ChatGPT: Augmenting or Replacing Intelligence in Economic Surveys?

Sungho Park*

Einaudi Institute for Economics and Finance

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Abstract

This paper examines whether ChatGPT can serve as a proxy for human survey respondents in economics research by replicating established survey-based studies using the Italian Survey of Consumer Expectations (ISCE). Analyzing performance across three dimensions: processing novel information, forming economic expectations, and predicting persistent demographic traits. Using post-training data to avoid contamination bias, I compare gpt-4o-mini responses with human participants and find fundamental limitations in replacing human survey respondents. While the model occasionally captures aggregate statistical properties, it systematically fails to replicate human decision-making patterns, demonstrating consistently different responses to information treatments, inability to model how demographics influence risk perceptions, and failure to exhibit economic prudence. When demographic information is embedded, alignment further deteriorates. However, ChatGPT shows promise in complementary applications, achieving 74% accuracy in predicting income categories and 72% for consumption levels. The results demonstrate that while ChatGPT cannot replace survey participants, it offers value as an augmentative tool for identifying or imputing persistent traits.

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1 Introduction

Since the release of ChatGPT, a generative artificial intelligence (GenAI) model, on November 30, 2022, there has been a surge of interest in understanding the economic and financial implications of AI on economic phenomena including its effects on firm and worker productivity (Babina et al., 2024; Bertomeu et al., 2023; Noy and Zhang, 2023), firm values (Eisfeldt et al., 2023), asset management (Sheng et al., 2024), the macro-economy (Acemoglu et al., 2022; Acemoglu, 2021, 2024; Furman and Seamans, 2019). Furthermore, there has been an increased interest in using ChatGPT as a research tool in economics and finance, especially to replicate experiments and surveys (Korinek, 2023). Understanding how AI agents choose or "think" is crucial for assessing the potential consequences when certain decisions are delegated to AI agents, such as the replication of experiments and surveys. For example, if these models are trained with observations from choices made by humans, they may initially replicate human biases. This understanding becomes particularly important as humans increasingly delegate decision-making to the most conventionally available models. Furthermore, these models inherently have biases from the statistical process itself.

However, despite these concerns, very few papers in the literature deeply justify the use of ChatGPT as a simulated "homo-economicus" representative agent.[1] Indeed, it is rather unknown if ChatGPT even represents a "representative agent", that is, the average individual in society, or represents some agent's heterogeneity.[2]

Firstly, the framing of questions impacts ChatGPT's responses, which may mirror psychological phenomena in humans. It is unclear if this bias originates from the training data – notably, the contamination of training data with the test data, also known as look-ahead bias – or specific features of its architecture. Secondly, it is unknown if ChatGPT simply reproduces training data, or genuinely mimics human biases. Thirdly, the way one interacts with ChatGPT (e.g., user profiles, framing, or fine-tuning) alters response distributions and behavior. Lastly, ChatGPT has been noted to excel at identifying correlations, but struggle with causal relationships (Manning et al.,

[1] Examples of proposals and use cases include: Bybee (2023), Charness et al. (2023), Chen et al. (2023), Duraj et al. (2024), Eisfeldt and Schubert (2024), Horton (2023), Immorlica et al. (2024), Korinek (2023), Lopez-Lira and Tang (2023), Lo and Ross (2024), Manning et al. (2024), Mei et al. (2024), Michelacci and Wu (2024), Zarifhonarvar (2024)

[2] An individual's utility maximizing actions does not necessarily imply a collective of individuals will behave as such – evidently a choice which may seemingly maximize the utility of agents in aggregate, may not necessarily imply preferences of the individual (Kirman, 1992)

2024). In light of the proposed usages of ChatGPT in economics and finance research, this makes it imperative to understand *how ChatGPT reasons and responds to novel information, how it forms expectations, and furthermore if it can detect persistent traits among humans*.

Furthermore, despite the emerging usage in research in economics and finance, which often require numerical reasoning, a significant debate also exists regarding the numerical processing capabilities of large language models like ChatGPT. Levy (2024) demonstrates that even minor manipulations of financial data, such as shuffling the last few digits of accounting statements, lead to dramatically different predictions of corporate performance by AI models. This "look-ahead bias" suggests that models like ChatGPT may be relying more on pattern recognition than genuine numerical reasoning, raising serious questions about their suitability for economic analysis requiring precise quantitative judgment. While some studies find that LLMs can perform reasonably well on certain economic reasoning tasks (Bybee, 2023; Horton, 2023), others highlight significant limitations in their abilities to process information in ways consistent with human economic decision-making (Fedyk et al., 2024; Chen et al., 2024). This debate extends beyond numerical processing to question whether these models can effectively act as proxies for human survey respondents or as "digital twins" in economic experiments. Proponents suggest that LLMs can reduce research costs and generate high-frequency survey responses, while critics point to concerns about the models' ability to accurately represent human heterogeneity, process new information, or perform causal reasoning rather than merely identifying correlations (Manning et al., 2024).

An ideal setting to test the suitability of ChatGPT as a research tool in light of these questions is via surveys in the economics and finance literature. Firstly, should ChatGPT be able to replicate the responses of an average research participant, including responses to information treatments, this could have important implications for understanding both the origins of biases in ChatGPT's responses and its potential use in generating high-frequency survey measures that vary across time and research subject. If ChatGPT can effectively synthesize novel information, it could represent a valuable tool for researchers. Secondly, given the ubiquity of ChatGPT, understanding what kind of agent ChatGPT represents is imperative as the responses it generates could lead to economically meaningful effects through influencing users, who then influence ChatGPT itself – as users interact with ChatGPT, the system incorporates these responses into its training data, which it uses to update user interactions in the short-run and incorporates into the pre-training dataset for subsequent models released by OpenAI. This feedback loop makes it essential to determine the similarity of ChatGPT responses to humans in surveys within the economics and finance literature, as such sim-

ilarity or heterogeneity could lead to changes in human/machine behavior in the long run. Lastly, responses to certain or persistently survey responses could inform the extent of ChatGPT's ability in not only being a useful imputation device, but possibly discerning correlations and causation.

In light of this, I replicate elements from two survey-based papers in economics and finance, and examine the responses to those surveys, as well as examine if ChatGPT can accurately guess more persistent features of survey respondents. I focus on three key dimensions of survey responses which the surveys examine: reaction to new information from Guiso and Jappelli (2024b), elicitation of expectations from Guiso and Jappelli (2024a), and prediction of respondents' persistent traits from the same survey. The papers are based on the Italian Survey of Consumer Expectations (ISCE), which conveniently was administered post-training of the ChatGPT model used in the paper, ruling out any contamination from the survey responses in the training data for ChatGPT. I first examine how respondents react to new information, as these reactions depend fundamentally on their previously elicited expectations. Expectations, in turn, are shaped by persistent traits of respondents, which I analyze as elements influencing the response process.

My findings reveal substantial limitations in using ChatGPT as a proxy for human survey respondents. While the model can sometimes capture the aggregate statistical properties (first and second moments) of response distributions for expectations about idiosyncratic and aggregate factors, the actual response patterns often differ fundamentally from human data, and these differences are starker when demographic traits are injected, in contrast to Fedyk et al. (2024). Moreover, the model fails to reproduce how demographic characteristics influence economic risk perceptions, sometimes predicting effects directly opposite to those observed in human data. Particularly concerning is the model's inability to demonstrate economic prudence - the precautionary saving motive observed in human responses. Most alarmingly, ChatGPT processes new information in ways that contradict human behavior - where humans respond positively to certain information treatments. Notably, ChatGPT consistently demonstrates negative responses for information treatments related to additional information on a disaster (i.e. the economic damages, and the mortality + economic costs) when humans demonstrate otherwise. Furthermore, ChatGPT's outputs for survey responses are notably lower variance than that of humans, consistent with prior literature which observes responses to experiements with ChatGPT result in outcomes of far lower variance (del Rio-Chanona et al., 2025). While ChatGPT excels at predicting static traits like current income and consumption based on demographics (with accuracy rates of approximately 74%), it struggles to form expectations or forecast future economic variables, suggesting limited abilities for economic

reasoning that extends beyond recognition of persistent patterns.

Contribution to the Literature

Recent research in economics and finance has begun exploring the properties and potential applications of ChatGPT, examining both how ChatGPT processes information and how it can be harnessed as a research tool.[3] However, little is known about *how* ChatGPT would respond if it were presented with traditional, unstructured surveys or questionnaires originally designed for humans, nor its similarity or divergence with human responses – especially in the context of economics and finance. Indeed, most prior work even in the fields of statistics and computer sciences, focuses on bespoke questionnaires to probe LLM responses, thus making direct comparisons to naturally generated human survey data more difficult.[4]

A notable exception is Fedyk et al. (2024), who design a survey to elicit human investment preferences and then pose the same questions to ChatGPT after providing demographic cues. Their results suggest that ChatGPT can successfully approximate demographic heterogeneity in investment behavior. Yet, such an approach – where surveys for humans are administered *after* ChatGPT has already been released – presents a risk of "preference contamination."[5] Another notable exception, is Zarifhonarvar (2024), which replications the elicitation of expectations from the New York Fed Consumer Expectations using ChatGPT.

In this paper, I contribute to the literature by administering pre-existing surveys in economics and finance to ChatGPT which *were administered after the release of ChatGPT's training data cutoff of October 2023*, mitigating potential concerns related to the contamination of the test set from the training set (look-forward bias).[6] By comparing ChatGPT's responses with human responses gathered after the cutoff date for the training data of ChatGPT, I also provide new insights

[3] See, for example, Bybee (2023), Charness et al. (2023), Chen et al. (2023), Duraj et al. (2024), Eisfeldt and Schubert (2024), Horton (2023), Immorlica et al. (2024), Korinek (2023), Lopez-Lira and Tang (2023), Lo and Ross (2024), Mei et al. (2024), Michelacci and Wu (2024).

[4] Scherrer et al. (2023) offers a notable contribution from statistics/computer science in examining how ChatGPT responds to moral or social dilemmas, but their bespoke survey questions complicate direct comparison with human responses on pre-existing surveys.

[5] In other words, ChatGPT's responses evolve based on human feedback, and human responses can also be shaped by exposure to ChatGPT's outputs.

[6] This is, in contrast to Zarifhonarvar (2024) which uses the NY Fed Survey of Consumer Expectations, which was well administered *before* the cutoff date of ChatGPT's training data.

into how ChatGPT's answers may (or may not) influence – or be influenced by – human behavior. Identifying whether ChatGPT's response distribution is aligned or misaligned with human responses, especially across demographics and cultural backgrounds, is essential for understanding the future impact of ChatGPT on economic and financial decision-making. One particularly attractive aspect of this approach is that, for pre-existing surveys, the inputs post-ChatGPT do not have this issue of input contamination, and for information treatments, they can be seen as some outcome of an "interaction" with AI. Under this framework, pre-existing surveys can be treated as "uncontaminated" survey questions, while user variations (such as stating that the user is from a specific demographic) can be explored to see how ChatGPT's responses to information treatments may change.

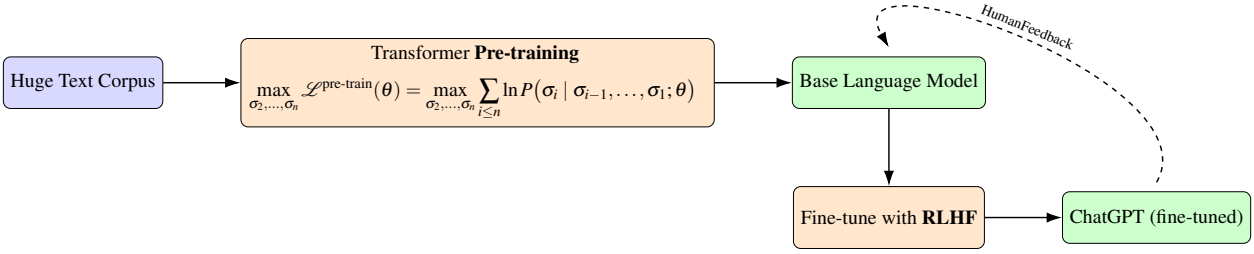
This research also contributes to the discussion on deploying ChatGPT as a research tool. While various studies propose or illustrate its use in replicating economic experiments and models, there remains limited justification for treating ChatGPT as a viable "representative agent." Moreover, findings on ChatGPT's alignment with human responses have been inconsistent.[7] In the finance literature, Bybee (2023) finds that ChatGPT's binary macroeconomic expectations are somewhat predictive of survey-based macro expectations, yet does not investigate whether ChatGPT mirrors human survey responses or how it reacts to specific information treatments. By eliciting ChatGPT's responses to established, pre-structured finance and economics surveys – and comparing those responses to human data collected prior to ChatGPT's existence – I demonstrate the feasibility and limitations of using LLMs as "survey respondents" in research. This includes examining how ChatGPT's answers vary under different demographic prompts, linguistic settings, and information treatments, thereby highlighting the potential advantages and pitfalls of aggregating preferences through ChatGPT. My approach contributes to the broader literature on survey methods in economics and finance – especially with respect to subjective beliefs and decision-making processes – which, despite growing interest in heterogeneous beliefs, remains relatively under explored.

Additionally, by examining survey responses, my research contributes to the literature on preference aggregation in economics and finance research, particularly related to the assumptions behind representative agents vs. heterogeneous agents models (Kirman, 1992). Given the inherent

[7]For example, Mei et al. (2024) and Horton (2023) observe that ChatGPT's answers often resemble human responses, whereas Fedyk et al. (2024), Chen et al. (2024), Ouyang et al. (2024), Kim et al. (2024), and Ross et al. (2024) do not.

nature of ChatGPT as a preference aggregator, and a possible nature as an individual preference *dis-aggregator*, it is necessary to understand these features of ChatGPT to understand the effects of its interactions with users of different demographics, influencing economic behavior.

2 What is ChatGPT?



A Simple Illustration of ChatGPT's Training Process

ChatGPT is a *large language model*. A large language model aims to *approximate* the *text generating process*, $\mu : \Sigma^* \to \Sigma^*$ where $\mu(\sigma) = \mathbb{P}[\sigma_n|\sigma_{n-1},....,\sigma_1]$, where Σ^* is the space of strings.[8] The text generating function is a function $m(\sigma;\theta) : \Sigma^* \to \Sigma^*$ for $\theta \in \Theta$, the space of parameters of the model. I define a trained LLM, such as ChatGPT, given a training set $\mathscr{T} \subset \Sigma^*$, is defined as $\hat{m}(\sigma,\mathscr{T}) \equiv m(\sigma;\hat{\theta}(\mathscr{T}))$ (Ludwig et al., 2025).

