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# Exponential Growth Bias in the Prediction of COVID-19 Spread and Economic Expectation

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# ABSTRACT

## Exponential Growth Bias in the Prediction of COVID-19 Spread and Economic Expectation*

Exponential growth bias (EGB) is the pervasive tendency of people to perceive a growth process as linear when, in fact, it is exponential. In this paper, we document that people exhibit EGB when asked to predict the number of COVID-19 positive cases in the future. The bias is positively correlated with optimistic expectations about the future macroeconomic conditions and personal economic circumstances, and investment in a risky asset. We design four interventions to correct EGB and evaluate them through a randomized experiment. In the first treatment (*Step*), participants make predictions in several short steps; in the second and third treatments (*Feedback-N* and *Feedback-G*) participants are given feedback about their prediction errors either in the form of numbers or graphs; and in the fourth treatment (*Forecast*), participants are offered a forecast range of the future number of cases, based on a statistical model. Our results show that a) Step helps mitigate EGB relative to *Baseline*, b) *Feedback-N, Feedback-G*, and *Forecast* significantly reduce bias relative to both *Baseline* and *Step*, c) the interventions decrease risky investment and help moderate future economic expectations through the reduction in EGB. The results suggest that nudges, such as behaviorally informed communication strategies, which correct EGB can also help rationalize economic expectations.

**JEL Classification:** I12, I18, C91, D84
**Keywords:** COVID-19, economic expectation, exponential growth bias

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# 1 Introduction

Legend has it that the King asked Sissa ibn Dahir, the inventor of *Chaturanga*, the Indian precursor of modern-day chess, what reward he wanted for his invention. Ibn Dahir, or so the story went, said that he wished to receive a single grain on the first square of the chessboard, and double that of the previous square on every subsequent one. The King thought the reward was modest and granted it, only to realize soon that the final square demanded more than what his kingdom was worth. The story, perhaps apocryphal, bears testimony to a bias quite pervasive in the human psyche – namely, the exponential growth bias (EGB, henceforth). EGB refers to underestimation of the future value given a specific present value, caused by the tendency to linearize an exponential data generating process. Such tendencies are well documented in the psychology literature (Wagenaar and Timmers, 1979; Jones, 1979). In Economics, EGB has been shown to decrease savings, increase borrowings, and favor short term investments (Stango and Zinman, 2009) and lower asset accumulation (Levy and Tasoff, 2016). These findings are, in part, driven by a general inability to quantify the effects of compounding (Goda et al., 2015), a limitation that also characterized the King. A natural setting where the impact of EGB can have real consequences is the COVID-19 pandemic, given the findings of several epidemiological studies that the early transmission path of the disease is exponential (Chowell et al., 2016; Zhao et al., 2020). This is also confirmed by Figure A.1(A) and (C), which plot the number of COVID-19 positive cases in the US and India, respectively. A few studies in the recent past have documented EGB in predicting the number of future cases and have shown it to be associated with lower compliance behavior (Banerjee et al., 2005; Lammers et al., 2020). The mechanism implied in these studies is the following: If a person does not foresee the speed with which the disease spreads, she is unlikely to correctly estimate the risk associated with not following the standard safety compliance norms. Likewise, a person discounting the future spread of the disease may also harbor positive expectations about the economy and relatively less concern. Figure A.1(A) and (B) show that the google search intensity of the keyword, 'coronavirus' sharply rises in the US, but keywords concerning economic conditions, like ‘economy,’ ‘recession,’ or ‘stock market,’ do not increase commensurately.[1] The mute concern about the economic circumstances coincides with a double-digit unemployment rate and real GDP growth rate of -31.7% per annum, in the second quarter of 2020.[2] The pattern, similar in India, is a stylized fact that offers suggestive evidence that concern about the economy is not dominant despite the sharply rising number of cases. Such positive economic expectations may result in less than optimal precautionary savings or more than optimal investments in risky assets, thus resulting in significant micro and macro-economic consequences (Bachmann and Elstner, 2015; Beaudry and Willems, 2018). Further, although EGB has been studied for some time now, we know surprisingly little about potential policy interventions that can eliminate EGB and mitigate its consequences on economic choices and expectations.[3]

In this paper, we conduct a between-subject experiment on Amazon MTurk, with 700 subjects, to answer the following three critical questions of considerable policy relevance:

1. Does EGB exist in the prediction of the future number of COVID-19 cases, and if yes, is it associated with economic expectations?

2. Do behavioral policy interventions in the form of simple nudges mitigate EGB?

3. Do interventions which help reduce EGB causally help rationalize economic expectations?

Our experiment comprises of a baseline treatment, four treatments that test behavioral interventions, and one diagnostic treatment. In the baseline treatment, we present data points on the actual number of cases from a real but unnamed country on Days 0, 5, and 10 and ask participants to predict the number of cases on Day 35. Following the prediction task, participants decide how much to invest out of $0.50 in an investment task,

[1] In a recent paper, Fetzer et al. (2020) use these keywords to construct a measure of economic anxiety and show that economic anxiety increases with the onset of the disease.

[2] Source: US Bureau of Economic Analysis

[3] We use economic expectation as a catch-all phrase to indicate future belief about macroeconomic outcomes such as economic growth and unemployment, as well as future perception of one’s own economic circumstances.

where the return is determined by the performance of the leading stock market of the country on Day 35. EGB, in our case, is a normalized difference between the actual and predicted number of cases on Day 35. Following the prediction and investment task, participants fill out a survey on economic expectations and demographic characteristics.[4] To understand whether prediction in smaller steps helps mitigate EGB and adjust economic expectations, we introduce the Step treatment, where participants predict the number of cases for Days 15, 20, 25, 30, and then Day 35. An investment task follows each prediction task. The next two treatments are inspired by the idea that feedback can be a useful nudge to help people make better decisions (Thaler and Sunstein, 2008). Feedback has been shown to help improve compliance with treatment schedules (Dayer et al., 2013), build trust in online market systems by bridging the information asymmetry between buyer and seller (Tadelis, 2016), affect performances (Vidal and Nossol, 2011; Gerhards and Siemer, 2016), improve learning and increase enrolment in schools (Andrabi et al., 2017) and increase self-confidence (Banerjee et al., 2020). We add a feedback mechanism on *Step*, through which participants learn about their prediction error after each prediction. In the Feedback-Number treatment, participants are given feedback in the form of raw numbers while in the Feedback-Graph treatment, participants receive feedback in the form of graphs. In the Forecast treatment, we fit a model on the actual data and offer participants a forecast range while informing them that, according to our model, there is a high chance that the range will contain the actual number of cases. The design of this intervention is motivated by recent studies that use forecasts as a way to manipulate expectations exogenously (Roth and Wohlfart, 2019). Such forecasts, informed by appropriate epidemiological models, can help anchor peoples' predictions and minimize EGB.[5]

[4]Our measures of economic outlook include Current Situation Index ($CSI$), Future Expectation Index ($FEI$), confidence about the recovery of growth and unemployment in 6 and 12 months ($GrUn_6$ and $GrUn_{12}$, respectively), the likelihood of family losing income and employment in 6 months ($IncJob_6$), and estimated time needed to find a new job in case of a job loss ($TimeJob$). The first two variables are from the Reserve Bank of India's quarterly publication on Consumer Confidence Survey, while the last four are adapted from the Survey of Consumers conducted by the University of Michigan.

[5]In this paper, we do not take a stand on how best to arrive at such forecasts, nor claim that our forecasting model is the most appropriate one. We use an exponential functional form to generate the forecasts and

Besides the four behavioral policy treatments, we implement an additional diagnostic treatment, the Series treatment, where participants predict numbers generated from a neutrally framed exponential series.

We find several interesting results. First, we find robust evidence of EGB in the prediction of COVID-19 cases. Second, EGB is positively associated with investment and optimistic economic expectations, meaning, an increase in the bias is associated with an increase in investment and a more positive economic outlook. Third, Step, Feedback, and Forecast treatments are effective in reducing EGB with respect to Baseline. While Step is unable to eliminate EGB, Feedback and Forecast successfully nullify the bias. Fourth, the treatments help rationalize both investment decisions and economic expectations. In particular, the interventions increase the risk perception and decrease investment in risky assets. Fifth, an IV estimation strategy uncovers the mechanism behind our findings and shows that the interventions affect investment and economic expectations through their effect on EGB.

