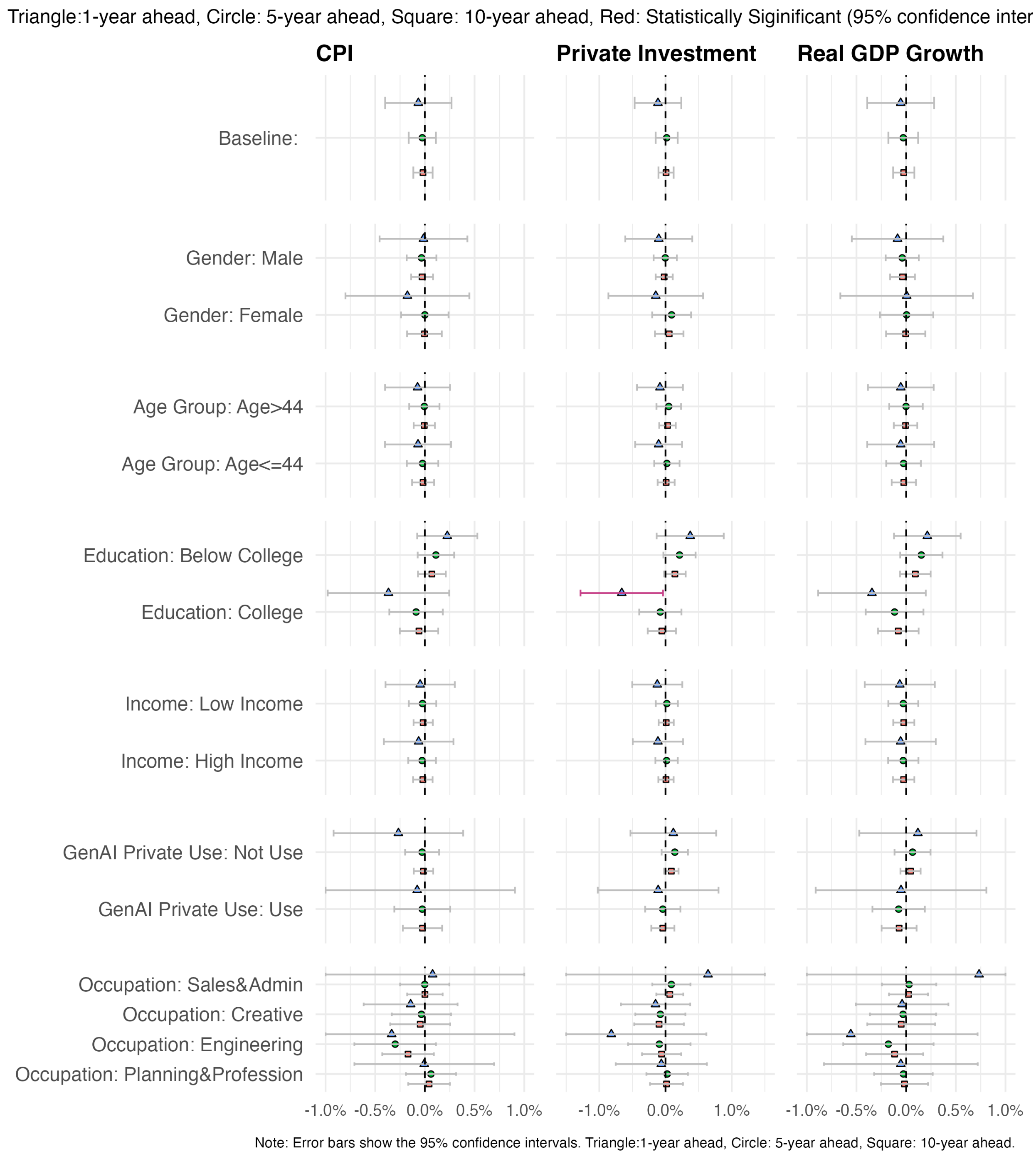
Notes: This figure presents the marginal effects of posterior beliefs on expectations for CPI, private investment, and real GDP. Both baseline and heterogeneous effects are estimated. The shapes of the points indicate the time horizon: triangles represent 1 year ahead, circles represent 5 years ahead, and squares represent 10 years ahead. The error bars depict the 95% confidence intervals. Statistically significant effects are highlighted in red, while effects that are not statistically significant and have large standard errors are truncated at the edges to improve visibility. 'High income' is defined as a dummy variable that takes the value of 1 if the income exceeds 10 million yen in Japan or 100,000 U.S. dollars in the U.S.

Figure D.3: Marginal effects of the posterior beliefs on views on respondent's jobs- Japan, 95% CI



Notes: This figure presents the marginal effects of posterior beliefs on expectations for CPI, private investment, and real GDP. Both baseline and heterogeneous effects are estimated. The shapes of the points indicate the time horizon: triangles represent 1 year ahead, circles represent 5 years ahead, and squares represent 10 years ahead. The error bars depict the 95% confidence intervals. Statistically significant effects are highlighted in red, while effects that are not statistically significant and have large standard errors are truncated at the edges to improve visibility. 'High income' is defined as a dummy variable that takes the value of 1 if the income exceeds 10 million yen in Japan or 100,000 U.S. dollars in the U.S.

Figure D.4: Marginal effects of the posterior beliefs on macroeconomic views - United States, 95% CI



Notes: This figure presents the marginal effects of posterior beliefs on expectations for CPI, private investment, and real GDP. Both baseline and heterogeneous effects are estimated. The shapes of the points indicate the time horizon: triangles represent 1 year ahead, circles represent 5 years ahead, and squares represent 10 years ahead. The error bars depict the 95% confidence intervals. Statistically significant effects are highlighted in red, while effects that are not statistically significant and have large standard errors are truncated at the edges to improve visibility. 'High income' is defined as a dummy variable that takes the value of 1 if the income exceeds 10 million yen in Japan or 100,000 U.S. dollars in the U.S.

Figure D.5: Marginal effects of the posterior beliefs on views on respondent's jobs- United States, 95% CI

Notes: This figure presents the marginal effects of posterior beliefs on expectations for CPI, private investment, and real GDP. Both baseline and heterogeneous effects are estimated. The shapes of the points indicate the time horizon: triangles represent 1 year ahead, circles represent 5 years ahead, and squares represent 10 years ahead. The error bars depict the 95% confidence intervals. Statistically significant effects are highlighted in red, while effects that are not statistically significant and have large standard errors are truncated at the edges to improve visibility. 'High income' is defined as a dummy variable that takes the value of 1 if the income exceeds 10 million yen in Japan or 100,000 U.S. dollars in the U.S.

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