The steps to recover $m(\sigma;\mathscr{T})$ ChatGPT involves three steps. The first step, pre-training, occurs via a process called self-supervised learning, which induces the model to represent the conditional probability distribution of preceding words based on its training data and some provided parameter $\theta \in \Theta$:

$$\mathscr{L}^{pre-train}(\theta) = \sum \ln P[\sigma_i|\sigma_{i-1},\cdots,\sigma_1;\theta]$$

During pre-training, language models inadvertently absorb biases present in their training datasets. These can include outdated associations, such as linking doctors predominantly with men and nurses with women—reflections of content spanning many decades. Following pre-training, instruction fine-tuning enhances the model's ability to respond appropriately to human directives

[8]This set Σ^* is extremely high dimensional. For instance, Italian is said to have around 2000000, which would make $\infty > |\Sigma^*| \geq 2^{2000000}$ at minimum.

through supervised learning. This process exposes the model to millions of examples across thousands of different instructional scenarios. The final phase employs reinforcement learning from human feedback (RLHF), where human evaluators' assessments guide the model in distinguishing between more and less desirable responses.

3 Data

3.1 Human Survey Data

My primary source of human data is the Italian Survey of Consumer Expectations (ISCE), a quarterly rotating panel collecting demographic information, income, wealth, consumption data, expectations, and beliefs from a representative sample of the Italian population. The ISCE, conducted quarterly since October 2023, is the principal dataset utilized in the studies summarized in Table 1. The variables discussed here refer specifically to October 2023 (wave 1), January 2024 (wave 2), and April 2024 (wave 3).

The survey encompasses demographic variables, household resources (including income and wealth components), consumption, individual expectations (such as anticipated changes in consumption, income, energy expenses, and health expenditures), and macroeconomic indicators including inflation, nominal interest rates, and GDP growth. The ISCE targets Italian residents aged between 18 and 75. A pilot survey involving 100 interviews was executed in September 2023, with subsequent interviews typically conducted within the first 7-15 days of each reference month. Wave 1 included 5,006 interviews, while waves 2 and 3 comprised 5,001 and 5,005 interviews, respectively. The retention rate between consecutive waves was 84% for wave 2 and 87% for wave 3.

The sampling method aligns closely with the Bank of Italy's Survey of Household Income and Wealth (SHIW), stratifying participants by geographical area (North-East, North-West, Centre, and South Italy), age groups (18-34, 35-44, 45-54, 55-64, over 65), gender, education level (college degree, high school diploma, less than high school), and employment status (employed or not employed).

For each part of the empirical strategy, I use the appropriate wave of the ISCE. The summary statistics for each corresponding analysis and the variables used for the analysis can be found in the Appendix.

Table 1: Papers to Test Similarity to Humans

Topic	**Paper**
Information Treatments	Guiso and Jappelli (2024b)
Expectations	Guiso and Jappelli (2024a)

3.2 Simulated Data

I use the "gpt-4o-mini" model available, via the OpenAI API in Python. This model is the most advanced model which users of the ChatGPT web version have access without subscription. While acknowledging that LLMs are not written in stone, the focus on gpt-4o-mini is particularly relevant because it represents the version of ChatGPT available to users for free, and ChatGPT is arguably the most popular LLM model available to general users. Given that humans would most likely delegate their decision-making to the most conventionally available model, understanding how this conventional model processes information and makes decisions represents an important first step in understanding the consequences of novel AI tools about which we actually know very little.

The model is trained on data produced until October 1, 2023. To optimize balance between reducing hallucinations and other uninformative variations in the output, while maintaining the variation in responses for humans, I follow Fedyk et al. (2024) and calibrate the responses using a temperature of 0.8, where 0 is a completely deterministic output, while a temperature of 2 results in maximum creative and unpredictable outputs.[9] The algorithm to generate the data is roughly sketched in Algorithm 1. I repeat my analysis later with a temperature of 1.0 for robustness.

[9]Temperatures above 1 are considered to be unreliable proxy of human responses.

Algorithm 1 Data Simulation without Demographics

Input: $\mathscr{D} := \{(\mathbf{y}_i)\}_{i=1}^N$ and $(q_1, \ldots, q_l)$. $\mathbf{y}_i$ is the target vector of outputs. $(q_1, \ldots, q_l)$ corresponds to the tuple of words constituting a question.

Output: A simulated dataset of observations $\hat{\mathscr{D}} := \{(\hat{\mathbf{y}}_i)\}_{i=1}^N$.

1: Generate a generic system prompt $(s_1, \ldots, s_k)$, a tuple of words, via a standard prompt template function
2: **for** $i = 1$ to N **do**
3: Input $(s_1, \ldots, s_k)$ as the system prompt for `ChatGPT`
4: Input question $(q_1, \ldots, q_l)$ into `ChatGPT` which then outputs $\hat{\mathbf{y}}_i$, the simulated output
5: **end for**
6: **return** $\hat{\mathscr{D}} := \{(\hat{\mathbf{y}}_i)\}_{i=1}^N$

The baseline simulation does not embed any demographic traits into the prompt other than the system prompt ChatGPT is an Italian survey respondent. Otherwise, the most relevant inputs for each exercise are chosen by the demographic variables determined by the results of the paper in question. The prompts used to generate the outputs can be found in the Appendix, as well as the summary statistics for the simulated data used in each analysis. All prompts in the main exercises are conducted in Italian, with the exception of predicting demographics from other fixed traits, including the answer to the expectations (i.e. guessing the policy function). The algorithm when demographics are included is roughly sketched in Algorithm 2.

Algorithm 2 Data Simulation with Demographics

Input: $\mathscr{D} := \{(\mathbf{y}_i, \mathbf{x}_i)\}_{i=1}^N$ and $(q_1, \ldots, q_l)$. $\mathbf{x}_i$ is a non-empty vector of demographic features corresponding to the target vector of outputs, $\mathbf{y}_i$. $(q_1, \ldots, q_l)$ corresponds to the tuple of words constituting a question.

Output: A simulated dataset of observations $\hat{\mathscr{D}} := \{(\hat{\mathbf{y}}_i, \mathbf{x}_i)\}_{i=1}^N$.

1: **for** $i = 1$ to N **do**
2: Generate a demographic-informed system prompt $(s_1, \ldots, s_k)$, a tuple of words, based on $\mathbf{x}_i$ via a prompt template function
3: Input $(s_1, \ldots, s_k)$ as the system prompt for `ChatGPT`
4: Input question $(q_1, \ldots, q_l)$ into `ChatGPT` which then outputs $\hat{\mathbf{y}}_i$, the simulated output conditioned on demographics $\mathbf{x}_i$
5: **end for**
6: **return** $\hat{\mathscr{D}} := \{(\hat{\mathbf{y}}_i, \mathbf{x}_i)\}_{i=1}^N$

4 Empirical Strategy

This section describes the empirical strategy used to examine the similarity and differences of ChatGPT survey responses with human ISCE survey responses. I focus on three key dimensions of survey responses: reaction to new information, elicitation of expectations, and prediction of respondents' persistent traits. I first examine how respondents react to new information, as these reactions depend fundamentally on their previously elicited expectations. Expectations, in turn, are shaped by persistent traits of respondents, which I analyze as a foundational element influencing the entire response process.

4.1 How Does ChatGPT Respond to New Information vs Humans?: Guiso and Jappelli (2024b)

To test how ChatGPT responds to new information vs human survey participants, I replicate Table 7 of Guiso and Jappelli (2024b) available in Appendix A.3.[10] The survey conducts a two-stage

[10] I cannot replicate Table 5, which uses the willingness to pay, as ChatGPT always responds "yes" to if it would contribute to a fund. I explore why later in the same section.

randomization, randomizing participants into two groups with different types of questions, and then within the groups three groups of different type of information treatments, as illustrated in Table 2. This gives us 6 groups: T1G1, T1G2, T2G1, T2G2, T3G1, T3G2.

Table 2: The structure of information treatments

First stage randomization: Describe flood consequence		
T1	**T2**	**T3**
Control group	Treatment: N of deaths	Treatment: N of deaths plus damages
Second stage randomization: Evoke free riding		
G1: No treatment		
G2: Treatment: Fund success depends on how many contribute		
Willingness to pay asked to all		

I seed each survey with this system prompt, in Italian:

> *Answer the questions in the most truthful and accurate way possible. You are participating in a survey in Italy. Current date: January 1, 2024.*

Afterwards, I elicit ChatGPT responses to the survey 840 times per each treatment group, similarly to the number of observations within each treatment group in the human survey, with the appropriate information and question for each treatment group. Further details including the questions themselves as well as summary statistics for human and ChatGPT simulated data can be found in Appendix A.

The primary specification Table 7 of Guiso and Jappelli (2024b) involves the following tobit specification:

$$y_i = \mathbf{1}\{y_i^* > 0\} \cdot y_i^* \tag{1}$$

where

$$y_i^* = d + \beta_1 T_{2,i} + \beta_2 T_{3,i} + \beta_3 G_{2,i} + \beta_4 T_{2,i} G_{2,i} + \beta_5 T_{3,i} G_{2,i} + u_i \tag{2}$$

Where G_2 is a dummy for if a question prompt invoking free-riding was administered, T_2 is a dummy agents were treated with the description of the number of deaths, and T_3 instead is a dummy

for if agents were treated with not only a description of the number of deaths, but the financial value associated with the damages. I bootstrap the standard errors (u_i) 10000 times within each treatment group (i.e. the treatment group is the sampling strata). I replicate the analysis with human data as well from Wave 2 of the ISCE, to compare the results with the simulated data.

A crucial limitation when interpreting regressions is that the bootstrapped confidence intervals therefore capture sampling uncertainty from the ChatGPT model, but this uncertainty fundamentally differs from the sampling uncertainty that would arise from surveying the actual Italian population. While this paper treats each ChatGPT response as equivalent to one draw from the Italian population, it is unlikely that in reality, this assumption holds. Regardless, the significance and direction of the coefficients in regressions with ChatGPT simulated data, can help inform at the least if ChatGPT can generate responses which at face value *seem similar to human responses*. Additionally, when demographics are included in the analysis, I hold the provided covariates fixed and assume these variables are independent of other unobserved characteristics that would typically influence survey responses. This assumption may not reflect the complex inter-dependencies present in real population data.

4.1.1 Embedding Demographics

To evaluate the performance of ChatGPT when demographics are embedded, I instead seed each survey with this system prompt.

> *Answer the questions in the most truthful and accurate way possible. You are participating in a survey in Italy. You are a [male/female], are [employed/unemployed/a student/a homemaker/retired], with a monthly family income [greater than 2500 euros/between 500 2500 euros]. Current date: January 1, 2024.*

Given computational constraints, I construct a matched sample by drawing the same number of observations for each demographic group as exists in the human data from Guiso and Jappelli (2024b). These demographic groups are defined by the intersection of college education status, employment status, gender, and monthly family income range, for each combination of information treatment group and question group. In the Wave 2 human data of the ISCE, I filter out observations with missing household income values and consolidate employed and self-employed workers into a single category. Household income is discretized into a binary variable indicating whether it exceeds the median value (2500 Euros). I classify each respondent into one of five employment

categories: ”Employed” (including self-employed), ”Unemployed,” ”Retired,” ”Homemaker,” or ”Student.” Observations that do not align with any of these employment categories are removed from the analysis (only one observation). I then run Equation 3 again, first by bootstrapping within each of the 6 treatment groups for both the regressions with human and simulated data, and then restricting for the simulated data the demographic group-treatment group pairs with more than 50 observations.

4.2 How Does ChatGPT Form Expectations?: Guiso and Jappelli (2024a)

To explore the similarity between human and ChatGPT-generated responses, I conduct two types of complementary analyses that examine both distributional properties and demographic heterogeneity in expectation formation. These analyses allow for a systematic comparison of how large language models like ChatGPT form expectations relative to humans across different demographic groups and risk categories. I elicit the distributions by first seeding the following prompt:

> *Answer the questions in the most truthful and accurate way possible. You are participating in a survey in Italy. Current date: October 1, 2023.*

4.2.1 Distributional Similarity Analysis

In the first analysis, I focus on the overall distributional properties of responses. I calculate three different correlation coefficients – Spearman rank correlation, Kendall's tau, and Pearson correlation – between the distributions generated by ChatGPT and the actual human responses. Each correlation measure captures a different aspect of similarity: Pearson measures linear relationships, Spearman assesses monotonic relationships using ranks, and Kendall provides a rank-based measure that is particularly robust to outliers. The coefficients are calculated using a rigorous bootstrap approach. For each iteration out of 10000, I draw the exact same number of observations as in the original dataset, calculate the mean and variance of these observations, and then compute the correlation coefficients between human and ChatGPT-generated data. This process is repeated 10,000 times to derive bootstrapped confidence intervals and precise estimates of the correlation coefficients. The large number of bootstrap iterations ensures stability in the estimates and reliable symmetric confidence intervals, particularly important when working with smaller demographic subgroups.

To provide a more granular assessment of distributional similarity, I also conduct t-tests comparing the average value of human and simulated data for each question within each response bin. This analysis complements the correlation measures by directly testing whether the allocation of points in the distributions differ significantly.

4.2.2 Embedding Demographics

The second analysis incorporates demographic information directly into the prompts provided to ChatGPT, allowing for an examination of how the model captures demographic heterogeneity in expectation formation. This analysis extends beyond simple distributional comparisons to investigate whether ChatGPT can replicate demographic patterns observed in human responses. I begin by restricting the sample to first-wave respondents to ensure temporal consistency and eliminate potential confounds from repeated survey participation. Using this sample, I categorize respondents according to several demographic characteristics determined by their explanatory power in underlying risk-factors per Guiso and Jappelli (2024a): When prompting ChatGPT, I explicitly

Demographic Variable	**Categorization**
Age	Above/below the age 49 years
Household size	Above/below the household size of 3 members
Geographic region	”South” versus ”North or Centre” of Italy
Education	College-educated versus non-college-educated
Housing status	Homeowners versus non-homeowners

include these demographic characteristics, enabling the model to potentially tailor its responses to different demographic profiles. I set the system prompt to the following, in Italian:

> *You are taking part in a survey in Italy. You are [college-educated/non-college educated], a [homeowner/non-homeowner], living with [above 3 household members/below 3 household members], are [above/below] the age of 49 years, and you come from the [North or Centre/South] of Italy. Current date: 1 October 2023.*

To calculate correlation coefficients in this demographic-embedded analysis, I construct bootstrap samples that preserve the original distribution of demographic characteristics. This stratified bootstrap approach ensures that the resampling process maintains the demographic composition of the

original dataset. For each demographic stratum, I draw samples with replacement while maintaining the proportional representation of that stratum in the overall sample. This approach prevents over- or under-representation of any demographic group in the bootstrap iterations. I calculate Pearson, Kendall, and Spearman correlation measures separately for each question-demographic group combination and also pooled across all questions. This dual approach allows for identification of both question-specific patterns and general trends in how demographic characteristics influence expectation formation. To ensure statistical reliability, I restrict the analysis to demographic groups with more than 50 observations, providing sufficient statistical power for meaningful comparisons while avoiding unstable estimates from very small subgroups. Beyond correlation analysis, I replicate the regression specification using the most salient variables from Guiso and Jappelli (2024a), specifically focusing on the results presented in Tables 2, 3, and 9 of their study.[11] The first specification examines how demographic characteristics influence risk perceptions across different domains:

$$y_i = d + \beta_1 \mathbf{1}_{\{\text{HH Members}>3\}_i} + \beta_2 \mathbf{1}_{\{\text{Age}>49\}_i} + \beta_3 \mathbf{1}_{\{\text{College}\}_i} + \beta_4 \mathbf{1}_{\{\text{Homeowner}\}_i} + \beta_5 \mathbf{1}_{\{\text{North or Centre}\}_i} + u_i \quad (3)$$