Our paper contributes to three literatures. First, we contribute to the literature on judgment and decision making by documenting systematic errors in the prediction of future COVID-19 cases. Much of the literature takes a hypothetical route to document EGB. We measure EGB using real-world data and context, while at the same time controlling for other confounds, such as overconfidence. While EGB has been documented in prior studies, very few have come up with policy interventions aimed at mitigating it. Such interventions are essential since the welfare loss on account of EGB is potentially significant. To the best of our knowledge, ours is the first paper which successfully tests four behavioral policies that minimize, and in most cases eliminate, EGB.[6] Third, the interventions

focus on the effect of forecast suggestions on EGB, as a proof of concept. In reality, policymakers should employ experts to determine the future growth path of disease.

[6] A related study by Lammers et al. (2020) shows that correcting misperceptions about the growth rate of the coronavirus disease increases support for social distancing. While they test the role of increasing the frequency of prediction in reducing bias, we test and compare four interventions to that end. In fact, the strategy proposed in their paper does not eliminate bias, three of our interventions do. Further, our interventions are arguably more policy-relevant with a clear recommendation for the government. Also, our paper aims to uncover the relationship between EGB and economic outlook, unlike theirs, whose focus

we test are cheap, minimally invasive, and, therefore, fall under the rubric of behavioral nudges. In most cases, the biases are eliminated, implying large gains from "nano-sized investments."

The other literature we contribute to pertains to expectation formation about the macroeconomy, which shows that households have limited information or pay limited attention to news related to the economy (Sims, 2003; Reis, 2006). Such limitations are associated with inaccurate expectations, which have important implications for economic choices (Amromin and Sharpe, 2014; Barsky and Sims, 2012; Greenwood and Shleifer, 2014; Hanspal et al., 2020; Malmendier and Nagel, 2011). To the best of our knowledge, ours is the first paper to show that EGB has a causal effect on expectation formation. In doing so, we investigate the intersection between the literatures on behavioral bias and consumer sentiment as measured by surveys but go beyond by incorporating real investment decisions. Second, there is a fractured view in the literature about what constitutes consumer confidence, with some claiming that it largely captures "animal spirits" (Blanchard, 1993; Hall, 1993), while others believing that it does contain substantive information about the future state of the world (Cochrane, 1994). Our paper shows that consumer sentiments captured through such surveys are prejudiced by EGB. Failure to account for such behavioral biases in surveys may result in a wedge between ex-ante expectations and ex-post realizations (Souleles, 2004). It can also lead to incorrect estimates of the predictive power of consumer confidence on the future real economy, which has been found in studies such as Ludvigson (2004). Our study advocates correction for such psychological factors to make responses from such surveys more meaningful. Finally, we contribute to this literature by showing that correcting EGB about the disease spread has a causal effect on rationalizing economic expectations of individuals, thereby enabling them to make more informed and accurate economic decisions.

We contribute to a third and rapidly growing literature related to the economic con-

is on compliance. The two studies developed independently.

sequences of the spread of COVID-19. Some of the papers in this literature document the effect of COVID-19 on economic anxiety (Fetzer et al., 2020), perception about growth path of GDP (Dietrich et al., 2020), risk-taking behavior among Chinese survey respondents (Bu et al., 2020), consumer spending (Andersen et al., 2020; Cox et al., 2020), and the labor market (Adams-Prassl et al., 2020; Bick et al., 2020). Other studies investigate the effect of lockdowns and FED's interest rate response to COVID-19 on household beliefs about macroeconomic outcomes (Coibion et al., 2020; Binder, 2020). We contribute to this literature by providing persuasive evidence that EGB, in the context of a contagion spread, is a significant driver of miscalibrated macroeconomic expectations. Overall, we believe our paper makes important contributions to the emerging field of behavioral-health economics.

The rest of the paper is organized as follows: Section 2 lays out the experimental design and procedure. Section 3 presents the main results, and Section 4 concludes.

# 2 Experimental Design

We use actual data on the number of reported COVID-19 positive cases from the US over 35 days for this experiment. However, the participants are told that the number of cases corresponds to an unnamed but real country, W, to control for confounding effects associated with prior knowledge, perceptions about the local context, et cetera. We start by describing the **Baseline** treatment and then proceed to the four behavioral interventions designed to reduce bias.

### Baseline

We show participants data points on the number of cases for Day 0 (corresponds to 07/03/2020), Day 5, and Day 10. The numbers are 338, 1312, and 4661, respectively. Based on the information provided, participants make some decisions in the following two stages - the **prediction stage** and the **investment stage**. In the prediction stage, the participants predict the number of cases for Day 35. The prediction task is accuracy rewarding, i.e., if the prediction is within 5% of the actual number, then the participant receives a bonus of $0.50. Subsequently, they enter the investment stage, where we give them an initial endowment of $0.50, out of which they can invest any amount in a risky prospect. The returns to the prospect are determined by the actual performance on Day 35 (relative to Day 10) of the leading stock market of country W.[7] Following the investment stage, the participants respond to a survey on economic expectations and demographic information. In addition to the incentive described above, each participant receives an amount of $0.55 as participation fee.

We denote the actual and predicted number of cases for Day $i$ by $N_i$ and $P_i$, respectively, for $i \in \{0, 5, 10, 15, 20, 25, 30, 35\}$. $Bias_{35,10}$ is the difference between $N_{35}$ and $P_{35}$, relative to the difference between $N_{35}$ and $N_{10}$, i.e., $Bias_{35,10} = \frac{N_{35}-P_{35}}{N_{35}-N_{10}}$. Intuitively, it is the prediction error for Day 35 relative to the maximum possible error on Day 35.

**Step**

Instead of asking participants to predict the number of COVID-19 cases straightaway for Day 35, we ask them to predict the number of cases in smaller steps. In particular, after seeing $N_0$, $N_5$, and $N_{10}$, participants predict $P_{15}$, $P_{20}$, $P_{25}$, $P_{30}$, and then, $P_{35}$. In the investment stage, we give the participants $0.50 at the start of each Day, from which they can invest any amount in a risky project. The returns to the investment made on Day $i$ are calculated by the actual performance on Day $i + 5$ of the same stock market as in the Baseline. In all, there are 5 prediction stages and 4 investment stages. The comparison of $Bias_{35,10}$ between Step and Baseline tells us whether letting people predict in smaller steps helps in decreasing EGB. Besides $Bias_{35,10}$, the treatment design allows us to compute EGB for each Day that prediction is made, with respect to the previous

[7] The real stock market data are taken from the NASDAQ composite index, and the actual returns are calculated based on the movement of the index over the same period over which the predictions are made.

Day. For example, $Bias_{35,30} = \frac{N_{35}-P_{35}}{N_{35}-N_{30}}$. Similarly, we obtain $Bias_{30,25}$, $Bias_{25,20}$, $Bias_{20,15}$, $Bias_{15,10}$ and compute the average of these as $AverageBias$. Since the biases cumulate over each Day, intuitively, $Bias_{35,10}$ captures the total bias, whereas $AverageBias$ represents the average bias for a Day. Our subsequent treatments build on Step, and as a result, this treatment serves as a second baseline treatment with which the following treatments are compared.

**Feedback**

In the Feedback treatments, we build a feedback mechanism on top of the Step treatment, where participants are given feedback about the prediction errors after they make their predictions. Participants are shown $N_0$, $N_5$, and $N_{10}$, following which they move on to the prediction and investment stage for Day 15. Before proceeding to the prediction stage for Day 20, they are shown $N_{15}$ and the corresponding prediction error. Participants receive feedback in the other prediction stages as well. We introduce two variations in the visual presentation of the feedback. In the **Feedback-Number** treatment (Feedback-N, henceforth), the information about the actual number of cases and the prediction error is given in the form of raw numbers. In the **Feedback-Graph** treatment (Feedback-G, henceforth), the same information is provided in the form of graphs. An example of the kind of graphs used can be found on Screen 8 in the experimental instructions (for Feedback-G) (Appendix C). The investment stages are the same as in Step. The Feedback-N and Feedback-G treatments allow us to compare $Bias_{35,10}$ with respect to the baseline and $Bias_{35,10}$, and $AverageBias$ with respect to the Step treatment.

**Forecast**

For the forecast treatment, we fit an exponential model based on the actual data using curve fitting techniques and obtain forecasts about the number of cases for each Day. We offer participants the 90% confidence interval associated with the forecast for Day 15 after they are shown $N_0$, $N_5$, and $N_{10}$. They are told that, according to a simple mathematical model, which best approximates the data, there is 90% chance of the actual number lying within the range. Forecast bounds are shown in all the prediction stages. The investment stage is the same as in Step. Once again, the design of Forecast allows us to compare $Bias_{35,10}$ with Baseline and Step and *AverageBias* with Step.

Notice, though we did not reveal the name of the country and period from which the data was obtained for reasons stated earlier, the predictions may still be colored by other factors such as overconfidence. In that case, the prediction error may arise, not from EGB, but from subjective perceptions of the future, plausibly led by beliefs about the discovery of a vaccine or the improvement in administrative efficiency due to richer information, and improved learning. To address such confound(s), we design the sixth treatment, *Series*, where participants undertake prediction tasks based on numbers that follow a well-defined mathematical formula of the form $Ak^{t-1}$, where $t \in \{1, 2, 3, 4, 5, 6, 7, 8\}$. $A$, in our case, is trivially chosen to give us $N_0$, while $k$ is obtained by minimizing the squared deviation from the actual number of cases. Finally, the formula that generates the numbers in Series turns out to be $350 \times 2.87^{t-1}$. Like in Step, participants are shown the first three numbers of the geometric progression series and asked to predict the next five numbers. Each prediction stage is succeeded by an investment stage. The Series treatment is neutrally framed and free of any reference to COVID-19. Therefore, this allows us to measure EGB, free from confounds such as those discussed above. Nevertheless, $\{N_i\}_{i=0}^{35}$ in *Step* is isomorphic to the GP-series in *Series*. A comparison of the predictions in the two treatments permits us to confirm if our prediction error is indeed EGB. The experimental design is summarized in Table A1.

### Outcomes

We capture EGB through *AverageBias* and $Bias_{35,10}$. The investments made in the investment stages constitute our second outcome variable. In Baseline, there is only one investment stage, where investment is made on Day 10, returns of which is realized on Day 35 ($Invest_{35}$). In the other treatments, the investment made on Day $i-5$, the return for which is expected on Day $i$, is denoted by $Invest_i$. The relevant investment variables are $Invest_{20}$, $Invest_{25}$, $Invest_{30}$, and $Invest_{35}$. At the end of the experiment, participants respond to a survey, the questions of which are combined to obtain the following measures of economic expectations: $CSI$, $FEI$, $GrUn_6$, $UnIn_6$, $GrUn_{12}$, and $TimeJob$. $CSI$ and $FEI$ are standard measures used by the Indian central bank (RBI) to capture consumer confidence: $CSI$ captures the perception of the current situation relative to one year ago, while $FEI$ captures expectations one year ahead. An index value of over (below) 100 indicates an optimistic (pessimistic) outlook. $GrUn_6$ and $GrUn_{12}$ quantify the confidence in the recovery of the growth, and unemployment rates to their pre-COVID values within 6 months and 12 months, respectively. $IncJob_6$ indicates the perceived likelihood of a reduction in family income or loss of job within the next 6 months. Finally, $TimeJob$ measures expectations about the number of months it will take to find a comparable job in case of job loss. These six metrics, collectively, allow us to assess expectations related to the macroeconomy and personal economic circumstances. The detailed survey instrument is provided in Appendix C, and the variable definitions are given in Table A2.

The experiment was conducted on Amazon-MTurk with a participant pool from India, through the web-based experimental platform oTree (Chen et al., 2016). MTurk is a widely used platform for experimental research (Bordalo et al., 2019; Cavallo, 2017; D'Acunto, 2015; Dellavigna and Pope, 2018). Recent evidence suggests that the quality of answers on MTurk is highly similar to those obtained in lab experiments. For example, Coppock (2019) conducts 15 replication experiments to show that results from MTurk's convenience sample are similar to those from nationally representative surveys. Besides being a valid platform for collecting experimental data, MTurk also provides a safe and quick way in which a large number of participants from different parts of the country can be reached during a pandemic.

# 3 Results

Figure 1(A) demonstrates our first result. The figure plots the actual number of reported cases and mean predictions, separately for the five treatments. There is a substantial gap between the actual and the predicted number of cases, particularly in Baseline and Step. For instance, $N_{35}$ is 556676, while mean $P_{35}$ for Baseline, Step, Feedback-N, Feedback-G, and Forecast treatments are 33325, 118844, 495668, 500233, and 480460, respectively. Likewise, there is a distinct difference between $N_i$ and $P_i$ for $i \in \{15, 20, 25, 30\}$, which diminishes in Feedback-N, Feedback-G, and Forecast. We normalize the differences as described in Section 2 to obtain $Bias_{35,10}$ and $AverageBias$, which are analyzed below.

Figures 1(B) and 1(C) plot the mean of $Bias_{35,10}$ and $AverageBias$ for each treatment, respectively. We test if they are statistically different from 0. $Bias_{35,10}$ is 0.94 for Baseline and 0.77 for Step ($t - tests$, $p - value < 0.01$, for both). This means that participants under-predict the actual number of cases on Day 35 by 94 and 77 percent, respectively. However, $Bias_{35,10}$ is not significantly different from 0 for Feedback-N, Feedback-G, and Forecast. $AverageBias$, too, is positive and significant for Step ($t - test, p - value < 0.01$). It continues to be positive and significant but quantitatively smaller for the other treatment groups. Thus, our first main result is the following:

**Result 1.** *Participants exhibit significant levels of EGB in the Baseline and Step treatments, but not in the Feedback and Forecast treatments.*

Next, we turn to the economic implications of EGB. In this paper, we focus on two outcomes – investment and economic expectations, which we regress on the appropriate measures of EGB.[8] Table A3 in Appendix A shows that EGB is a positive predictor of $Invest_{35}$, $CSI$, $FEI$, $GrUn_6$, and $GrUn_{12}$. On the whole, individuals with higher EGB are more likely to have positive economic expectations and invest more in risky assets. Notwithstanding this robust association between EGB on one hand and investment and

[8]In the analysis that follows we use the appropriate definitions of EGB, according to the context. When the outcome is $Invest_{35}$ ($Invest/EconomicExpectation$), we use $Bias_{35,10}$ ($Bias/AverageBias$) as EGB.

economic expectations on the other, the regression coefficients are likely to be biased because of endogeneity, and therefore, the important question is whether EGB causally affects the outcome variables. We address this question later.

We document two facts till now: first, we show that participants in our sample demonstrate EGB, and two, EGB is robustly associated with investment and economic expectations. We next turn to whether our policy interventions can help reduce EGB. To test the effectiveness with respect to Baseline and Step, we regress $Bias_{35,10}$ and $Bias$ on the treatment dummies, controlling for the following variables: $Income$, $Education$, $Health$, $ContainmentZone$, $RiskPreference$, $Female$, $Age$, $Caste$, and $Religion$.[9] The standard errors are clustered at the individual level, and the $p-values$ are corrected for multiple hypotheses using the approach described in Young (2019).[10] Figure 2(A) plots the treatment effects of Step, Feedback-N, Feedback-G, and Forecast on $Bias_{35,10}$, relative to Baseline. The coefficients are negative and significant at the 1% level, indicating that $Bias_{35,10}$ significantly decreases in all the four treatments relative to Baseline. In Figure 2(B), we illustrate the treatment effects of Feedback-N, Feedback-G, and Forecast on $Bias_{35,10}$ and $Bias$, relative to Step. In the models that analyze $Bias$ across treatments, we run a pooled OLS regression, with standard errors clustered at the individual level.[11] Relative to Step, $Bias_{35,10}$ decreases by 0.743, 0.755, and 0.671, whereas $Bias$ decreases by 1.104, 1.114, and 0.966 in Feedback-N, Feedback-G, and Forecast, respectively. The coefficients are significant at 1% level. However, there are no significant differences in the treatment effects of Feedback-N, Feedback-G, and Forecast on EGB. We report the regression coefficients for each of the above treatment comparisons in Table A4. Our second main result is :

**Result 2.** *EGB is significantly lower in the Step, Feedback and Forecast treatments relative to Baseline. EGB is significantly lower in the Feedback and Forecast treatments relative to Step.*

[9] $RiskPreference$ is measured using a survey question which has been experimentally validated by Dohmen et al. (2011)

[10] Appendix B presents a detailed note on multiple hypotheses correction. For the variable definitions, see Table A2. All the analyses use this basic empirical specification.