In this equation, y_i represents the risk perception measure, the variance of the elicited distributions for changes in idiosyncratic or aggregate risk factors, for individual i across nine different risk categories (consumption, income, health, energy, GDP, unemployment, inflation, interest rate, and house price risks). The coefficients β_1 through β_5 quantify the marginal effect of each demographic characteristic on risk perception, holding other variables constant. By estimating this model separately for human and ChatGPT-generated responses, I can directly compare how demographic factors differentially influence risk perceptions in humans versus AI. The second specification explores the relationship between expected consumption growth and its the second moment of the distribution of the consumption growth:

$$\mathbb{E}_i \left[\frac{c_{t+1} - c_t}{c_t} \right] = d + \beta \mathbb{E}_i \left[\left(\frac{c_{t+1} - c_t}{c_t} \right)^2 \right] + u_i \quad (4)$$

This specification is derived from the following relationship:

$$\mathbb{E} \left[\frac{c_{t+1} - c_t}{c_t} \right] \simeq -\frac{u'(c_t)}{u''(c_t)c_t} \frac{r - \delta}{1 + r} \underbrace{- \frac{u'''(c_t)c_t}{u''(c_t)}}_{=\text{Prudence}} \frac{1}{2} \mathbb{E} \left[\left(\frac{c_{t+1} - c_t}{c_t} \right)^2 \right]$$

[11] The original tables are available in Appendix B.4. The only difference, being Age is discretion, and North and Centre is combined into one binary variable

The regression examines whether respondents who expect higher consumption growth also perceive higher variance in their consumption prospects, with the coefficient β capturing the strength of this relationship. Importantly, this coefficient has a direct economic interpretation related to prudence – the notion that riskier future income leads to precautionary savings for agents. A negative β coefficient would be consistent with prudent behavior, where individuals expecting higher consumption uncertainty reduce their current consumption, thereby increasing expected consumption growth

For both regression specifications, standard errors (u_i) are calculated by bootstrapping within each demographic group 10,000 times. This approach provides robust inference by accounting for potential heteroskedasticity and within-group correlation in the error terms. The bootstrapping procedure involves repeatedly resampling with replacement within each demographic stratum, estimating the model on each bootstrap sample, and calculating the standard deviation of the resulting distribution of parameter estimates. The demographic stratification in the bootstrap ensures that the standard errors accurately reflect the uncertainty associated with each demographic subgroup, allowing for precise statistical comparisons between human and ChatGPT-generated response patterns.

Similar to the previous regressions with ChatGPT simulated data, a crucial limitation when interpreting regressions is that the bootstrapped confidence intervals therefore capture sampling uncertainty from the ChatGPT model, but this uncertainty likely differs from the sampling uncertainty that would arise from surveying the actual Italian population Additionally, I hold the provided demographic traits fixed and assume these variables are independent of other unobserved characteristics that would typically influence survey responses. This assumption may not reflect the complex inter-dependencies present in real population data. Regardless, this exercise would help seeing if at face value, if ChatGPT can replicate some of the response patterns observed in humans.

4.3 Demographic Predictions

Following Fedyk et al. (2024), I analyze three sociodemographic factors – gender, age, and employment status – as predictors of monthly household income and consumption. These outcomes were selected for their economic significance and relative persistence across time periods.

To ensure computational tractability, I primarily restrict my analysis from Wave 1 of the ISCE

as it is the closest wave to the end of the ChatGPT training data, binarize age using a threshold of 49 years (the median age in Wave 1 of the ISCE from October 2023) and consolidate employment status into two categories: unemployed and employed (combining traditional employment and self-employment), and furthermore exclude all other forms of employment status in my data (i.e. retired). I exclude demographic subgroups with fewer than 50 observations to ensure sufficient statistical power. For each analysis, I sample demographic combinations with the same frequency as observed in the human reference data to maintain demographic representativeness. I also restrict my analysis to those individuals who report household and individual income in Wave 1 (October 2023) of the ISCE, as well as those who explicitly report home-ownership vs rental status. Future realized household income and consumption are taken from future waves of the ISCE administered in October 2024 and January 2024, while current income and consumption are taken from wave 1 of the ISCE administered in October 2023.

To ensure robust statistical comparison between human and ChatGPT-generated data, I implement a bootstrap methodology to calculate my metric considered as well as their standard errors. For each unique demographic combination with at least 50 observations, I draw 10,000 bootstrap samples of equivalent size to the original demographic group. Within each sample, I calculate average income or consumption values using the midpoints of the ISCE-reported bins, performing this calculation separately for both human and ChatGPT datasets.

These calculated averages are then classified back into their original income/consumption bins. A "match" occurs when the binned averages for both human and ChatGPT data coincide for a specific demographic group. The percentage of such matches across all demographic combinations constitutes my primary accuracy metric.

To complement this categorical approach, I additionally conduct a binary classification analysis, simply distinguishing between values above or below median thresholds (2500 Euros for income; 1250 Euros for consumption). This dichotomous measure captures fundamental patterns of income or consumption persistence across demographic groups, offering a more elemental perspective on predictive alignment.

Finally, I quantify the strength and direction of association between human and model-generated data by calculating three correlation coefficients – Pearson, Kendall, and Spearman – for the average consumption or income values, providing multiple statistical lenses through which to evaluate the relationship.

I repeat this analysis for current income/consumption in October 2024, as well as future in-

come/consumptions in 4 months (January 2024), and 12 months (October 2024), to see if ChatGPT has any predicative power for the future as well.

Variable	**Categorization**
Gender	Male/Female
Age	Above/below 49 years (median age)
Employment status	Employed/Unemployed

I implement a stratified paired bootstrap procedure with 10,000 iterations to generate robust statistical inferences. Each strata is a unique combination of Gender, Age and Employment status.[12] For each iteration, I draw paired samples with replacement within each demographic subgroup, calculate mean monthly household income and consumption, categorize these values into the same bins used in the original survey, and create binary indicators for values above/below median thresholds. I evaluate predictive performance using two metrics: (1) classification accuracy – the percentage of demographic subgroups where the predicted income/consumption category matches the actual category in the human data, and (2) numeric correlation – the Pearson correlation coefficient between predicted and observed economic values across all subgroups. To assess ChatGPT's ability to predict future economic outcomes, I elicit expected annual household income and consumption one year ahead. I compare these predictions against two benchmarks: actual reported values in Wave 2 of the ISCE and expected monthly values consistent with the annual growth rates reported by participants. This analysis focuses on how accurately ChatGPT predicts average current and future income and consumption for defined demographic groups. It provides insight into whether large language models have implicitly learned the relationships relevant income and consumption patterns across demographic groups, and whether they can generate plausible forecasts based on these relationships.

[12] $2^3 = 8$ categories. While stratified sampling in a real survey includes geographic regions, the fit of the model is very poor with geographic regions, hence I exclude it from the analysis.

5 Results and Discussion

5.1 How Does ChatGPT Respond to New Information vs Humans?: Guiso and Jappelli (2024b)

The results for the baseline regression in Table A5 reveals fundamental disparities between simulated and human responses to information treatments. While human data demonstrates significant positive effects from both treatments (T3 and T2), the simulated data exhibits consistently negative and highly significant responses. I also run the same regression on the human data, but instead this time splitting the sample into High AI users, survey participants documented to have used AI more than once a month in the ISCE, as well as Low AI users which I classify otherwise. This is to rule out the possibility that ChatGPT is simply reflecting the behaviMy of how its users, who it may have influenced to respond akin to it, or that ChatGPT is reflecting any over-representation in the behaviMy of its primary users in its training set. Given that the survey was administered *well after the cutoff of the gpt-4o-mini training data*, I can also rule out any contamination effects of the survey responses entering the training set of ChatGPT.[13] The contrast in regression coefficients persists across all specifications. These contradictions also extend to question group effects (G2), where the simulated data shows significant positive effects in some specifications while human data shows negative or non-significant effects. The simulated data suggests AI reacts negatively to free-riding scenarios.

Unlike humans, ChatGPT consistently contributes to disaster funds, in line with previous literature documenting its greater altruism and cooperation (Mei et al., 2024). This suggests a fundamental inconsistency between the AI's stated preferences and its elicited actions in certain cases – where the response is altruistic when explicitly prompted about ethics or cooperation, but deviates when these values are implicit considerations. To further explore this, I elicit questions on trust from the 5th wave of ISCE.[14] The results can be found in Table A7, where I conduct a t-test in difference in means between the human generated responses and simulated ChatGPT responses. ChatGPT responds with consistently higher trust measures in its simulated responses compared to humans. These systematic differences highlight significant differences in how current simulations

[13] While the question on AI usage was administered in Wave 3 of the ISCE, while the information treatment was administered in Wave 2, it is unlikely that users which use ChatGPT more than once a week have not used ChatGPT relatively more than the complement group, in the 12 months preceding Wave 3

[14] The questions can be found in Appendix A.2

model human information processing and decision-making. Interestingly, a t-test comparing high AI users and low AI users in Table A8 reveal no statistical differences between the two groups in average reported trust, pointing to the likelihood indeed this stems from the model's bias.

This inconsistency between stated and revealed preferences highlights significant limitations in using AI models as proxies for human behavior in economic experiments. Examining Table A6 more closely reveals additional critical differences: while human data demonstrates large positive treatment effects of T3 and T2, the full sample simulated data shows directionally opposite effects for T3 and much smaller positive effects for T2. The restricted sample, which restricts the analysis to demographic – treatment groups with more than 50 observations – further diverges with negative coefficients for both treatments. The question group effect (G2) also exhibits contradictory patterns with the baseline analysis in Table A5 – broadly positive in simulated data's full sample but negative in human data – which shows demographic information *worsened alignment with human data*. The interaction terms similarly differ, with T3G2 significantly negative in the full sample simulation but near zero in human data. Even demographic effects, while directionally consistent, show significant magnitude differences. These findings demonstrate that while ChatGPT may reproduce certain demographic patterns, they fundamentally diverge in processing social dilemmas, particularly regarding public goods contributions and responses to information about free-riding – suggesting the ChatGPT cannot reliably simulate human behavior in response to novel information even when carefully matched on demographic characteristics.

5.2 How Does ChatGPT Form Expectations?: Guiso and Jappelli (2024a)

Having established that ChatGPT struggles to reliably replicate human responses to novel information, I investigate whether if it could aggregate historical information to form human-like expectations. My baseline correlation analysis compared the means and standard deviations of distributions generated by both humans and ChatGPT across multiple questions. As shown in Table B3, the distributions generated by ChatGPT exhibited strong correlations with human data. These findings suggest that ChatGPT can effectively capture the first and second moments (means and standard deviations) of human expectation distributions when responding to the administered questions. This is in line with the results from Fedyk et al. (2024), which shows that ChatGPT generated responses to questions about opinions on investment products are highly correlated on average with human responses. However, departing from the moments, I find that the allocation of

points themselves into bins differs greatly between ChatGPT simulated responses and human responses are statistically different as seen in Table B9, demonstrating that even while the moments across questions may be highly correlated, the responses distribution itself is quite different with regards to human vs ChatGPT generated data. In addition, Figure 5 shows that ChatGPT generated responses are far more pessimistic and right-skewed than human generated distributions with the exception of expected interest rate and interest rate changes. Furthermore, any deviations from human responses do not seem to be driven by human groups using AI more than another group: The correlations coefficients are both similar, not if slightly higher for low-AI users (as previously defined) as opposed to high-AI users as it can be seen in Table B5 and Table B6. The same observation about the skew of the distribution also holds when sub-setting the human data by low vs high AI users as seen in Figure 6. This assures that this result is due to the model itself rather than the underlying basin of users, and that ChatGPT, while the responses correlated, does not perfectly emulate the allocation of points in the distribution elicited by the human data for each question.

However, when embedded with demographics, as seen in B4 – the ChatGPT generated standard deviations are statistically significantly and negatively correlated with the average moments for the human data for question-demographic group. The correlation for the means also decrease. This is in contrast with Fedyk et al. (2024) which suggests such treatment reduces heterogeneity between human and GPT simulated survey responses. I explore this further by calculating the coefficients by each question in Table B7. I find that only questions about Household Income, Consumption, Household Labor Income, and Mortgage Interest Rate have even one type of correlation coefficient where the direction aligns with that of human responses and is statistically significant. For other questions, it is insignificant or even statistically significantly negative (i.e. Gas/Energy Bill). This shows that while demographic responses may help the accuracy of certain responses, it does not necessarily for all in contrast to Fedyk et al. (2024). Furthermore, when computing the correlation of the average mean and standard deviation of the human and ChatGPT generated data by the value (0 vs 1) of each demographic trait considered in this section, as seen in Table B8, while the mean (first moment) is positively and statistically significantly correlated, this is not the case for the standard deviation (second moment) where the correlation is negative and statistically significant. ChatGPT in fact, may struggle to incorporate demographic information into its responses – and respond in even more biased ways.

Furthermore, Table B10 reveals disparities between results for the regression in Equation 4 using human versus ChatGPT-generated data. For household size, human responses show con-

sistently positive and significant coefficients across all nine risk categories, whereas ChatGPT produces coefficients that are either insignificant (consumption, unemployment, inflation, interest rate) or actually negative and significant (health, energy, GDP), with only income and house price risks showing the correct direction. Age effects are similarly misaligned – while humans consistently demonstrate strong negative coefficients for all risks (all significant at 1% level), ChatGPT only captures this pattern for income, interest rate, and house price risks, showing insignificant effects for consumption, energy, and inflation, and even positive significant coefficients for GDP and unemployment risks. For homeownership, ChatGPT not only fails to reproduce the uniformly negative significant effects seen in human data, but actually predicts positive significant coefficients for health and energy risks. College education shows mixed results, with some alignment for GDP and inflation risks. Regional patterns (North/Centre) demonstrate the greatest consistency, though ChatGPT notably predicts a positive coefficient for energy risk, opposite to human responses. These findings suggest that although ChatGPT may have absorbed some general economic knowledge, it lacks a nuanced understanding of how demographic characteristics shape economic risk perceptions. This does not seem to be driven by difference in groups which have high AI usage vs those that do not. As seen in Table B11 – for household size, humans with low AI usage show consistently positive and significant coefficients across all nine risk categories, whereas ChatGPT produces coefficients that are either insignificant or negative and significant. High-AI users demonstrate a different pattern from both groups – their household size coefficients are statistically insignificant across all risk categories. Age effects show varying patterns: low-AI humans demonstrate strong negative coefficients for all risks, while high-AI users maintain negative coefficients but with reduced significance for several risk categories, while ChatGPT simulated responses shows a mix of negative, insignificant, and positive coefficients. Regional effects (North/Centre) show greater consistency in direction across groups, though high AI users' coefficients lose significance for unemployment and interest rate risks. The homeownership effect reveals perhaps the starkest divergence: low AI humans perceive significantly lower risks across all categories, high AI users show an insignificant effect for all risks except interest rate risk – ChatGPT simulated responses predict contradictory significant effects for some risks. This lends to credibility that regardless of AI usage, ChatGPT – generated responses fail to reproduce or directly contradicting these human patterns.