[11] We pool $Bias_{15}$, $Bias_{20}$, $Bias_{25}$, $Bias_{30}$, and $Bias_{35}$ observed on each of the days together to obtain the dependent variable $Bias$. Additionally, the models control for Day.

We now examine the impact of Feedback-N, Feedback-G, and Forecast on the participants' investment decision. Figure 2(C) presents the treatment effects of Step, Feedback-N, Feedback-G, and Forecast on $Invest_{35}$, relative to Baseline. The negative coefficients indicate that participants in the Step, Feedback-N, Feedback-G, and Forecast treatments, invest significantly less relative to those in Baseline. In Figure 2(D), we compare the treatment effects of Feedback-N, Feedback-G, and Forecast on $Invest_{35}$ and $Invest$, with respect to Step.[12] We find that the treatment effect on both Invest and $Invest_{35}$ are negative when Feedback-N, Feedback-G, and Forecast treatments are compared with Step. These results are also reported in Table A5. Overall, our interventions, aimed at reducing EGB, also discourage risky investments.

**Result 3.** *Investment is significantly lower in the Step, Feedback, and Forecast treatments relative to Baseline treatments. Investment is significantly lower in the Feedback and Forecast treatments relative to Step.*

Do our interventions have a dampening effect on economic expectations as well? $CSI$, which has a value of 98.94 in the Baseline (see Table A2), decreases in the Step, Feedback-N, Feedback-G, and Forecast. In Figure 3(A), we see that the effects of the first two treatments are small and significant at the 10% level, that of the last two are significant at the 1% level and 5% level, respectively. However, the treatments do not decrease $CSI$ with respect to Step. Overall, our treatments do not have large effects on CSI, and not surprisingly, since $CSI$ measures current outlook and treatments are primarily expected to correct future perceptions. Participants in Baseline, as observed from Table A2, are optimistic about the future relative to the present, with the mean $FEI$ being 100.88. Figure 3(B) shows that in Step, Feedback-N, Feedback-G, and Forecast, $FEI$ is significantly less than in Baseline. The treatment effects are significant at the 1% level. $FEI$ is also less in Feedback-N, Feedback-G, and Forecast treatments compared to Step. These ef-

[12] As in the case of $Bias$, $Invest$ is obtained by pooling $Invest_{20}$, $Invest_{25}$, $Invest_{30}$, and $Invest_{35}$ together. We compare $Invest$ across treatments in Figure 2(D) by running a pooled OLS regressions, with control variables including Day and standard errors clustered at the individual level.

fects are smaller than that when compared with Baseline but are significant at the 1% level. Likewise, the treatments reduce $GrUn_6$ relative to Baseline and Step (except when Feedback-N is compared with Step). The results are similar for $GrUn_{12}$. These indicate that participants in the treatment conditions have lower confidence that growth and unemployment will go back to the pre-COVID levels in 6 or 12 months. Feedback-N and Forecast also increase the perceived likelihood of one's family losing income or job in 6 months ($IncJob_6$), vis-à-vis Step, and Baseline. The estimated number of months needed to get a job in 6 months or $TimeJob$ increases in all the treatments, when compared to the Baseline. When compared to Step, the increase in $TimeJob$ is seen only in Feedback-N. We also report these regression results in Tables A6 to A11. The results offer compelling evidence that our treatments Feedback-N, Feedback-G, and Forecast moderate economic expectations.

**Result 4.** *Economic expectations about the future are lower in the Step, Feedback, and Forecast treatments relative to Baseline. The effects persist but are smaller when Feedback and Forecast treatments are compared to Step.*

What is the mechanism through which the interventions reduce risky investments and alter future economic expectations? We propose the following causal mechanism through which Step, Feedback-N, Feedback-G, and Forecast affect the outcome variables: the exogenous treatment causally decreases EGB with respect to Baseline, which in turn changes the investment decisions and economic expectations. Table 1 reports the two-stage least-square estimates of the effect of $Bias_{35,10}$ on $Invest_{35}$ and economic expectations, using the treatment Step as an IV. Is the treatment a valid IV? Participants are randomly assigned to either Step or Baseline, thus making the treatment assignment exogenous by definition. The treatment is correlated with EGB, as is clear from Figure 2(A). Column (1) in Table 1 reports the first stage: the negative and significant coefficient corresponding to Step implies that Step reduces $Bias_{35,10}$ significantly relative to Baseline. The first-stage relationship is strong; however, the exclusion restriction requires that Step does not affect the outcome variables through mechanisms other than $Bias_{35,10}$. Note, the difference between Baseline and Step is only in the intermediate steps through which one predicts the number of cases on Day 35. Just introducing a procedural change in the form of intermediate steps should not have any effect on psychological or other factors, other than EGB. Thus, in our view, the exclusion restriction holds and that the treatment affects $Invest_{35}$ or economic expectations only through its effect on $Bias_{35,10}$. Column (2) in Table 1 suggests that a 0.1 unit increase in $Bias_{35,10}$ causes increase in $Invest_{35}$ by \$0.08. Similarly, Columns (3) - (8) in Table 1 offer the IV estimates of the effect of $Bias_{35,10}$ on economic expectations. The IV estimates are significant at 1% level for all the indicators of economic expectations except $IncJob_6$ (which is significant at the 5 % level). Table A12 presents the IV estimates of EGB on investment and economic expectations with the other treatments as instruments and Baseline as the comparison group. Table A13 does the same with Step as comparison. The above analysis offers causal evidence that our interventions help rationalize investments and economic expectations through their effect on EGB. Clearly, the salience of the severity of the COVID-19 pandemic makes the participants adjust their expectations.

**Result 5.** *The mechanism through which the interventions affect economic expectations is the following: the treatments decrease EGB, which then decreases investments and moderates economic expectations.*

Can the prediction error be attributed to biases other than EGB, such as overconfidence? A comparison between the predicted number of cases in Step, framed in terms of COVID-19, and the neutrally framed Series helps answer the question. Notice, the sequence of numbers in Series is generated from a function which closely approximates the COVID-19 data points in Step. We test for equality of predictions made in Step and Series for each of the five days in Table A14 and find no significant difference. This indicates that the prediction error in Step (and Baseline) treatment does indeed identify EGB.

# 4 Discussion and Conclusion

In this paper, we use an incentivized lab experiment to investigate the relationship between exponential growth bias (EGB) - the human tendency to linearize exponential data - in the context of COVID-19 spread and economic expectations. First, we document robust evidence of EGB in the context of predicting the number of cases in the future. Second, we show that EGB is causally associated with a more optimistic expectation about the economy. Third, we design four minimally invasive behavioral interventions, which successfully decrease EGB and help rationalize economic expectations. Fourth, we identify a precise causal mechanism between EGB and macroeconomic expectations.

Our results show that EGB can be corrected using simple, behaviorally informed policy tools. This finding is in contrast to past studies that acknowledge the difficulty in correcting EGB (Wagenaar and Timmers, 1979; Levy and Tasoff, 2016; Christandl and Fetchenhauer, 2009; Levy and Tasoff, 2017). The Feedback treatments suggest that a policymaker should make the errors that people make in predicting the future number of cases salient. If the King was given feedback about his prediction error in the first few squares, perhaps he could have guessed what the true value of the reward he was about to grant. Forecast treatment is even more policy-relevant. Governments usually have health experts and epidemiologists at their disposal, who can deploy appropriate mathematical models to forecast the growth path of diseases such as COVID-19. Our study shows that public campaign about the possible trajectory of such diseases may go a long way in reducing EGB. Such forecasts can play the role of an anchor or focal point, around which people's perceptions about the future number of cases, and therefore, economic expectations are formed. Interestingly, the more policy-relevant treatments, namely, Feedback-N, Feedback-G, and Forecast are successful in eliminating EGB. Our preferred interpretation of why these treatments are successful in eliminating EGB is that unlike in past studies (for example, Lammers et al. (2020)), our design offers multiple corrective opportunities, either in the form of feedback or forecast. We do not find any significant difference in the

EGB between the feedback and forecast treatments – a result which runs contrary to other findings in the literature (Blunden et al., 2019). Our interventions decrease EGB and consequently rationalize economic expectations. An important corollary emerges from this paper – sentiment indices, widely followed by popular press, are largely taken as articles of faith, particularly by the private corporate sector. Our study finds that such indices are prejudiced by behavioral biases such as EGB. Failure to account for such biases in surveys aimed at capturing consumers' 'confidence' or 'sentiment' may have little predictive value about the future real economy.

It is important to note that while we study EGB in the context of prediction of the future number of COVID-19 cases, the conclusions we draw are relevant for numerous other contexts, where the underlying data generating process is exponential. For instance, urban planning for the future may be suboptimal in the presence of exponential population growth; loan repayment plans may go haywire if the debt growth is incorrectly estimated; transition to renewable energy may be slower if the growth path of non-renewable energy usage and climate change are not accurately perceived. Our research points to behavioral policy interventions that can mitigate EGB in these cases as well and lead to optimal economic decisions.

Finally, a caveat: in this paper, we assume that inaccurate macroeconomic expectations (relative to those who correctly perceive the number of COVID-19 cases) are welfare decreasing. While showing the welfare consequences of incorrect belief is beyond the scope of our paper, for that, we rely on the evidence from past literature. For example, Beaudry and Willems (2018) show that overly-optimistic growth expectations for a country induce economic contractions in the future through excessive debt accumulation. Other papers have shown that flawed expectations can lead to business cycles (Mian et al., 2017), over-optimistic firms suffer welfare losses through misallocation (Bachmann and Elstner, 2015) and are more highly leveraged (Jochem and Peters, 2015). The interpretations of our findings are simply predicated on this literature.

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# 5 Figures and Tables

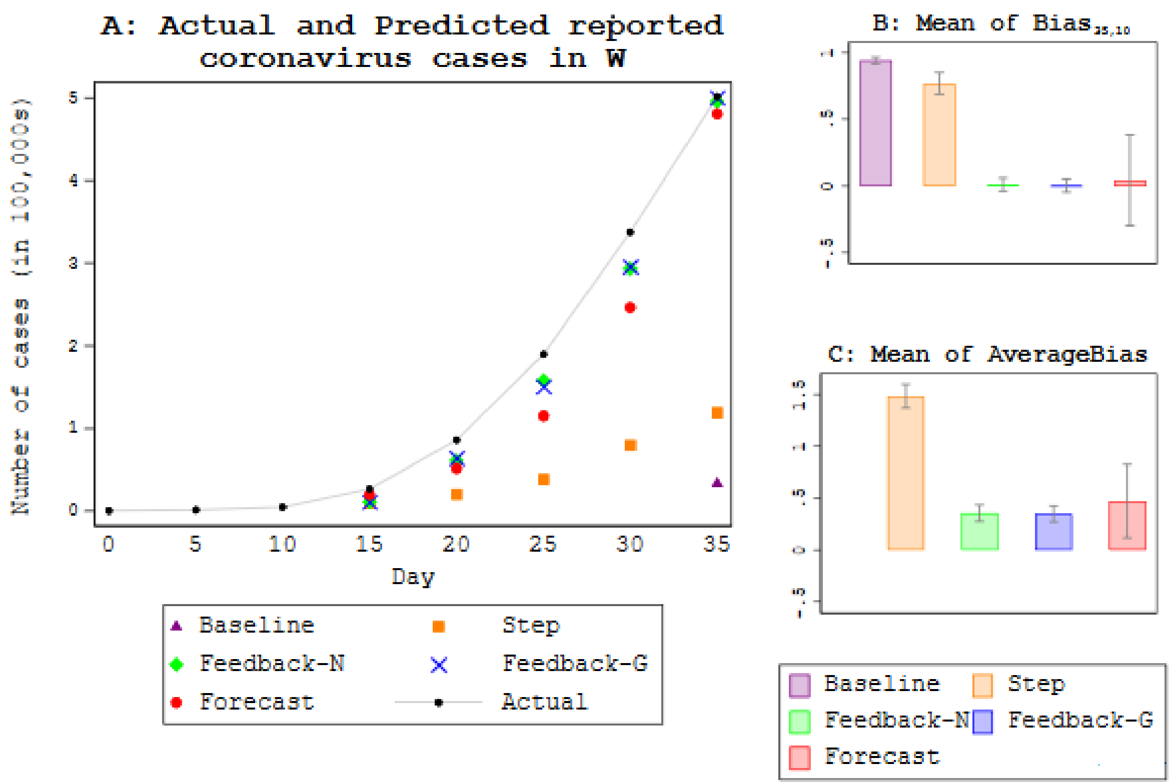


*Figure 1: Prediction Bias*

*Note: Panel A plots the actual number and mean predicted number of coronavirus cases. Panel B and Panel C reports the mean of $Bias_{35,10}$ and AverageBias, respectively. Each error bar represents the 95% confidence interval from the one-sample t-test for the hypothesis that bias is zero.*