The starkest difference between human and ChatGPT simulated responses can be seen in Table B12 where I run the regression as seen in Equation 4. I find that interestingly the regression in the

ChatGPT simulated data shows households do not show *prudence* as opposed to the human data – the coefficients are significant in the negative direction. Table B13 also shows statistically zero to positive coefficients for both Low AI and High AI human users, which is in contrast with the simulated ChatGPT data. A limitation of this exercise is that due to only replicating one Wave (Wave 1), adding individual fixed effects nor exploiting temporal variation is not possible – and furthermore these results should not be interpreted as causal. However, the difference between the human data and ChatGPT data generated results is very stark regardless.

Hence, in all it seems that ChatGPT cannot reliably generate expectations or distributions of expectations based on previous data formed by Italian households, and shows GPT is incapable of synthesizing current information into future expectations akin to humans, at least with the training data it possesses.

5.3 Demographic Predictions

Given ChatGPT cannot reliably generate expectations or distributions of expectations with its underlying data, I now see if ChatGPT can reliably predict *more persistent traits* – notably consumption and income. As seen in Table C2 ChatGPT is good at predicting income, with an accuracy of 74% – that is, 74% of the demographic group combinations on average – for predicting the income bin and accuracy of 90% for predicting if income is above median (2500) or not. This is likewise for consumption, where in Table C3, where the accuracy is 72.5% and 87.3% respectively for the analogous metrics. Both traits show positive, and statistically significant correlations of the average income and consumption between ChatGPT simulated data and human data.

Now, I repeat the analysis on monthly income and total consumption for the future, as in, comparing the predicted income with the actual future realized monthly income. We can see that while the predictions for both 4 months and 12 months into the future are worse when we consider the ISCE-reported income bins, as seen in Table C4, the accuracy for it being above the median is high regardless. A similar pattern, as seen in Table C5, holds for future consumption, further solidifying this observation – while the accuracy in regards to the the ISCE-reported income bins is statistically significant and above 50% for consumption 12 months and 4 months into the future, it is statistically indistinguishable from 50% – which is no better than a coin flip, which is not the case for below/above median total consumption (in Wave 1).

To examine if the inability to predict the future is related to the inability to form expectations

on the future, I repeat the elicitation of the distribution of future income from Section 4.2 with the demographic traits considered in My exercise, and then using the same procedure as the current household income and consumption, calculate the correlation of the expected growth in consumption and income with that of the human data. The results, in Table C6, shows that the correlations are systematically lower than their counterparts for current household income and consumption from Table C2 and Table C3 respectively, lending credibility to the hypothesis.

Overall, this shows that ChatGPT may be actually useful for projecting persistent traits such as monthly household income being above or below the median.

5.3.1 Extension: Recovering the Policy Function

Furthermore, it could be the case while ChatGPT cannot generate expectations of distributions with the underlying data well. While due to the dimensionality of the outcome variable, a credible bootstrap algorithm is implausible, I feed into ChatGPT the distributions of variables determined to be crucial for consumption risk according to Guiso and Jappelli (2024a), and ask ChatGPT if each individual owns a home, if he/she is college educated, if the individual's age is greater than 49, if the individual lives in the North or Centre of Italy or the South, and if the individual has more than 3 household members. I use the full sample of individuals from Wave 1 of the ISCE. The results, in Table C7, show that age being greater than 49, homeownership status, and residing in the north or centre have accuracy scores of above 50% consistently – that is ChatGPT correctly guessed the applicable feature for above 50% of the Wave 1 ISCE participants – in particular homeownership has consistently high accuracy rates of above 60%. For a household having more than 3 members, it guessed above 50% correctly for 3/5 questions. This shows that for some possibly persistent traits, ChatGPT may accurately guess these traits given the outcome of a question. Hence, while ChatGPT may not be able to accurately replicate the expectations or responses to information treatments of survey participants, it can complement surveys by predicting the appropriate demographics corresponding to a survey's answers – which can augment survey-based studies which face incomplete information collection.

6 Robustness

A concern for my results could be that in Section 4.1 and Section 4.2.2, the failure to replicate human responses are driven by the lack of variation by my choice of the temperature parameter. To alleviate these concerns, I choose the maximum temperature parameter recommended in replicating human responses, a temperature of 1, and then replicate my results for Section 4.1 and Section 4.2.2, with the difference being I take 100 bootstrap samples, rather than 10000, for the confidence intervals.[15] The results are available in Section D.1 in Table D.1 and Table D9 for Section 4.1, and Table D12 and Table D.2. The answers are nearly qualitatively unchanged, and in fact diverge even more from human responses, particularly in regards to the positive significance of the G2 coefficient in Table D.1 and the magnitude of coefficient on consumption risk in Table D.2. This goes to show that the temperature parameter does not explain the full issues in the lack of alignment with human responses, and that my results for the original analysis still holds. Hence, the low variance of of the outcome variable generated by ChatGPT does not seem to be a matter of the temperature parameter, but more so an inherent feature of the model, which also noted noted in the context of laboratory market experiments in del Rio-Chanona et al. (2025).

Another concern with Section 4.1 is that the baseline responses could be disaster specific, as in ChatGPT incorporate the information it has about disaster ex-ante, biasing the responses with look-ahead bias. To alleviate this concern, I remove any references in the prompt to the flood affected-region (Romagna), and run the baseline exercise from Section 4.1 again with a model temperature of 0.8. The results are available in Table D11. As one can see, while the direction and significance of coefficient T2 and G2 for Equation (1) (corresponding to Equation (7) in Table A5) differs from Table A5, the direction of G2 is opposite of human responses from Guiso and Jappelli (2024b), and in Equation (2) (corresponding to Equation (8) in Table A5) the results in significance and direction are the same, showing that the failure to replicate human responses still exists – alleviating the concern about the non-replication of human responses being specific to the specific mentioned in the prompt.

Lastly, I also repeat Section 4.1, with the same number of total observations as the regressions with human data (5001), as well as the same number within each treatment group, by drawing a new sample of observations with a model temperature of 0.8. The results are available in Table D10. One can observe that in contrast to Table A5, the coefficients on T2G2, T3G2, and G2 are

[15] The difference, however, is inconsequential for symmetric confidence intervals

positive and significant. However, the direction of T3 and T2 coefficients are the same (negative) and significant. this may imply that ChatGPT may simply not consistently react to free-riding treatments as opposed to treatments about additional information on the extent of the disaster (information on mortality vs mortality + economic costs). The results also closely follow that from Table D.1. Combined with the inconsistency of the coefficients involving G2 in Table D11, as well, it seems that ChatGPT fails to consistently replicate results related to information treatment regarding free-riding, often contradicting the responses of humans, and consistently fails to replicate human responses to additional information about disasters. This goes to further show that ChatGPT cannot consistently replicate responses of humans when it comes to reacting to new information.

7 Conclusion

My findings reveal significant constraints in using ChatGPT as a proxy for human survey respondents i.e. replacing human survey participants, while highlighting potential complementary applications i.e. augmenting human survey participants.

My results demonstrate that while ChatGPT can sometimes capture the aggregate statistical properties (first and second moments) of response distributions, fundamental differences exist in how the model responds to information compared to humans. Most notably, ChatGPT demonstrates negative responses to information treatments where humans exhibit positive ones, fails to accurately model demographic effects on economic risk perceptions, and cannot replicate the economic prudence observed in human responses. These limitations are even more evident when demographic information is embedded in prompts, contradicting previous findings that such demographic cues improve alignment with human data (Fedyk et al., 2024). The model's inability to respond to information about disasters and information about free-riding in ways consistent with human behavior further underscores the limitations of using ChatGPT to simulate human economic decision-making.

However, ChatGPT does show promising capabilities in predicting persistent traits based on demographic characteristics. The model achieves nearly 74% accuracy in predicting current income categories and 72% accuracy for consumption levels based on demographic profiles. These findings suggest that while ChatGPT cannot reliably replicate human participants in economic surveys, it may serve as a valuable *complementary* tool, that is, augmented intelligence, for survey

research. This would particularly be the case in scenarios with incomplete demographic information. Furthermore, ChatGPT's outputs for survey responses are notably lower variance than that of humans, consistent with prior literature which observes responses to experiments with ChatGPT result in outcomes of far lower variance than that in humans (del Rio-Chanona et al., 2025). In other words model's strength may not lie in generating human-like economic expectations or processing novel information, but rather in identifying relationships between demographic profiles and persistent economic traits.

Future research should focus on exploring these complementary applications, particularly how AI models might help researchers recover missing demographic information in survey data. The limitations identified in this study highlight the importance of human participation in economic research and caution against overreliance on AI simulations for understanding economic behavior. Rather than replacing human survey participants, ChatGPT and similar models may have potential in augmenting survey methodologies combined with irreplaceable value from human responses.

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Appendix

A Novel Information Processing

A.1 Summary Statistics

Table A1: Summary Statistics by Group – Baseline Human Data

	T1G1			T1G2			T2G1			T2G2			T3G1			T3G2		
Variable	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.
High AI	735	0.109	0.312	737	0.079	0.269	735	0.120	0.325	706	0.089	0.285	722	0.120	0.326	703	0.108	0.311
Amount contributed	840	33.08	91.79	827	36.81	105.51	830	42.50	125.07	840	45.15	139.53	837	40.09	120.33	827	43.33	144.06

Notes: High AI is a binary indicator (1 stands for AI usage is greater or equal once per week, 0 for otherwise); Amount contributed is the amount that the survey participant agreed to contribute (midpoint of the elicited bin of the amount contributed).

Table A2: Summary Statistics by Group – ChatGPT Simulated Data

	T1G1			T1G2			T2G1			T2G2			T3G1			T3G2		
Variable	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.
Amount Contributed	840	34.98	4.83	840	32.40	6.93	840	30.26	9.61	840	26.81	10.94	840	33.88	5.95	840	28.71	10.17

Notes: Amount contributed is the amount that the survey participant agreed to contribute (midpoint of the elicited bin of the amount contributed).

Table A3: Summary Statistics by Treatment Group (ChatGPT Simulated Data with Demographics)

	T1G1			T1G2			T2G1			T2G2			T3G1			T3G2		
Variable	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.
HH Income $>$ 2500	763	0.341	0.474	743	0.316	0.465	753	0.329	0.470	759	0.310	0.463	759	0.336	0.473	740	0.311	0.463
Amount Contributed	763	39.44	33.86	743	45.86	42.92	753	42.78	44.98	759	48.74	50.60	759	38.85	36.44	740	37.32	34.57
College	763	0.223	0.416	743	0.248	0.432	753	0.210	0.407	759	0.261	0.439	759	0.228	0.420	740	0.230	0.421
Male	763	0.505	0.500	743	0.495	0.500	753	0.497	0.500	759	0.503	0.500	759	0.510	0.500	740	0.522	0.500
Employed	763	0.523	0.500	743	0.501	0.500	753	0.515	0.500	759	0.509	0.500	759	0.522	0.500	740	0.528	0.500
Homemaker	763	0.122	0.327	743	0.133	0.340	753	0.114	0.318	759	0.108	0.311	759	0.144	0.351	740	0.108	0.311
Retired	763	0.197	0.398	743	0.202	0.402	753	0.203	0.403	759	0.194	0.395	759	0.171	0.377	740	0.178	0.383
Student	763	0.039	0.194	743	0.030	0.170	753	0.032	0.176	759	0.051	0.221	759	0.038	0.192	740	0.043	0.204
Unemployed	763	0.119	0.324	743	0.135	0.342	753	0.135	0.342	759	0.138	0.345	759	0.125	0.331	740	0.142	0.349

Notes: HH Income $>$ 2500 indicates households with a total monthly income of more than 2500 Euros; Amount Contributed is the elicited amount contributed to the natural disaster fund; College indicates college education; Male indicates male gender. Employed, Homemaker, Retired, Student, and Unemployed are indicators for various employment statuses.

Table A4: Summary Statistics by Treatment Group (Human Data)

	T1G1			T1G2			T2G1			T2G2			T3G1			T3G2		
Variable	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.
HH Income $>$ 2500	763	0.341	0.474	743	0.316	0.465	753	0.329	0.470	759	0.310	0.463	759	0.336	0.473	740	0.311	0.463
Amount Contributed	763	34.21	94.99	743	39.14	110.21	753	44.43	128.00	759	47.97	145.29	759	41.41	122.87	740	43.26	137.96
College	763	0.223	0.416	743	0.248	0.432	753	0.210	0.407	759	0.261	0.439	759	0.228	0.420	740	0.230	0.421
Male	763	0.505	0.500	743	0.495	0.500	753	0.497	0.500	759	0.503	0.500	759	0.510	0.500	740	0.522	0.500
Employed	763	0.523	0.500	743	0.501	0.500	753	0.515	0.500	759	0.509	0.500	759	0.522	0.500	740	0.528	0.500
Homemaker	763	0.122	0.327	743	0.133	0.340	753	0.114	0.318	759	0.108	0.311	759	0.144	0.351	740	0.108	0.311
Retired	763	0.197	0.398	743	0.202	0.402	753	0.203	0.403	759	0.194	0.395	759	0.171	0.377	740	0.178	0.383
Student	763	0.039	0.194	743	0.030	0.170	753	0.032	0.176	759	0.051	0.221	759	0.038	0.192	740	0.043	0.204
Unemployed	763	0.119	0.324	743	0.135	0.342	753	0.135	0.342	759	0.138	0.345	759	0.125	0.331	740	0.142	0.349

Notes: HH Income $>$ 2500 indicates households with a total monthly income of more than 2500 Euros; Amount Contributed is the elicited amount contributed to the natural disaster fund; College indicates college education; Male indicates male gender. Employed, Homemaker, Retired, Student, and Unemployed are indicators for various employment statuses. Data is from the ISCE Wave 1, restricted to observations with more than 50 observations per employment status-HH income $>$ 2500-college education-gender combination.

A.2 Survey Question Format

The Treatment Groups are as follows:

T1:

(No additional information provided)

T2:

In Romagna, the evening between May 16 and 17, an unprecedented amount of rain in just a few hours raised river levels until they overflowed. Practically all the waterways between Rimini and Bologna, twenty-one in total, breached their banks or overflowed, flooding vast areas of Romagna. Fifteen people died, and approximately 40 thousand were evacuated.

T3:

In Romagna, the evening between May 16 and 17, an unprecedented amount of rain in just a few hours raised river levels until they overflowed. Practically all the waterways between Rimini and Bologna, twenty-one in total, breached their banks or overflowed, flooding vast areas of Romagna. Fifteen people died, and approximately 40 thousand were evacuated. The Region has calculated damages of almost 9 billion euros for roads, schools, embankments and canals, and to repair damages to homes and businesses.

The corresponding questions are as follows, where {info} corresponds to the treatment group prompts above (no info if T1):

Questions asked to Group 2 (G4_1)

Consider the following information: {info}

Containing environmental degradation and securing areas exposed to hydrogeological risk (floods, landslides, etc.) requires a substantial amount of public resources. To finance these investments, would you be in favor of creating a dedicated public fund?