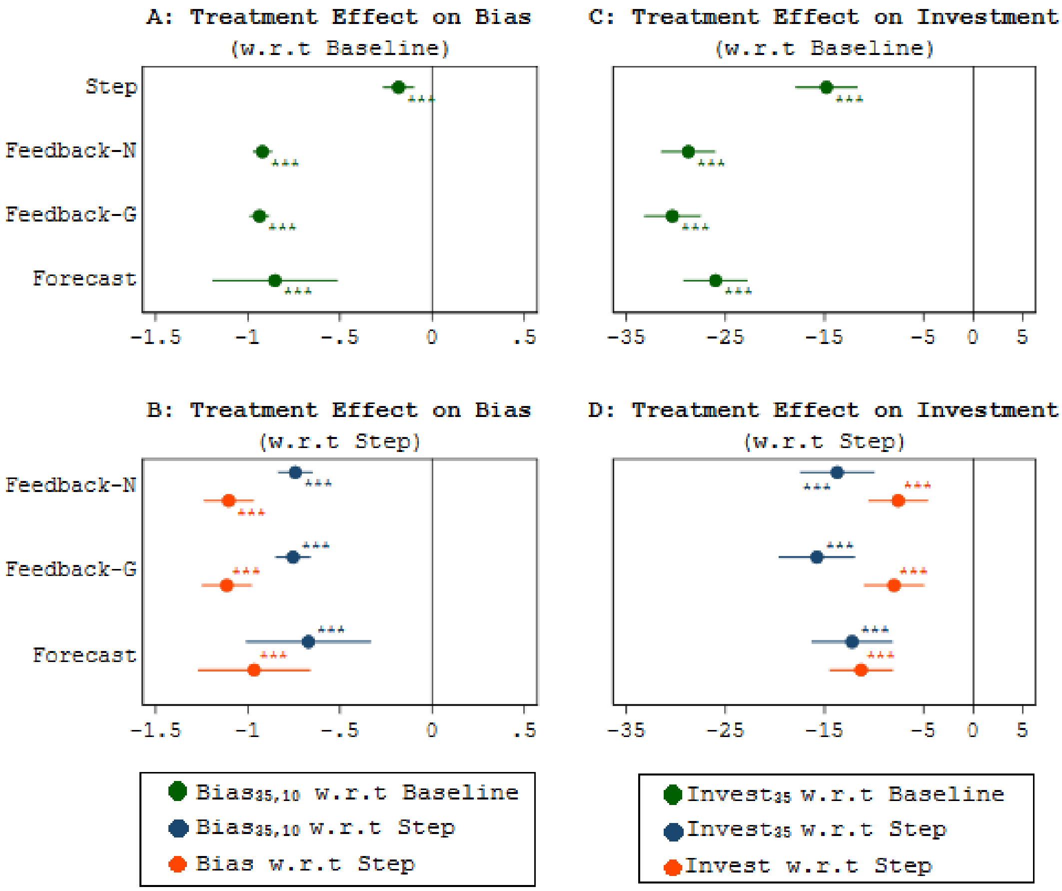


*Figure 2: Treatment Effect on Bias and Investment*

*Note: The figure plots the treatment effect size of EGB and investment. Panel A (C) shows the coefficients of treatment dummies regressed on $Bias_{35,10}$ ($Invest_{35}$), with Baseline as reference. Panel B shows the OLS (pooled OLS) estimates of the effect of Feedback-N, Feedback-G, and Forecast on $Bias_{35,10}$ (Bias), with respect to Step. Panel D shows the OLS (pooled OLS) estimates of the effect of Feedback-N, Feedback-G, and Forecast on $Invest_{35}$ (Invest), with respect to Step. OLS regressions control for Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. Pooled OLS regressions additionally controls for Day and cluster standard errors on individuals. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

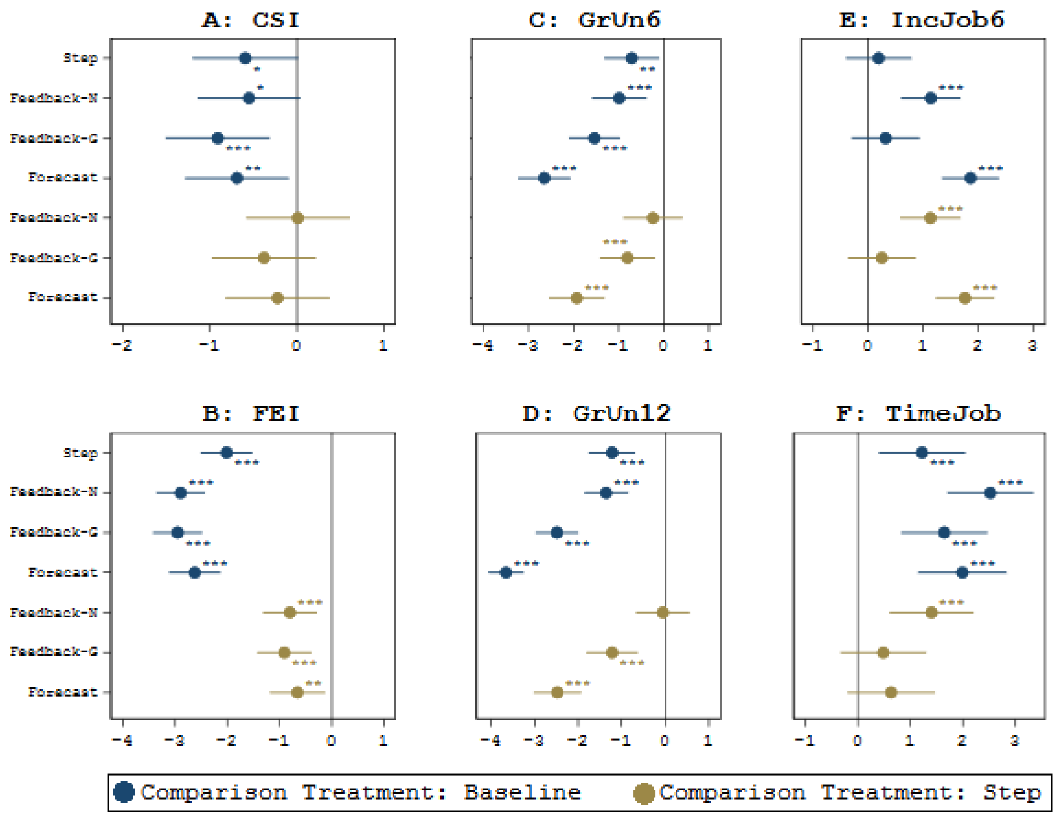


*Figure 3: Treatment Effect on Economic Outlook*

*Note: Panels A, B, C, D, E and F plot the OLS estimates of the treatment effect size on CI, FEI, $GrUn_6$, $GrUn_{12}$, $IncJob_6$, and TimeJob. Each panel shows the treatment effect of Step, Feedback-N, Feedback-G, and Forecast from Baseline in the upper half and of Feedback-N, Feedback-G, and Forecast from Step in the lower half. All specifications include controls for Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * p<0.10, ** p<0.05, *** p<0.01*

*Table 1: Bias, Investment and Economic Outlook (2SLS)*

| | First Stage | Second Stage | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLES | **EGB** | **$\mathbf{Invest_{35}}$** | **CSI** | **FEI** | **$\mathbf{GrUn_6}$** | **$\mathbf{GrUn_{12}}$** | **$\mathbf{IncJob_6}$** | **TimeJob** |
| **Step** | -0.182*** | | | | | | | |
| | (0.0431) | | | | | | | |
| **$\widehat{\mathbf{EGB}}$** | | 81.26*** | 3.258*** | 11.05*** | 3.898*** | 6.708*** | -1.042** | -6.703*** |
| | | (19.19) | (1.760) | (2.858) | (1.762) | (1.992) | (1.671) | (2.797) |
| **Constant** | 0.831*** | -7.414 | 98.42*** | 92.71*** | 1.646 | -0.0581 | 4.921*** | 9.242*** |
| | (0.188) | (20.42) | (1.873) | (3.042) | (1.875) | (2.120) | (1.778) | (2.976) |
| Observations | 265 | 265 | 265 | 265 | 265 | 265 | 265 | 265 |
| Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Note: This table reports the first stage and second stage results from the 2SLS regression estimation of EGB ($Bias_{35,10}$) on investment and economic expectations. Column (1) reports the first stage OLS estimates from regression of EGB on the instrument variable Step. The fitted values obtained from the first stage, $\widehat{EGB}$, is regressed on $Invest_{35}$, CSI, FEI, $GrUn_6$, $GrUn_{12}$, $IncJob_6$ and TimeJob to obtain the second stage IV estimators in Columns (2) to (8). Observations are from Baseline and Step. All specifications control for Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

# A Appendix for Online Publication

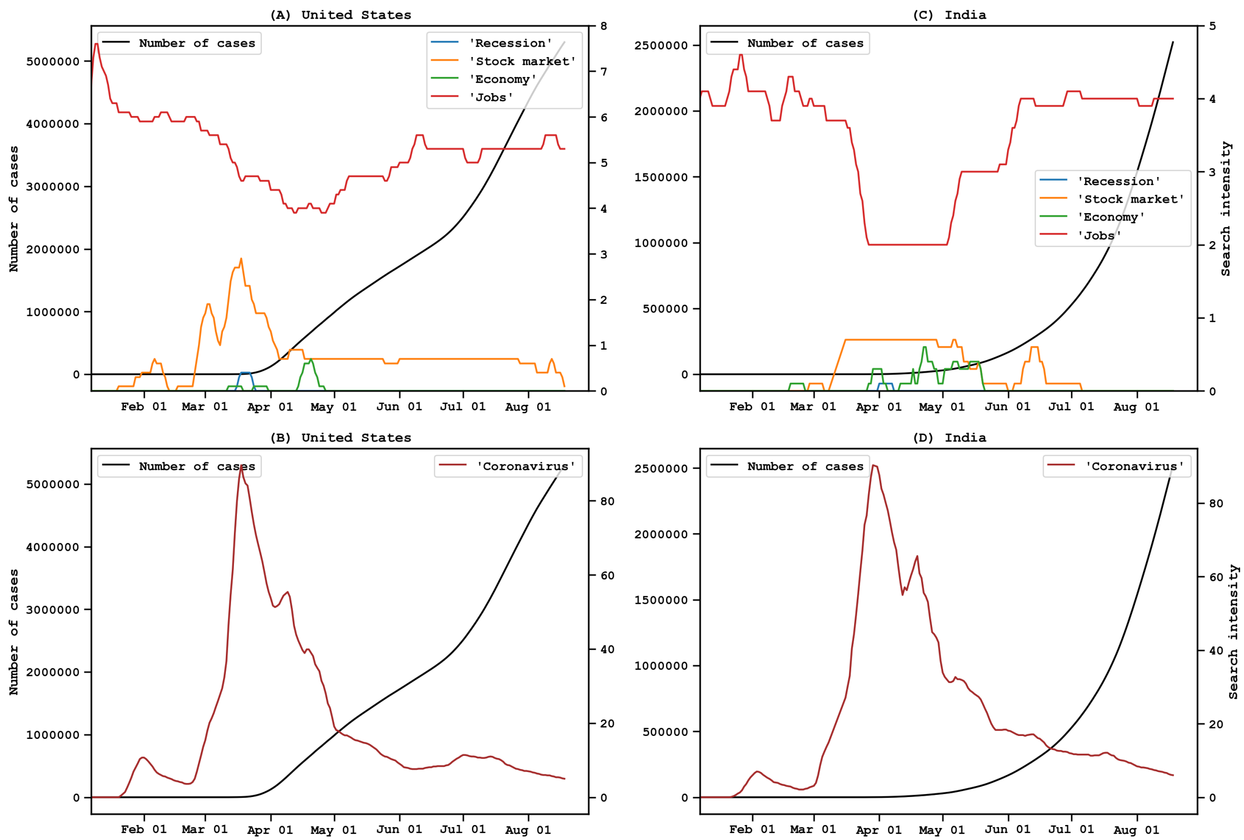


*Figure A.1: Growth of coronavirus, Google search intensity of coronavirus and economy*

*Note: Panel A (C) plots the seven-day moving average of search intensity of keywords 'Stock market', 'Economy', 'Recession' and 'Jobs' on the right y-axis and the seven-day moving average of the number of COVID-19 cases on the left y-axis for US (India). Panel B (D) plots the seven day moving average of search intensity of the keyword 'Coronavirus' on the right y-axis and the seven-day moving average of the number of COVID-19 cases on the left y-axis for the US (India).*

*Table A1: Experimental Design*

| | | | | | |
|---|---|---|---|---|---|
| **Part I: Experiment** | Country W is picked such that the participant is not from this country. Participant is shown number of reported cases in W on Day 0, Day 5, and Day 10 | | | | |
| **Between Subject Treatment** | **Baseline** | **Step** | **Feedback-N** | **Feedback-G** | **Forecast** |
| Prediction Stage 1 | Day 35 | Day 15 | Day 15 | Day 15 | Day 15 |
| Investment Stage 1 | Day 35 | Day 20 | Day 20 | Day 20 | Day 20 |
| Prediction Stage 2 | | Day 20 | Day 20 | Day 20 | Day 20 |
| Investment Stage 2 | | Day 25 | Day 25 | Day 25 | Day 25 |
| Prediction Stage 3 | | Day 25 | Day 25 | Day 25 | Day 25 |
| Investment Stage 3 | | Day 30 | Day 30 | Day 30 | Day 30 |
| Prediction Stage 4 | | Day 30 | Day 30 | Day 30 | Day 30 |
| Investment Stage 4 | | Day 35 | Day 35 | Day 35 | Day 35 |
| Prediction Stage 5 | | Day 35 | Day 35 | Day 35 | Day 35 |
| **Part II: Survey on Economic Expectations and Demographic Information** | Survey on expectation of macroeconomic conditions and own economic circumstances, and basic demographic information | | | | |

*The table summarizes the experimental design used in the paper. In each Prediction Stage, participants are asked to predict the number of reported cases in W for the day mentioned alongside. Feedback is presented in the form of number (graph) in Feedback-N (Feedback-G) on the prediction error of the previous Prediction Stage. Forecast shows the 90% confidence interval on forecasts in the Prediction Stage. In each Investment Stage, participants are asked to invest any amount from $0 to $0.50, returns of which are calculated on the basis of the stock market performance in W on the day mentioned alongside. Part II can be referred from Instructions (Survey) in Appendix C.*

*Table A2: Summary Statistics*

| Variable | Definition | Baseline | Step | Feedback-N | Feedback-G | Forecast |
|---|---|---|---|---|---|---|
| $Bias_{i,j}$ | Difference between actual and predicted number on Day $i$, relative to the change in actual number of COVID-19 cases between Day $i$ and Day $j$ $(= \frac{N_i - P_i}{N_i - N_j})$ , $i, j \in \{15, 20, 25, 30, 35\}$ | | | | | |
| $Invest_i$ | Investment made for return on Day $i$, $i \in \{20, 25, 30, 35\}$ | | | | | |
| **EGB Outcomes** | | | | | | |
| $Bias_{35,10}$ | $Bias_{i,j}$ for $i = 35$ and $j = 10$ | 0.94 | 0.77 | 0.01 | 0.00 | 0.04 |
| $AverageBias$ | $(Bias_{15,10} + Bias_{20,15} + Bias_{25,20} + Bias_{30,25} + Bias_{35,30})$ / 5 | | 1.48 | 0.36 | 0.35 | 0.47 |
| **Economic Outcomes** | | | | | | |
| $Invest_{35}$ | $Invest_i$ for $i = 35$ | 45.44 | 31.00 | 16.21 | 14.85 | 19.26 |
| $FEI$ | Future Expectation Index $(= 100 + Q11 + Q12 + Q13 + Q14 + Q15)$ | 100.88 | 98.90 | 97.98 | 97.81 | 98.21 |
| $CSI$ | Current Situation Index $(= 100 + Q6 + Q7 + Q8 + Q9 + Q10)$ | 98.94 | 98.45 | 98.29 | 97.88 | 98.31 |
| $GrUn_6$ | Confidence about recovery of growth and unemployment in 6 months $(= \frac{(Q4.a+Q5.a)}{2})$ | 5.98 | 5.35 | 4.84 | 4.31 | 3.34 |
| $GrUn_{12}$ | Confidence about recovery of growth and unemployment in 12 months $(= \frac{(Q4.b+Q5.b)}{2})$ | 7.09 | 5.88 | 5.62 | 4.52 | 3.42 |
| $IncJob_6$ | Likelihood of family losing income and employment in 6 months $(= \frac{(Q1+Q2)}{2})$ | 5.86 | 6.02 | 6.93 | 6.08 | 7.66 |
| $JobTime$ | Time (in months) needed to find a new job in case of a job loss $(= Q3)$ | 6.98 | 8.20 | 9.50 | 8.55 | 8.85 |
| **Demographics** | | | | | | |
| Income | Monthly income categories from 1-12 (1-less than Rs.10,000, 12- more than Rs.1,00,000) | 4.43 | 4.53 | 4.66 | 4.55 | 3.84 |
| Education | Highest educational achivement (1-Class X, 2- Class XII, 3- Bachelor, 4-Master, 5-Higher than masters) | 3.27 | 3.40 | 3.35 | 3.35 | 3.28 |
| Health | Health condition on a scale of 1-5 (1-Very Poor health, 5- Very good health) | 4.24 | 4.09 | 4.08 | 4.15 | 4.15 |
| ContainmentZone | Distance from containment zones in walking time (1-0 minutes, 2- less than 15 minutes, 3-15-30 minutes, 4- more than 30 minutes) | 1.78 | 1.67 | 1.73 | 1.69 | 1.39 |
| RiskPreference | Risk preference on a scale of 1-10 (1- not willing to take risks at all, 10- very willing to take risks) | 6.08 | 6.15 | 5.74 | 5.67 | 6.13 |
| Female | Proportion of females | 0.28 | 0.26 | 0.34 | 0.37 | 0.29 |
| Age | Age (in years) | 32.39 | 31.93 | 32.75 | 33.52 | 32.31 |
| Religion: Hindu | Proportion of Hindus | 0.78 | 0.76 | 0.79 | 0.76 | 0.80 |
| Caste: General | Proportion of General Castes | 0.45 | 0.43 | 0.42 | 0.52 | 0.49 |
| Caste: OBC | Proportion of Other Backward Castes | 0.46 | 0.44 | 0.46 | 0.43 | 0.42 |
| **Sample Size** | | 128 | 137 | 121 | 124 | 121 |