- Yes

- No
- I don't know

Question asked to Group 3 (G4_2)

Consider the following information: {info}

Containing environmental degradation and securing areas exposed to hydrogeological risk (floods, landslides, etc.) requires a substantial amount of public resources. Success depends on the size of the fund. If few contribute or contribute little, the risk containment policy fails. How much are you willing to contribute? To finance these investments, would you be in favor of creating a dedicated public fund?

- Yes
- No
- I don't know

Questions asked to Group 1 (G5_1)

Previously you were asked '[G4_1 question text]' and you answered: '[G4_1 answer]'

Consider the following information: {info}

How much would you be willing to contribute to this fund each year?

- 5~10 Euro
- 10~20 Euro
- 20~50 Euro
- 50~100 Euro
- 100~200 Euro
- 200~300 Euro

- 300~400 Euro
- 400~500 Euro
- 500~1000 Euro
- More than 1000 Euro

Questions asked to Group 2 (G5_2)

Previously you were asked '[G4_2 question text]' and you answered: '[G4_2 answer]'

Consider the following information: {info}

How much would you be willing to contribute to this fund each year?

- 5~10 Euro
- 10~20 Euro
- 20~50 Euro
- 50~100 Euro
- 100~200 Euro
- 200~300 Euro
- 300~400 Euro
- 400~500 Euro
- 500~1000 Euro
- More than 1000 Euro

A.3 Tables from Guiso and Jappelli (2024b)

Table 7. Tobit estimates of the effect of treatments on WTP

Treatment	Tobit	Tobit
T2	28.878	27.481
	(9.724)***	(7.066)***
T3	22.351	24.1888
	(9.734)**	(7.097)**
G2	-7.859	-7.558
	(9.989)	(5.607)
T2G2	-2.832	
	(13.897)	
T3G2	3.744	
	(13.922)	
P-value test : $\beta_1 = \beta_2$	0.497	0.631
P-value test $\beta_4 = \beta_5 = 0$	0.891	
Average of LHS variable	73.48	73.48
N. of observations	5,001	5,001

Note. The first regression reports marginal effects calculated from Tobit regressions for the amount that respondent intend to contribute to the fund. The estimated equation is $y_i = \beta_1 T_2 + \beta_2 T_3 + \beta_3 G_2 + \beta_4 T_2 G_2 + \beta_5 T_3 G_2 + \varepsilon_i$.. The second column restricts to zero the effects of the joint first-stage and second stage treatments. Heteroskedasticity consistent standard errors are reported in parentheses. One star indicates statistical significance at the 10%, two stars at the 5%, three stars at the 1%. The table also reports the *p*-values of a chi-square test of the listed null.

Figure 1: Table 7 of Guiso and Jappelli (2024b)

A.4 Information Treatment Regressions

Table A5: Baseline Tobit Regression Results

	Full Sample		High AI		Low AI		Simulated Data	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T3	22.351**	24.188***	9.609	7.845	29.664***	25.881***	-1.095***	-2.393***
	(8.964)	(7.065)	(21.753)	(21.247)	(9.957)	(7.975)	(0.263)	(0.246)
T2	28.878***	27.481***	11.620	0.961	36.885***	32.014***	-4.714***	-5.155***
	(9.114)	(7.003)	(20.582)	(19.654)	(10.617)	(8.063)	(0.373)	(0.294)
G2	-7.859	-7.558	11.786	1.113	-2.992	-8.849	-2.571***	-3.730***
	(9.343)	(5.578)	(34.551)	(16.384)	(10.164)	(6.276)	(0.295)	(0.236)
T2G2	-2.832		-26.305		-9.812		-0.881	
	(13.666)		(43.698)		(15.323)		(0.582)	
T3G2	3.744		-5.123		-7.585		-2.595***	
	(13.812)		(45.108)		(15.151)		(0.500)	
Mean of D.V.	40.156	40.156	40.708	40.708	39.168	39.168	31.175	31.175
Var of D.V.	14979.253	14979.253	11806.454	11806.454	14393.183	14393.183	78.557	78.557
N	5001	5001	452	452	3886	3886	5040	5040

Notes: Standard errors are computed with a stratified bootstrapped within each of the 6 information treatment groups of 10000 draws, where I draw a sample size identical to the original size of each of the 6 information treatment groups. The outcome variable (D.V.) is the amount contributed to the disaster fund. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Regression Results

	Full Sample				Restricted				Human Data	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
T3	-0.452	-4.250***	-0.596	-4.519***	-2.642**	-2.460***	-3.301*	-2.707**	22.049**	21.727***
	(1.134)	(0.806)	(1.811)	(1.363)	(1.203)	(0.717)	(1.972)	(1.089)	(9.476)	(7.332)
T2	4.529***	3.615***	3.333	3.126**	0.381	-1.710**	-1.432	-2.349*	31.261***	29.017***
	(1.218)	(0.870)	(2.061)	(1.582)	(1.478)	(0.848)	(2.533)	(1.424)	(9.660)	(7.453)
G2	7.231***	4.048***	6.418***	3.627***	3.386***	1.872***	-9.895***	-10.168***	-50.324	-7.126
	(1.181)	(0.690)	(1.983)	(1.222)	(1.039)	(0.390)	(1.630)	(0.979)	(9.869)	(5.863)
T2G2	-1.874		-0.459		-4.702***		-2.094		-40.590	
	(1.742)		(3.176)		(1.690)		(2.652)		(14.471)	
T3G2	-7.695***		-7.948***		0.351		1.222		0.672	
	(1.613)		(2.698)		(1.392)		(2.110)		(14.209)	
Employed	9.752***	9.689***			5.309***	5.297***				
	(0.771)	(0.771)			(0.456)	(0.448)				
Retired	4.259***	4.213***			-1.480*	-0.374				
	(1.038)	(1.042)			(0.879)	(0.806)				
Male	12.402***	12.387***			3.298***	3.323***				
	(0.706)	(0.698)			(0.572)	(0.564)				
HH Income $>$ 2500	54.307***	54.312***			61.550***	61.553***				
	(0.972)	(0.970)			(2.613)	(2.607)				
College	33.263***	33.335***								
	(1.027)	(1.038)								
Mean of D.V.	42.167	42.167	42.167	42.167	26.952	26.952	26.952	26.952	40.156	40.156
Var of D.V.	1697.627	1697.627	1697.627	1697.627	567.234	567.234	567.234	567.234	14979.253	14979.253
N	4517	4517	4517	4517	1898	1898	1898	1898	4517	4517

Note: Restricted refers to ChatGPT generated simulated samples where groups (tuples) of employed-retired-male-HH Income $>$ 2500-college- information treatment group where less than 50 observations exist are dropped. Full sample refers to samples in which this restriction in not applied, and instead simply just groups (tuples) of employed-retired-male-HH Income $>$ 2500-college with less than 50 observations are dropped. Standard errors are bootstrapped 10000 times, within each combination of demographic groups (Employment-Gender-Income$>$ 2500-College). The outcome variable (D.V.) is the amount contributed to the disaster fund. Bootstrap standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.5 Trust

	Human Data	Simulated Data	P-value
People	5.25	6.85	0.00
Govt.	4.23	5.95	0.00
Police	6.06	7.08	0.00
Judiciary	5.07	7.75	0.00
Health System	5.73	8.97	0.00
Civil Protection	6.65	9.89	0.00

Notes: Both datasets contain 5003 observations. I sampled a paired bootstrap of 1000 draws in the human and simulated data with the original number of samples, and conducted a t-test in difference in means.

Table A7: Trust Ratings

	High AI	Low AI	P-value
People	5.27	5.10	0.13
Govt.	4.22	4.22	0.98
Police	6.06	6.01	0.67
Judiciary	5.07	4.99	0.54
Health System	5.72	5.82	0.38
Civil Protection	6.66	6.58	0.53

Notes: The results displayed are from a t-test with paired bootstrap of 1000 draws in the human and simulated data with the original number of samples, and conducted a t-test in difference in means.

Table A8: High AI vs Low AI

B Expectation Formation

B.1 Survey Question Format

All the questions follow a similar format: "In the next 12 months, you expect that (yMy household's income / total consumption / gas and energy bills / health expenditures / house price / GDP / inflation):[16]

Interval		Probability (%)
will decrease by more than 8%	g_1	p_1
will decrease between 6 and 8%	g_2	p_2
will decrease between 4 and 6%	g_3	p_3
will decrease between 2 and 4%	g_4	p_4
will decrease between 0 and 2%	g_5	p_5
will remain constant	g_6	p_6
will increase between 0 and 2%	g_7	p_7
will increase between 2 and 4%	g_8	p_8
will increase between 4 and 6%	g_9	p_9
will increase between 6 and 8%	g_{10}	p_{10}
will increase more than 8%	g_{11}	p_{11}
Total		100

[16]The format of the questions referring to unemployment and interest is different since respondents are presented with only positive intervals ranging from 0 to "over 14%" for unemployment and from 0 to "over 8%" for interest rate.

B.2 Summary Statistics

Table B1: Summary Statistics for ChatGPT Simulated Data with Demographics

Variable	Obs	Mean	Std. dev.	Min	Max
$\mathbb{E}\Delta$ HH Income	4,814	-3.3849	0.5584	-6.5500	0.6000
SDΔ HH Income	4,814	4.0649	0.5075	2.3537	6.3583
$\mathbb{E}\Delta$ HH Labor Income	4,814	-3.2898	0.6628	-7.2000	0.4000
SDΔ HH Labor Income	4,814	4.0383	0.4894	2.4799	6.3710
$\mathbb{E}\Delta$ Consumption	4,814	-3.3427	0.3174	-5.3300	0.6000
SDΔConsumption	4,814	3.9825	0.3099	2.3537	5.9640
$\mathbb{E}\Delta$ Health Expenses	4,814	-0.6533	2.0065	-3.8900	4.5000
SDΔHealth Expenses	4,814	3.3520	0.6160	1.4491	5.1176
$\mathbb{E}\Delta$ Energy Bill	4,814	-2.4200	1.1999	-3.8980	4.0000
SDΔEnergy Bill	4,814	3.8538	0.4426	1.9339	5.3329
$\mathbb{E}\Delta$ House Price	4,814	-2.4183	1.2645	-5.9700	2.1500
SDΔHouse Price	4,814	3.5719	0.6479	1.3077	5.8258
$\mathbb{E}\Delta$ GDP	4,814	-1.4045	1.1383	-4.7400	1.7000
SDΔGDP	4,814	3.0553	0.6726	1.7436	5.5360
$\mathbb{E}\Delta$ Unemployment	4,814	0.4375	0.8267	-3.9900	3.2000
SDΔUnemployment	4,814	2.6724	0.3752	1.5460	4.6555
$\mathbb{E}\Delta$ Inflation	4,814	6.4258	0.9415	4.3000	11.0412
SDΔInflation	4,814	3.1942	0.4797	1.8856	4.7945
$\mathbb{E}\Delta$ Interest Rate	4,814	3.0034	0.3577	1.9000	4.4000
SDΔInterest Rate	4,814	1.9544	0.2614	1.3416	2.6721
$\mathbb{E}\Delta$ Mortgage Interest Rate	4,814	3.9578	0.3908	2.7000	4.9000
SDΔMortgage Interest Rate	4,814	2.0674	0.1445	1.3964	2.6721
College	4,814	0.2048	0.4036	0	1
Homeowner	4,814	0.7605	0.4268	0	1
North or Centre	4,814	0.6651	0.4720	0	1
Age>49	4,814	0.4790	0.4996	0	1
HH Members>3	4,814	0.2518	0.4341	0	1

Notes: $\mathbb{E}\Delta$ represents expected change in variable from the elicited distribution.

SDΔ represents standard deviation of the distribution of the elicited distributions.

North or South indicates if an individual lives in Northern or Central Italy.

HH Members>3 indicates an individual having more than 3 family members in the household.

Age>49 indicates an individual being older than the age of 49.

College indicates college education.

Homeowner indicates if an individual owns his or her own home.

Table B2: Summary Statistics for Human Data (Restricted)

Variable	Obs	Mean	Std. dev.	Min	Max
$\mathbb{E}\Delta$ HH Income	4,814	-1.1938	3.7149	-10	10
SDΔHH Income	4,814	2.1851	2.1644	0	10
$\mathbb{E}\Delta$ HH Labor Income	4,814	-0.7416	3.5409	-10	10
SDΔ HH Labor Income	4,814	1.9585	2.1752	0	10
$\mathbb{E}\Delta$ Consumption	4,814	0.5180	4.1630	-10	10
SDΔConsumption	4,814	2.2139	2.1583	0	10
$\mathbb{E}\Delta$ Health Expenses	4,814	0.9474	3.5589	-10	10
SDΔHealth Expenses	4,814	2.0305	2.1875	0	10
$\mathbb{E}\Delta$ Energy Bill	4,814	2.1326	3.9643	-10	10
SDΔEnergy Bill	4,814	2.0073	2.0782	0	10
$\mathbb{E}\Delta$ House Price	4,814	0.0327	3.5068	-10	10
SDΔHouse Price	4,814	1.7864	2.1525	0	10
$\mathbb{E}\Delta$ GDP	4,814	-1.7700	3.9274	-10	10
SDΔGDP	4,814	1.8904	2.1079	0	10
$\mathbb{E}\Delta$ Unemployment	4,814	1.6160	4.0764	-10	10
SDΔUnemployment	4,814	1.8937	2.0658	0	10
$\mathbb{E}\Delta$ Inflation	4,814	9.2793	3.5037	1	14
SDΔInflation	4,814	1.4927	1.6225	0	6.5
$\mathbb{E}\Delta$ Interest Rate	4,814	11.8662	20.1571	1	80
SDΔInterest Rate	4,814	7.8434	12.9772	0	39.5
$\mathbb{E}\Delta$ Mortgage Interest Rate	4,814	21.4955	26.1248	1	80
SDΔMortgage Interest Rate	4,814	10.7817	14.3706	0	39.5
Homeowner	4,814	0.7605	0.4268	0	1
College	4,814	0.2048	0.4036	0	1
HH Members>3	4,814	0.2518	0.4341	0	1
Age>49	4,814	0.4790	0.4996	0	1
North or Centre	4,814	0.6651	0.4720	0	1

Notes: $\mathbb{E}\Delta$ represents expected change in variable from the elicited distribution.

SD represents standard deviation of the distribution of the elicited distributions.

Human Data restricted to Homeowner-College-HH Members>3-Age>49-North or South groups with more than 50 obs.

North or South indicates if an individual lives in Northern or Central Italy.

HH Members>3 indicates an individual having more than 3 family members in the household.

Age>49 indicates an individual being older than the age of 49.

College indicates college education.

Homeowner indicates if an individual owns his or her own home.

B.3 Correlation Analysis

Table B3: Correlation Coefficients Between Datasets (Bootstrap Analysis)

	Pearson	Spearman	Kendall
ρ_μ	0.830^{***}	0.628^{***}	0.528^{***}
	(0.003)	(0.003)	(0.004)
ρ_σ	0.732^{***}	0.626^{***}	0.431^{***}
	(0.011)	(0.021)	(0.031)

Note: The point estimates and symmetric bootstrap intervals are calculated after random pair bootstrap design, where I drawing the same number of observations per question 10000 times in the human and ChatGPT simulated data independently, calculating the *averages* of the mean and standard deviation of the elicited distributions per each draw and question respectively, and then calculating for each draw the correlation coefficients across the AI generated *averages* of the mean and standard deviation with that of the human data, and then finally constructing symmetric standard errors and point estimates through this procedure. Bootstrap standard errors are in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B4: Correlation Coefficients Between Human and ChatGPT Responses with Demographics

	Pearson	Spearman	Kendall
ρ_μ	0.761***	0.739***	0.534***
	(0.005)	(0.006)	(0.007)
ρ_σ	-0.697***	-0.284***	-0.159***
	(0.008)	(0.013)	(0.011)

Note: Standard errors are in parenthesis. The point estimates and symmetric bootstrap intervals are calculated after random pair bootstrap design, where I drawing the same number of observations per question-demographic group 10000 times in the human and ChatGPT simulated data independently, calculating the *averages* of the mean and standard deviation of the elicited distributions per each draw and question-demographic group respectively, and then calculating for each draw the correlation coefficients across the AI generated *averages* of the mean and standard deviation with that of the human data, and then finally constructing symmetric standard errors and point estimates through this procedure. Bootstrap standard errors are in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B5: Correlation Coefficients Between Datasets (Bootstrap Analysis) – High AI

	Pearson	Spearman	Kendall
ρ_μ	0.905^{***}	0.775^{***}	0.665^{***}
	(0.006)	(0.021)	(0.028)
ρ_σ	0.850^{***}	0.708^{***}	0.576^{***}
	(0.028)	(0.072)	(0.076)

Note: The point estimates and symmetric bootstrap intervals are calculated after random pair bootstrap design, where I drawing the same number of observations per question-demographic group 10000 times in the human and ChatGPT simulated data independently, calculating the *averages* of the mean and standard deviation of the elicited distributions per each draw and question-demographic group respectively, and then calculating for each draw the correlation coefficients across the AI generated *averages* of the mean and standard deviation with that of the human data, and then finally constructing symmetric standard errors and point estimates through this procedure. I restrict my sample to individuals who reported using AI tools once a week or more. Bootstrap standard errors are in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B6: Correlation Coefficients Between Datasets (Bootstrap Analysis) – Low AI

	Pearson	Spearman	Kendall
ρ_μ	0.907^{***}	0.764^{***}	0.652^{***}
	(0.002)	(0.014)	(0.021)
ρ_σ	0.835^{***}	0.718^{***}	0.556^{***}
	(0.010)	(0.031)	(0.035)

Note: The point estimates and symmetric bootstrap intervals are calculated after random pair bootstrap design, where I drawing the same number of observations per question-demographic group 10000 times in the human and ChatGPT simulated data independently, calculating the *averages* of the mean and standard deviation of the elicited distributions per each draw and question-demographic group respectively, and then calculating for each draw the correlation coefficients across the AI generated *averages* of the mean and standard deviation with that of the human data, and then finally constructing symmetric standard errors and point estimates through this procedure. I restrict my sample to individuals who did not report using AI tools once a week or more. Bootstrap standard errors are in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B7: Bootstrap Estimates of Correlation Coefficients by Question

	Pearson		Kendall		Spearman	
Question Topic	μ	σ	μ	σ	μ	σ
HH Income	0.4588***	0.3437***	0.3119***	0.2701***	0.4392***	0.3867***
	(0.146)	(0.088)	(0.108)	(0.064)	(0.141)	(0.087)
HH Labor Income	0.4958***	0.3378***	0.3196***	0.2417***	0.4483***	0.3430***
	(0.116)	(0.094)	(0.100)	(0.074)	(0.129)	(0.100)
Consumption	0.4016***	0.0278	0.3120***	0.0192	0.4471***	0.0223
	(0.124)	(0.174)	(0.101)	(0.126)	(0.134)	(0.179)
Health Expenses	0.0052	-0.1217	0.0274	-0.0794	0.0364	-0.1078
	(0.382)	(0.201)	(0.275)	(0.138)	(0.395)	(0.189)
Energy Bill	-0.2994***	-0.3255***	-0.1509**	-0.2351***	-0.2314**	-0.3287***
	(0.103)	(0.109)	(0.073)	(0.082)	(0.102)	(0.113)
House Price	0.0764	0.5740***	0.0185	0.3975***	0.0278	0.5301***
	(0.155)	(0.086)	(0.111)	(0.081)	(0.154)	(0.100)
GDP	0.1928	0.3889***	0.1495	0.2631***	0.2130	0.3781***
	(0.150)	(0.094)	(0.106)	(0.072)	(0.152)	(0.099)
Unemployment	0.1276	-0.0021	0.0883	0.0026	0.1213	-0.0032
	(0.187)	(0.147)	(0.126)	(0.101)	(0.175)	(0.138)
Inflation	0.5588***	0.5315***	0.3817***	0.3675***	0.5336***	0.5107***
	(0.111)	(0.089)	(0.093)	(0.077)	(0.123)	(0.100)
Interest Rate	0.0635	0.1286	0.0327	0.0652	0.0578	0.1025
	(0.093)	(0.099)	(0.068)	(0.074)	(0.101)	(0.109)
Mortgage Interest Rate	0.2555**	0.4441***	0.1740**	0.3115***	0.2529**	0.4410***
	(0.104)	(0.114)	(0.078)	(0.093)	(0.113)	(0.124)

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. μ and σ represent correlations computed on the mean and standard deviation of the distribution, respectively. Standard errors from bootstrap samples shown in parentheses. The

Table B8: Bootstrap Estimates of Correlation Coefficients by Group

	Pearson		Kendall		Spearman	
Group	μ	σ	μ	σ	μ	σ
Homeowner	0.7736***	-0.7555***	0.5682***	-0.0849***	0.7448***	-0.2016***
	(0.0049)	(0.0044)	(0.0117)	(0.0176)	(0.0074)	(0.0172)
College	0.8099***	-0.7472***	0.5556***	-0.0058*	0.7174***	-0.0917***
	(0.0032)	(0.0037)	(0.0120)	(0.0296)	(0.0088)	(0.0290)
North or Centre	0.7918***	-0.7451***	0.5606***	-0.0494***	0.7444***	-0.1618***
	(0.0039)	(0.0050)	(0.0117)	(0.0185)	(0.0075)	(0.0156)
Age $>$ 49	0.7918***	-0.7311***	0.5749***	-0.0980***	0.7504***	-0.2193***
	(0.0035)	(0.0058)	(0.0124)	(0.0170)	(0.0105)	(0.0180)
HH Members $>$ 3	0.7967***	-0.7507***	0.5764***	-0.0727***	0.7547***	-0.1883***
	(0.0039)	(0.0045)	(0.0131)	(0.0261)	(0.0052)	(0.0278)

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. μ and σ represent correlations computed on the mean and standard deviation of the distribution, respectively. Standard errors shown in parentheses. Results based on 1000 bootstrap samples for each group.

B.4 Tables from Guiso and Jappelli (2024a)

Table 2 – Idiosyncratic risks

	Consumption risk	Income risk	Health risk	Energy risk
Male	0.002	-0.000	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Age 35 to 50	-0.005	-0.012	-0.003	-0.002
	(0.003)	(0.003)***	(0.003)	(0.003)
Age 51 to 65	-0.013	-0.023	-0.013	-0.013
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Age 66 to 75	-0.031	-0.045	-0.029	-0.026
	(0.004)***	(0.004)***	(0.004)***	(0.003)***
Family size	0.005	0.005	0.004	0.004
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
College degree	-0.010	-0.010	-0.012	-0.012
	(0.003)***	(0.003)***	(0.003)***	(0.002)***
North	-0.021	-0.022	-0.020	-0.019
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Centre	-0.015	-0.015	-0.012	-0.011
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Employed	0.000	0.001	-0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Self-employed	0.005	0.010	0.003	0.002
	(0.004)	(0.004)**	(0.004)	(0.004)
Log cash-on-hand	-0.001	-0.002	-0.000	-0.000
	(0.001)	(0.001)**	(0.001)	(0.001)
Homeowner	-0.016	-0.018	-0.017	-0.014
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Wave 2	-0.042	-0.031	-0.041	-0.041
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Wave 3	-0.047	-0.036	-0.047	-0.045
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Wave 4	-0.051	-0.043	-0.049	-0.047
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
R^2	0.06	0.06	0.06	0.06
N	20,015	20,015	20,015	20,015

Note. OLS regression estimations. Standard errors in parentheses. * significance at 10%, ** significance at 5%, *** significance at 1%.

Figure 2: Table 2 from Guiso and Jappelli (2024a)

Table 3. Aggregate risks

	GDP risk	Unemployment risk	Inflation risk	Interest rate risk	House price risk
Male	-0.002	-0.002	-0.000	0.001	0.002
	(0.002)	(0.001)*	(0.002)	(0.000)	(0.002)
Age 35 to 50	-0.004	-0.003	-0.004	-0.002	-0.003
	(0.003)	(0.002)	(0.003)	(0.001)***	(0.003)
Age 51 to 65	-0.013	-0.008	-0.013	-0.005	-0.013
	(0.003)***	(0.002)***	(0.003)***	(0.001)***	(0.003)***
Age 66 to 75	-0.028	-0.017	-0.026	-0.008	-0.027
	(0.004)***	(0.002)***	(0.003)***	(0.001)***	(0.003)***
Family size	0.005	0.003	0.004	0.001	0.004
	(0.001)***	(0.001)***	(0.001)***	(0.000)***	(0.001)***
College degree	-0.013	-0.009	-0.012	-0.002	-0.012
	(0.003)***	(0.002)***	(0.002)***	(0.001)***	(0.002)***
North	-0.019	-0.012	-0.019	-0.004	-0.018
	(0.003)***	(0.002)***	(0.002)***	(0.001)***	(0.003)***
Centre	-0.013	-0.008	-0.011	-0.002	-0.009
	(0.003)***	(0.002)***	(0.003)***	(0.001)***	(0.003)***
Employed	0.001	0.000	0.001	0.000	0.001
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)
Self-employed	0.003	0.003	0.001	0.001	0.005
	(0.004)	(0.003)	(0.004)	(0.001)	(0.004)
Log cash-on-hand	-0.002	-0.001	-0.001	0.000	-0.001
	(0.001)**	(0.001)*	(0.001)	(0.000)	(0.001)
Homeowner	-0.018	-0.009	-0.015	-0.003	-0.013
	(0.003)***	(0.002)***	(0.003)***	(0.001)***	(0.003)***
Wave 2	-0.037	-0.025	-0.040	-0.008	-0.040
	(0.002)***	(0.001)***	(0.002)***	(0.000)***	(0.002)***
Wave 3	-0.040	-0.027	-0.042	-0.009	-0.043
	(0.002)***	(0.001)***	(0.002)***	(0.000)***	(0.002)***
Wave 4	-0.040	-0.027	-0.042	-0.009	-0.044
	(0.002)***	(0.001)***	(0.002)***	(0.000)***	(0.002)***
R^2	0.05	0.05	0.06	0.05	0.05
N	20,015	20,015	20,015	20,015	20,015

Note. OLS regression estimates. Standard errors in parentheses. * significance at 10%, ** significance at 5%, *** significance at 1%

Figure 3: Table 3 from Guiso and Jappelli (2024a)

Table 9. Euler equation estimates

	OLS	Fixed effect	Fixed effect	IV Fixed effect	IV Fixed effect
Interest rate	-0.078	0.024	0.014	0.014	0.015
	(0.012)***	(0.017)	(0.017)	(0.017)	(0.017)
pec2	1.165	1.426	1.800	1.539	1.326
	(0.095)***	(0.124)***	(0.122)***	(0.273)***	(0.264)***
Wave 2	0.003	0.003	0.002	0.002	0.002
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Wave 3	0.003	0.002	0.002	0.002	0.001
	(0.001)***	(0.001)***	(0.001)**	(0.001)**	(0.001)*
Wave 4	0.002	0.001	0.001	0.000	0.000
	(0.001)**	(0.001)*	(0.001)	(0.001)	(0.001)
Income growth			0.259	0.256	0.254
			(0.011)***	(0.011)***	(0.011)***
Constant	0.005	0.001	0.004	0.005	0.005
	(0.001)***	(0.001)*	(0.001)***	(0.001)***	(0.001)***
R^2	0.01	0.01	0.06		
N	20,015	18,031	18,031	18,031	18,031

Note. The dependent variable is expected consumption growth. Consumption risk is the 2nd conditional moment of the distribution of expected consumption growth. Column (1) presents OLS estimations; columns (2) and (3) are panel fixed effects estimations; column (4) presents instrumental variable fixed effects panel estimations using micro risks as instruments; column (5) presents instrumental variable fixed effects panel estimations using micro and macro risks as instruments. Standard errors in parentheses. * significance at 10%, ** significance at 5%, *** significance at 1%.

Figure 4: Table 9 from Guiso and Jappelli (2024a)

B.5 Distributional Plots and Tests

Figure 5: Distribution of Points Allocated: Human vs ChatGPT Simulated Responses

	HH Income				HH Labor Income				Consumption		
	Human	Simulated	P-value		Human	Simulated	P-value		Human	Simulated	P-value
g1	12.5	11.7	.02	g1	10.6	11.4	.02	g1	8.7	10.0	.00
g2	6.1	15.1	.00	g2	4.7	14.5	.00	g2	3.9	14.8	.00
g3	6.0	18.7	.00	g3	4.6	18.2	.00	g3	4.3	19.6	.00
g4	6.5	22.0	.00	g4	5.1	21.9	.00	g4	4.5	24.2	.00
g5	6.3	11.6	.00	g5	6.0	12.8	.00	g5	5.2	11.4	.00
g6	39.3	5.8	.00	g6	43.9	6.2	.00	g6	33.6	5.3	.00
g7	7.7	5.6	.00	g7	9.2	5.6	.00	g7	8.8	5.0	.00
g8	4.9	4.5	.01	g8	5.1	4.4	.00	g8	8.3	4.4	.00
g9	3.4	2.8	.00	g9	3.5	2.7	.00	g9	7.2	2.8	.00
g10	3.0	1.7	.00	g10	3.0	1.6	.00	g10	5.7	1.8	.00
g11	4.4	0.7	.00	g11	4.5	0.8	.00	g11	9.8	0.7	.00
	Health Expenses				**Gas Bill**				**House Price**		
	Human	Simulated	P-value		Human	Simulated	P-value		Human	Simulated	P-value
g1	5.8	3.1	.00	g1	4.5	6.8	.00	g1	7.3	6.7	.04
g2	2.9	6.0	.00	g2	2.2	11.4	.00	g2	3.4	10.3	.00
g3	2.7	9.1	.00	g3	2.3	16.1	.00	g3	3.8	15.3	.00
g4	2.9	13.6	.00	g4	2.9	21.2	.00	g4	4.5	20.8	.00
g5	4.0	19.3	.00	g5	3.5	18.3	.00	g5	5.6	18.6	.00
g6	42.7	16.1	.00	g6	29.7	8.6	.00	g6	46.9	10.1	.00
g7	9.2	11.8	.00	g7	10.9	5.9	.00	g7	7.8	7.3	.05
g8	8.4	9.6	.00	g8	11.3	4.8	.00	g8	6.0	5.3	.00
g9	6.8	6.0	.00	g9	9.7	3.4	.00	g9	4.9	3.1	.00
g10	5.3	3.4	.00	g10	8.2	2.1	.00	g10	3.8	1.6	.00
g11	9.4	2.1	.00	g11	14.9	1.5	.00	g11	6.2	0.7	.00
	GDP				**Inflation**				**Unemployment**		
	Human	Simulated	P-value		Human	Simulated	P-value		Human	Simulated	P-value
g1	15.4	2.3	.00	g1	4.9	0.0	.00	g1	6.7	4.5	.00
g2	5.7	5.1	.00	g2	2.6	0.1	.00	g2	6.5	18.0	.00
g3	7.0	12.3	.00	g3	3.7	2.8	.00	g3	9.7	28.1	.00
g4	9.1	21.2	.00	g4	5.3	14.3	.00	g4	14.6	25.0	.00
g5	11.1	24.5	.00	g5	6.9	25.4	.00	g5	15.1	13.1	.00
g6	27.0	10.2	.00	g6	23.7	15.4	.00	g6	12.3	5.9	.00
g7	11.7	11.3	.34	g7	11.4	17.7	.00	g7	9.7	3.3	.00
g8	4.6	6.7	.00	g8	12.3	13.0	.02	g8	25.5	1.9	.00
g9	2.9	3.9	.00	g9	9.7	6.4	.00				
g10	2.1	1.4	.00	g10	7.0	4.3	.00				
g11	3.6	0.7	.00	g11	12.6	0.8	.00				
	Interest Rate				**Mortgage Interest Rate**						
	Human	Simulated	P-value		Human	Simulated	P-value				
g1	46.2	36.0	.00	g1	11.5	15.5	.00				
g2	21.3	39.3	.00	g2	19.3	42.4	.00				
g3	13.1	17.1	.00	g3	28.6	27.9	.20				
g4	7.3	5.7	.00	g4	17.9	10.2	.00				
g5	12.0	1.9	.00	g5	22.8	3.9	.00				

Notes: The data represents a pairwise bootstrapped two-sample t-test comparing the distribution of responses between human participants and ChatGPT simulated data across demographic groups (g1-g11). p-values indicate the statistical significance of differences between human and simulated responses for each variable. Values represent percentages of responses within each group. All variables measured as expected changes relative to baseline period.

Table B9: Balance Table Across Multiple Panels

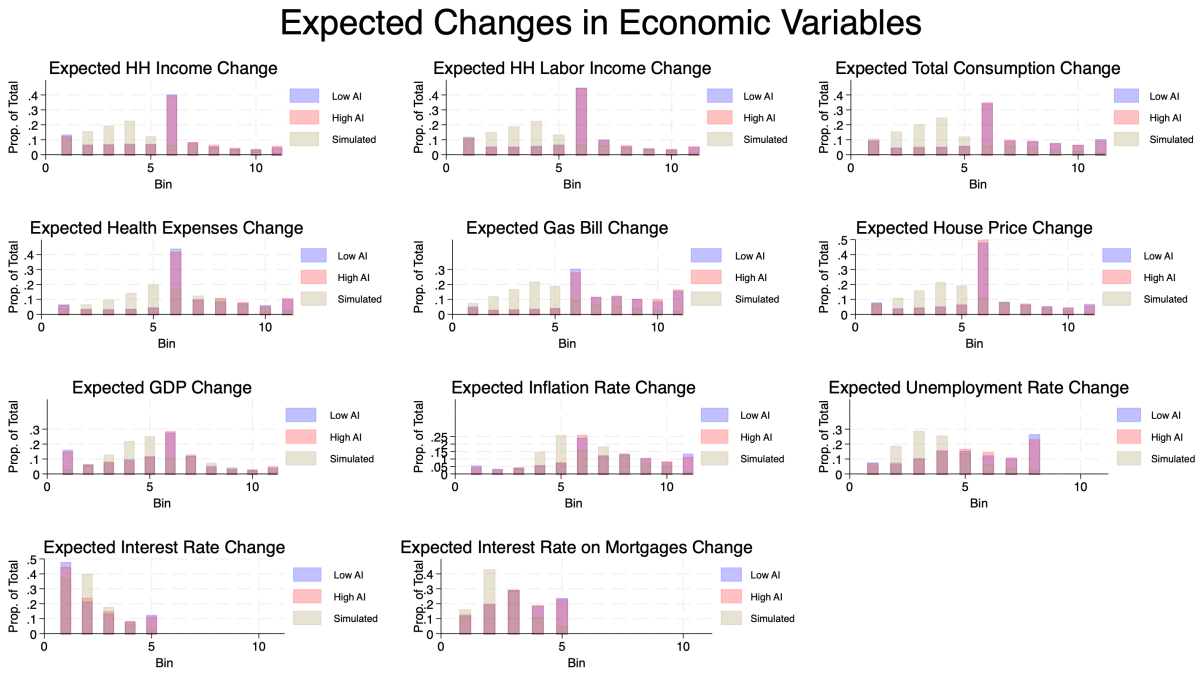

Figure 6: Distribution of Points Allocated: GPT vs Human Data by High or Low AI Use

B.6 Regression Results

Table B10: Regression Results: Human vs ChatGPT Responses

Variable	Consumption Risk	Income Risk	Health Risk	Energy Risk	GDP Risk	Unemp. Risk	Inflation Risk	Interest Rate Risk	House Price Risk
Panel A: Human Responses									
HH Members >3	0.011**	0.008*	0.014***	0.009**	0.012***	0.008***	0.011***	0.518***	0.015***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.002)	(0.004)	(0.154)	(0.005)
Age >49	-0.027***	-0.033***	-0.023***	-0.025***	-0.029***	-0.011***	-0.027***	-1.099***	-0.029***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.132)	(0.004)
College	-0.002	-0.005	-0.006	-0.008*	-0.013***	-0.006**	-0.010**	-0.227	-0.010**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.003)	(0.005)	(0.163)	(0.005)
Homeowner	-0.021***	-0.028***	-0.024***	-0.020***	-0.026***	-0.013***	-0.025***	-0.688***	-0.017***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.003)	(0.005)	(0.157)	(0.005)
North or Centre	-0.025***	-0.021***	-0.023***	-0.021***	-0.024***	-0.013***	-0.022***	-0.630***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.138)	(0.004)
Mean of D.V.	0.096	0.086	0.089	0.083	0.080	0.049	0.079	2.299	0.078
Var of D.V.	0.018	0.016	0.017	0.015	0.016	0.005	0.015	18.872	0.016
N	4,814	4,814	4,814	4,814	4,814	4,814	4,814	4,814	4,814
Panel B: ChatGPT Simulated Responses									
HH Members >3	0.001	0.003*	-0.003**	-0.005***	-0.003**	0.000	0.001	0.000	0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Age >49	-0.001	-0.005***	0.001	-0.000	0.009***	0.003***	0.000	-0.004***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
College	0.000	-0.005***	0.011***	0.007***	-0.013***	-0.012***	0.002*	0.005***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
Homeowner	-0.001	-0.007***	0.018***	0.009***	-0.009***	-0.015***	0.000	0.003***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
North or Centre	-0.002**	-0.013***	-0.004***	0.004***	-0.012***	-0.014***	-0.001	-0.000	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Mean of D.V.	0.160	0.165	0.116	0.150	0.098	0.104	0.073	0.039	0.132
Var of D.V.	0.001	0.002	0.002	0.001	0.002	0.001	0.000	0.000	0.002
N	4,814	4,814	4,814	4,814	4,814	4,814	4,814	4,814	4,814

Note: Each column corresponds to a regression for a different perceived risk. Panel A reports estimates using actual human survey responses; Panel B uses ChatGPT-simulated responses (with demographics embedded). Standard errors are in parentheses. The final rows report the mean, variance, and sample size of the dependent variable. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B11: Regression Results High AI vs Low AI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Low AI									
Variable	Consumption Risk	Income Risk	Health Risk	Energy Risk	GDP Risk	Unemp. Risk	Inflation Risk	Interest Rate Risk	House Price Risk
HH Members >3	0.275***	0.210**	0.255***	0.211**	0.223**	0.211***	0.226***	1.738***	0.239***
	(0.087)	(0.088)	(0.089)	(0.085)	(0.088)	(0.067)	(0.085)	(0.553)	(0.090)
Age >49	-0.402***	-0.581***	-0.353***	-0.384***	-0.496***	-0.276***	-0.441***	-3.267***	-0.467***
	(0.080)	(0.079)	(0.081)	(0.076)	(0.076)	(0.061)	(0.076)	(0.476)	(0.078)
North or Centre	-0.315***	-0.253***	-0.312***	-0.241***	-0.323***	-0.176***	-0.284***	-1.682***	-0.179**
	(0.082)	(0.083)	(0.083)	(0.080)	(0.082)	(0.063)	(0.079)	(0.499)	(0.083)
Homeowner	-0.348***	-0.468***	-0.325***	-0.308***	-0.427***	-0.310***	-0.411***	-2.185***	-0.236***
	(0.089)	(0.089)	(0.091)	(0.088)	(0.088)	(0.068)	(0.088)	(0.546)	(0.090)
College	0.071	-0.037	0.002	-0.035	-0.090	0.006	-0.096	-0.312	-0.038
	(0.093)	(0.091)	(0.094)	(0.089)	(0.090)	(0.069)	(0.087)	(0.580)	(0.091)
Mean of D.V.	2.254	1.985	2.057	2.038	1.917	1.516	1.913	7.990	1.815
Var of D.V.	4.693	4.759	4.811	4.318	4.484	2.662	4.317	170.272	4.688
N	3450	3450	3450	3450	3450	3450	3450	3450	3450
Panel B: High AI									
Variable	Consumption Risk	Income Risk	Health Risk	Energy Risk	GDP Risk	Unemp. Risk	Inflation Risk	Interest Rate Risk	House Price Risk
HH Members >3	0.292	0.203	0.022	-0.012	-0.071	0.030	-0.081	1.611	-0.046
	(0.250)	(0.259)	(0.265)	(0.249)	(0.246)	(0.184)	(0.248)	(1.546)	(0.246)
Age >49	-0.399*	-0.880***	-0.303	-0.557**	-0.576**	-0.328**	-0.598***	-4.289***	-0.547**
	(0.228)	(0.240)	(0.244)	(0.231)	(0.229)	(0.167)	(0.230)	(1.360)	(0.238)
North or Centre	-0.526**	-0.435*	-0.501**	-0.502**	-0.474**	-0.178	-0.453*	-1.804	-0.454*
	(0.250)	(0.248)	(0.247)	(0.244)	(0.237)	(0.172)	(0.236)	(1.376)	(0.237)
Homeowner	-0.109	-0.296	0.011	0.009	-0.258	-0.087	-0.029	-2.886*	-0.151
	(0.251)	(0.271)	(0.262)	(0.254)	(0.246)	(0.184)	(0.248)	(1.586)	(0.253)
College	0.442	0.220	0.419	0.352	0.139	0.047	0.345	0.539	0.630**
	(0.304)	(0.320)	(0.292)	(0.296)	(0.285)	(0.214)	(0.300)	(1.761)	(0.309)
Mean of D.V.	2.152	1.947	2.109	1.990	1.834	1.374	1.880	7.088	1.798
Var of D.V.	4.498	5.085	4.878	4.655	4.359	2.340	4.304	155.371	4.652
N	391	391	391	391	391	391	391	391	391

Notes: Each column corresponds to a regression for a different perceived risk. Panel A reports estimates using actual human survey responses for Low AI users which I define as survey respondents who use AI tools such as ChatGPT less than once a week; Panel B uses human survey responses for High AI users, which is defined as survey respondents who use AI tools such as ChatGPT once a week or more. Standard errors are in parentheses. The final rows report the mean, variance, and sample size of the dependent variable. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B12: Euler Equation Results

	Simulated Data		Human Data	
	(1)	(2)	(3)	(4)
Consumption Risk	-4.447***	-4.363***	0.168	1.343***
	(0.525)	(0.520)	(0.372)	(0.349)
Expected Labor Income Growth		0.031***		0.349***
		(0.007)		(0.025)
Mean of D.V.	-3.337	-3.337	0.518	0.518
Var of D.V.	0.101	0.101	17.331	17.331
N	4814	4814	4814	4814

Notes: The dependent variable is expected consumption growth. Consumption risk is the 2nd conditional moment of the distribution of expected consumption growth. Standard errors in parentheses, calculated through a bootstrap with with 10000 samples of identical sizes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B13: Regression Results: Low vs High AI Users

	Low AI		High AI	
	(1)	(2)	(3)	(4)
Consumption Risk	0.078	1.222***	-0.484	0.569
	(0.432)	(0.412)	(1.205)	(1.133)
Expected Labor Income Growth		0.347***		0.341***
		(0.030)		(0.093)
Mean of D.V.	0.514	0.514	0.340	0.340
Var of D.V.	17.372	17.372	19.015	19.015
N	3450	3450	391	391

Notes: The dependent variable is expected consumption growth. Consumption risk is the 2nd conditional moment of the distribution of expected consumption growth. High AI refers to individuals which responded using AI once a week or more in the ISCE, and Low AI refers otherwise. Standard errors in parentheses, calculated through a bootstrap with with 10000 samples of identical sizes. *** p<0.01, ** p<0.05, * p<0.1.

C Guessing Current Traits

C.1 Question Format

HH Income (October 2023)

An Italian [male / female], [aged 50–75 / aged 18–49] who is [employed / unemployed].

Given the above characteristics, into which bracket does the *average total monthly household income*, net of all taxes, fall for an Italian individual with these characteristics in October 2023? Please consider the entirety of earnings (income, pensions, transfers, income from property and from financial assets) of all household members.

HH Income (expected–January 2024)

An Italian [male / female], [aged 50–75 / aged 18–49] who is [employed / unemployed].

Given the above characteristics, into which bracket does the *average total monthly household income expected for January 2024*, net of all taxes, fall for an Italian individual with these characteristics in October 2023? Consider all forms of earnings for every household member (income, pensions, transfers, income from property and from financial assets).

HH Income (expected–one year ahead)

An Italian [male / female], [aged 50–75 / aged 18–49] who is [employed / unemployed].

Given the above characteristics, into which bracket does the *average total monthly household income expected one year from now*, net of all taxes, fall for an Italian individual with these characteristics in October 2023? Consider all forms of earnings for every household member (income, pensions, transfers, income from property and from financial assets).

Consumption (October 2023)

An Italian [male / female], [aged 50–75 / aged 18–49] who is [employed / unemployed].

Given the above characteristics, into which bracket do the *average total monthly household consumptions* fall for an Italian individual with these characteristics in October 2023? Consider all expenses (food and non-food consumption, rent, loan/mortgage payments, insurance, utilities, etc.) of all household members.

Consumption (expected–4 months ahead 2024)

An Italian [male / female], [aged 50–75 / aged 18–49] who is [employed / unemployed].

Given the above characteristics, into which bracket does the *average total monthly household consumption expected for January 2024* fall for an Italian individual with these characteristics in October 2023? Consider all expenses (food and non-food consumption, rent, loan/mortgage payments, insurance, utilities, etc.) of all household members.

Consumption (expected—one year ahead)

An Italian [male / female], [aged 50–75 / aged 18–49] who is [employed / unemployed].

Given the above characteristics, into which bracket does the *average total monthly household consumption expected one year from now* fall for an Italian individual with these characteristics in October 2023? Consider all expenses (food and non-food consumption, rent, loan/mortgage payments, insurance, utilities, etc.) of all household members.

E1 — HH income-growth distribution

An Italian [male / female], [aged 50–75 / aged 18–49] who is [employed / unemployed].

Distribute **exactly 100 points** across the following scenarios (write just the numbers; they must sum to 100). Over the next year, you expect that yMy family's *total annual income*, net of taxes and state transfers, compared with last year…

- will decrease by more than 8 %: _____
- will decrease by 6–8 %: _____
- will decrease by 4–6 %: _____
- will decrease by 2–4 %: _____
- will decrease by 0–2 %: _____
- will remain unchanged: _____
- will increase by 0–2 %: _____

- will increase by 2–4 %: _____
- will increase by 4–6 %: _____
- will increase by 6–8 %: _____
- will increase by more than 8 %: _____

E3 — consumption-growth distribution

An Italian [male / female], [aged 50–75 / aged 18–49] who is [employed / unemployed].

Distribute **exactly 100 points** across the following scenarios (numbers only; must sum to 100). Over the next year, you expect that My family's *total consumption* (all expenses)...

- will decrease by more than 8 %: _____
- will decrease by 6–8 %: _____
- will decrease by 4–6 %: _____
- will decrease by 2–4 %: _____
- will decrease by 0–2 %: _____
- will remain unchanged: _____
- will increase by 0–2 %: _____
- will increase by 2–4 %: _____
- will increase by 4–6 %: _____
- will increase by 6–8 %: _____
- will increase by more than 8 %: _____

C.2 Summary Statistics

Table C1: Summary Statistics Comparison: Human vs Simulated Data

	Human Data					ChatGPT Simulated Data				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Demographic Variables										
Male	2,842	0.559	0.497	0	1	2,842	0.559	0.497	0	1
Employed	2,842	0.840	0.366	0	1	2,842	0.840	0.366	0	1
Age > 49	2,842	0.347	0.476	0	1	2,842	0.347	0.476	0	1
Income and Cost Variables										
HH Income October 2023	2,842	2,230.03	1,809.65	750	20,000	2,842	1817.73	331.24	1,250	2,750
Consumption October 2023	2,842	1,510.29	1,568.25	750	20,000	2,842	1,647.26	202.50	1,250	2,250
Future Income Variables										
HH Income January 2024	2,325	2,268.48	1,682.95	750	20,000	2,842	1,813.16	328.68	750	2,250
HH Income October 2024	2,341	2,255.53	1,507.71	750	20,000	2,842	1,813.16	328.68	750	2,250
Expected Consumption Variables										
Consumption January 2024	2,325	1,513.66	1,684.57	750	20,000	2,842	1,637.93	208.54	1,250	1,750
Consumption October 2024	2,341	1,548.06	1,599.22	750	20,000	2,842	1,637.93	208.54	1,250	1,750

Notes: Human data represents the participants in the original Wave 1 ISCE dataset (in waves administered in October 2023, October 2024 and January 2024), while Simulated data represents AI-generated responses. I restrict my sample to individuals who reported individual income and household income, as well as those that explicitly reported home-ownership/rental status.

C.3 Accuracy of Current Traits

Table C2: Bootstrap Results for Current Total Household Income

Parameter	Mean	Std. Dev.	Significance
Accuracy (bin)	0.743	0.099	***
Accuracy (>2,500)	0.901	0.082	***
Pearson's ρ	0.707	0.042	***
Spearman's ρ	0.714	0.023	***
Kendall's τ	0.494	0.052	***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Results based on 10,000 pairs bootstrap iterations of human and simulated data, stratified by employment status, gender, and age>49. For each bootstrap sample, the same number of observations were drawn from each dataset. Accuracy (bin) represents the percentage of observations correctly classified into income bins. Accuracy (>2,500) represents the percentage of observations correctly classified as having income greater than 2,500 Euros.

Table C3: Bootstrap Results for Current Consumption

Parameter	Mean	Std. Dev.	Significance
Accuracy (bin)	0.725	0.135	***
Accuracy (>1,250)	0.873	0.088	***
Pearson's ρ	0.798	0.105	***
Spearman's ρ	0.707	0.124	***
Kendall's τ	0.538	0.115	***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Results based on 10,000 pairs bootstrap iterations of human and simulated data, stratified by employment status, gender, and age>49. For each bootstrap sample, the same number of observations were drawn from each dataset. Accuracy (bin) represents the percentage of observations correctly classified into consumption bins. Accuracy (>1,250) represents the percentage of observations correctly classified as having consumption greater than 1,250 Euros.

Table C4: Bootstrap Results for Future Income Predictions

Parameter	Mean	Std. Dev.	Significance
Income 4 Months in the Future			
Accuracy (bin)	0.248	0.017	***
Accuracy (>€2,500)	0.881	0.049	***
Pearson's ρ	0.187	0.277	
Spearman's ρ	0.147	0.310	
Kendall's τ	0.116	0.242	
Income 12 Months in the Future			
Accuracy (bin)	0.251	0.016	***
Accuracy (>€2,500)	0.965	0.062	***
Pearson's ρ	-0.256	0.178	
Spearman's ρ	-0.133	0.300	
Kendall's τ	-0.096	0.233	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Significance determined by whether 95% confidence intervals (±1.96 SE) include zero. Results based on 10,000 pairs bootstrap iterations of human and simulated data, stratified by employment status, gender, and age>49. For each bootstrap sample, the same number of observations were drawn from each dataset. Accuracy (bin) represents the percentage of observations correctly classified into future income bins. Accuracy (>€2,500) represents the percentage of observations correctly classified as having future income greater than €2,500.

Table C5: Bootstrap Results for Future Consumption Predictions

Parameter	Mean	Std. Dev.	Significance
Consumption 4 Months in the Future			
Accuracy (bin)	0.579	0.146	***
Accuracy (>€1,250)	0.999	0.013	***
Pearson's ρ	0.077	0.315	
Spearman's ρ	0.106	0.279	
Kendall's τ	0.061	0.233	
Consumption 12 Months in the Future			
Accuracy (bin)	0.574	0.116	***
Accuracy (>€1,250)	0.965	0.056	***
Pearson's ρ	-0.146	0.184	
Spearman's ρ	0.152	0.180	
Kendall's τ	0.143	0.159	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Significance determined by whether 95% confidence intervals (±1.96 SE) include zero. Results based on 10,000 bootstrap iterations. Accuracy (bin) represents the percentage of observations correctly classified into future consumption bins. Accuracy (>€2,500) represents the percentage of observations correctly classified as having future consumption greater than €2,500.

Table C6: Bootstrap Results for Expected Consumption and Income

Parameter	Mean	Std. Dev.	Significance
Mean Expected Consumption			
Pearson's ρ	0.619	0.155	***
Spearman's ρ	0.611	0.158	***
Kendall's τ	0.413	0.149	***
Mean Expected Income			
Pearson's ρ	0.507	0.124	***
Spearman's ρ	0.491	0.133	***
Kendall's τ	0.374	0.116	***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Results based on 10,000 pairs bootstrap iterations of human and simulated data, stratified by employment status, gender, and Age>49.

C.4 Extension: Recovering Policy Function

Table C7: Accuracy Scores by Economic Prediction Model

Variable	HH Income	Consumption	Health	House	GDP
Homeowner	0.6540	0.7435	0.7309	0.6996	0.6692
College	0.3616	0.2283	0.2557	0.2918	0.3404
Age $>$ 49	0.5178	0.5122	0.5569	0.5344	0.5070
North or Centre	0.5883	0.6568	0.6458	0.6410	0.6217
HH Members $>$ 3	0.4718	0.6872	0.4423	0.7275	0.6488

Note: Accuracy—shown above for five separate prediction targets—is the share of correct guesses of demographic traits given the elicited distribution of the change in a given variable across the full Wave 1 sample. ChatGPT crosses the 50 % threshold consistently for homeownership, age, and region, and in three of five cases for household size, suggesting that even if it cannot reproduce the full expectations distribution, it can still help impute persistent demographic traits when survey data are incomplete.

D Robustness

D.1 Information Treatment

Table D8: Regression Results: Simulated Data Analysis

	Simulated Data (temperature=1.0)	
	(1)	(2)
T3	-2.030***	-1.134***
	(0.491)	(0.285)
T2	-7.452***	-4.702***
	(0.475)	(0.320)
G2	2.452***	4.883***
	(0.402)	(0.282)
T2G2	5.500***	
	(0.682)	
T3G2	1.792***	
	(0.659)	
Mean of D.V.	29.73	29.73
Var of D.V.	107.84	107.84
N	5040	5040

Notes: Standard errors are computed with a stratified bootstrapped within each of the 6 information treatment groups of 100 draws, where I draw a sample size identical to the original size of each of the 6 information treatment groups. The outcome variable (D.V.) is the amount contributed to the disaster fund. As opposed to the baseline case of temperature of 0.8, I use a temperature of 1.0. Bootstrap standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D9: Regression Results: Simulated Data Analysis (Temperature = 1.0)

	Simulated Data (Temperature = 1.0)			
	(1)	(2)	(3)	(4)
T3	0.275	-5.044***	0.128	-5.326***
	(1.168)	(0.907)	(1.584)	(1.422)
T2	5.237***	3.696***	4.064**	3.219*
	(1.142)	(1.148)	(1.875)	(1.751)
G2	10.280***	5.647***	9.517***	5.262***
	(1.296)	(0.657)	(1.949)	(1.152)
T2G2	-3.148*		-1.757	
	(1.871)		(3.059)	
T3G2	-10.778***		-11.050***	
	(1.724)		(2.748)	
Employed	9.194***	9.108***		
	(0.855)	(0.717)		
Retired	4.615***	4.556***		
	(1.170)	(1.148)		
Male	12.187***	12.165***		
	(0.767)	(0.799)		
HH Income $>$ 2500	52.954***	52.960***		
	(1.035)	(1.028)		
College	33.261***	33.356***		
	(1.347)	(1.114)		
Mean of D.V.	42.068	42.068	42.068	42.068
Var of D.V.	1805.989	1805.989	1805.989	1805.989
N	4517	4517	4517	4517

Note: Simulated Data refers to ChatGPT generated simulated samples where groups (tuples) of employed-retired-male-HH Income $>$ 2500-college with less than 50 observations are dropped. Temperature parameter set to 1.0 for all simulations. Standard errors are bootstrapped 100 times, within each combination of demographic groups (Employment-Gender-Income$>$2500-College). The outcome variable (D.V.) is the amount contributed to the disaster fund. Bootstrap standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table D10: Regression Results: Simulated Data with Sample Size Identical to Human Data (N=5001)

	Simulated Data	
	(1)	(2)
T3	-4.026^{***}	-2.425^{***}
	(0.435)	(0.267)
T2	-10.137^{***}	-6.957^{***}
	(0.457)	(0.294)
G2	2.366^{***}	5.566^{***}
	(0.308)	(0.240)
T2G2	6.366^{***}	
	(0.578)	
T3G2	3.228^{***}	
	(0.534)	
Mean of D.V.	29.701	29.701
Var of D.V.	90.396	90.396
N	5001	5001

Notes: Standard errors are computed with a stratified bootstrapped within each of the 6 information treatment groups of 100 draws, where the sample size is identical to the original size of each of the 6 information treatment groups. The outcome variable (D.V.) is the amount contributed to the disaster fund. A baseline temperature of 0.8 is used to simulate the human treatment groups such that the number of observations in each treatment group are identical to that of the human data (summing up to 5001 observations). Bootstrap standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.1.1 New Question Format

The prompts are otherwise identical, except for that on groups T2G1, T2G2, T3G1, T3G2, where they are following this T2 and T3 respectively:

- T2: There was a flood that caused fifteen deaths and about 40,000 displaced people.
- T3: There was a flood that caused fifteen deaths and about 40,000 displaced people. The Region calculated damages of almost 9 billion for roads, schools, embankments and canals, as well as to repair damage to homes and businesses.

Table D11: Baseline Information Treatment Regression with Non-Romagna specific Prompt

	(1)	(2)
T3	0.595	-1.190***
	(0.400)	(0.260)
T2	1.095***	-3.643***
	(0.342)	(0.252)
G2	1.857***	-2.492***
	(0.300)	(0.244)
T2G2	-9.476***	
	(0.406)	
T3G2	-3.571***	
	(0.564)	
Mean of D.V.	30.579	30.579
Var of D.V.	75.552	75.552
N	5040	5040

Notes: Standard errors are computed with a stratified bootstrapped within each of the 6 information treatment groups of 10000 draws, where I draw a sample size identical to the original size of each of the 6 information treatment groups. The outcome variable (D.V.) is the amount contributed to the disaster fund. The sample is sampled using ChatGPT (temperature = 0.8) without demographics embedded, using a prompt which does not specify the location of the flood in Italy. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Expectation Formation

Table D12: Regression Results (Temperature = 1)

Variable	Consumption Risk	Income Risk	Health Risk	Energy Risk	GDP Risk	Unemp. Risk	Inflation Risk	Interest Rate Risk	House Price Risk
HH Members >3	0.001	0.004***	0.000	-0.004***	-0.001	0.000	0.002***	0.001	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Age >49	-0.001	-0.002	-0.002	-0.001	0.008***	0.001	0.000	-0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
North or Centre	-0.003***	-0.012***	-0.009***	0.002*	-0.012***	-0.014***	-0.001	0.001**	-0.014***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Homeowner	-0.003***	-0.007***	0.020***	0.007***	-0.012***	-0.018***	0.001	0.003***	-0.006***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
College	-0.001	-0.005***	0.009***	0.008***	-0.011***	-0.014***	0.003***	0.005***	-0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
Mean of D.V.	0.162	0.166	0.117	0.150	0.101	0.103	0.074	0.040	0.133
Var of D.V.	0.001	0.002	0.002	0.001	0.002	0.001	0.001	0.000	0.002
N	4814	4814	4814	4814	4814	4814	4814	4814	4814

Notes: Each column corresponds to a regression for a different perceived risk. Data is from a ChatGPT simulation, with a temperature of 1 (as opposed to a temperature of 0.8). Standard errors are in parentheses. The final rows report the mean, variance, and sample size of the dependent variable. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D13: Euler Equation (Temperature = 1)

	(1)	(2)
Consumption Risk	-6.453***	-6.379***
	(0.478)	(0.560)
Expected Labor Income Growth		0.030***
		(0.008)
Mean of D.V.	-3.280	-3.280
Var of D.V.	0.226	0.226
N	4814	4814

Notes: The dependent variable is expected consumption growth. Consumption risk is the 2nd conditional moment of the distribution of expected consumption growth. Data is from a ChatGPT simulation, with a temperature of 1 (as opposed to a temperature of 0.8). Standard errors in parentheses, calculated through a bootstrap with with 100 samples of identical sizes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$