*The table reports summary statistics of the outcome and control variables used in the paper. The categories under Religion are Buddhists, Christians, Hindus and Muslims. The categories under Caste are General, Scheduled Castes, Scheduled Tribes and Other Backward Castes. In this table, only the proportions of Hindu, General, and OBC are reported. In the econometric analysis, Religion and Caste are used as control variables with all the categories. Q1 - Q15 can be referred from Instructions (Survey) in Appendix C.*

*Table A3: OLS estimates from regressing Investment and Economic Expectations on EGB*

| VARIABLES | (1) **Invest** | (2) **$\mathbf{Invest_{35}}$** | (3) **CSI** | (4) **FEI** | (5) **$\mathbf{GrUn_{6}}$** | (6) **$\mathbf{GrUn_{12}}$** | (7) **$\mathbf{IncJob_{6}}$** | (8) **TimeJob** |
|---|---|---|---|---|---|---|---|---|
| | | | | ***(A) Without Controls*** | | | | |
| **EGB** | 1.46 | 5.712*** | 0.293*** | 0.337*** | 0.485*** | 0.510*** | 0.0240 | 0.121 |
| | (0.743) | (0.722) | (0.0951) | (0.0883) | (0.104) | (0.0952) | (0.0899) | (0.127) |
| Constant | 37.72*** | 23.56*** | 98.16*** | 98.53*** | 4.432*** | 4.957*** | 6.469*** | 8.307*** |
| | (1.742) | (0.747) | (0.122) | (0.114) | (0.134) | (0.123) | (0.116) | (0.163) |
| **R-squared** | 0.042 | 0.091 | 0.015 | 0.023 | 0.034 | 0.044 | 0.000 | 0.001 |
| **Observations** | 2,140 | 631 | 631 | 631 | 631 | 631 | 631 | 631 |
| **Control** | No | No | No | No | No | No | No | No |
| **Day** | Yes | No | No | No | No | No | No | No |
| | | | | ***(B) With Controls*** | | | | |
| **EGB** | 1.346 | 5.573*** | 0.241*** | 0.295*** | 0.390*** | 0.436*** | -0.0197 | 0.0911 |
| | (0.686) | (0.716) | (0.0903) | (0.0862) | (0.0979) | (0.0924) | (0.0883) | (0.128) |
| Constant | 36.72*** | 22.27*** | 98.32*** | 97.53*** | 3.159*** | 3.686*** | 5.173*** | 7.087*** |
| | (5.762) | (6.369) | (0.875) | (0.836) | (0.949) | (0.896) | (0.857) | (1.242) |
| **R-squared** | 0.073 | 0.128 | 0.143 | 0.102 | 0.170 | 0.132 | 0.068 | 0.016 |
| **Observations** | 2,140 | 631 | 631 | 631 | 631 | 631 | 631 | 631 |
| **Control** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Day** | Yes | No | No | No | No | No | No | No |

*This table reports the results from OLS and pooled OLS regressions between EGB and the outcome variables. EGB is Bias for Column (1), $Bias_{35,10}$ for Column (2), and AverageBias for Columns (3) - (8). Column (1) reports coefficients from a pooled OLS regression, where Invest is regressed on Bias of all Days. Day is controlled and standard errors are clustered on individuals in Column (1). Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. Panel A does not include control variables, while Panel B does. The standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

*Table A4: Effect of Treatment on EGB*

| | (Comparison Treatment: Baseline) | | | | (Comparison Treatment: Step) | | | (Comparison Treatment: Step) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | $\mathbf{Bias_{35,10}}$ | | | | $\mathbf{Bias_{35,10}}$ | | | **Bias** | | |
| | (1) Step | (2) Feedback-N | (3) Feedback-G | (4) Forecast | (5) Feedback-N | (6) Feedback-G | (7) Forecast | (8) Feedback-N | (9) Feedback-G | (10) Forecast |
| **Treatment** | -0.182*** | -0.921*** | -0.936*** | -0.852*** | -0.743*** | -0.755*** | -0.671*** | -1.104*** | -1.114*** | -0.966*** |
| | (0.0431) | (0.0269) | (0.0275) | (0.173) | (0.0483) | (0.0481) | (0.173) | (0.0688) | (0.0688) | (0.155) |
| Income | -0.0135* | -0.00362 | -0.000366 | 0.0446 | -0.0172* | -0.0138 | 0.0233 | -0.0219 | -0.0167 | 0.0144 |
| | (0.00783) | (0.00507) | (0.00496) | (0.0325) | (0.00920) | (0.00896) | (0.0325) | (0.0154) | (0.0152) | (0.0396) |
| Education | 0.0448 | 0.00918 | 0.0187 | -0.159 | 0.0366 | 0.0493 | -0.108 | 0.0326 | 0.0315 | -0.150 |
| | (0.0354) | (0.0221) | (0.0227) | (0.158) | (0.0364) | (0.0368) | (0.143) | (0.0487) | (0.0489) | (0.117) |
| Health | -0.0358 | 0.0344* | 0.0445** | -0.0935 | -0.0312 | -0.0156 | -0.151 | -0.0144 | -0.0271 | -0.130 |
| | (0.0250) | (0.0179) | (0.0180) | (0.104) | (0.0291) | (0.0284) | (0.0966) | (0.0508) | (0.0463) | (0.0937) |
| Religion | -0.0245 | -0.00955 | -0.0159 | -0.134 | -0.0120 | -0.0366 | -0.123 | -0.0389 | -0.0353 | -0.110 |
| | (0.0273) | (0.0168) | (0.0175) | (0.118) | (0.0307) | (0.0314) | (0.117) | (0.0433) | (0.0433) | (0.0883) |
| Caste | 0.00529 | -0.00347 | -0.00455 | -0.0303 | 0.0131 | 0.00562 | -0.0121 | 0.0198 | 0.00698 | -0.0158 |
| | (0.0154) | (0.00956) | (0.00954) | (0.0604) | (0.0175) | (0.0174) | (0.0623) | (0.0222) | (0.0223) | (0.0538) |
| ContainmentZone | 0.0280 | 0.00879 | 0.0105 | 0.0868 | 0.0213 | 0.0236 | 0.120 | 0.0251 | 0.0557 | 0.126 |
| | (0.0215) | (0.0132) | (0.0132) | (0.0827) | (0.0243) | (0.0237) | (0.0854) | (0.0366) | (0.0371) | (0.0956) |
| RiskPreference | 0.0263*** | 0.00222 | 0.00263 | -0.0182 | 0.0301*** | 0.0343*** | 0.00359 | 0.0491*** | 0.0494*** | 0.0335 |
| | (0.00822) | (0.00502) | (0.00535) | (0.0330) | (0.00896) | (0.00964) | (0.0337) | (0.0172) | (0.0183) | (0.0355) |
| Female | 0.0824* | -0.00966 | 0.00217 | -0.133 | 0.0371 | 0.0774 | -0.0816 | 0.0942 | 0.113* | -0.0835 |
| | (0.0484) | (0.0293) | (0.0295) | (0.191) | (0.0532) | (0.0521) | (0.192) | (0.0651) | (0.0662) | (0.193) |
| Age | -9.43e-05 | -0.00456** | -0.00104 | 0.000531 | -0.00246 | -9.49e-05 | 0.000425 | -0.00448 | -0.00335 | -0.00326 |
| | (0.00260) | (0.00179) | (0.00150) | (0.0124) | (0.00277) | (0.00242) | (0.0106) | (0.00384) | (0.00330) | (0.00693) |
| Day | | | | | | | | 0.0261*** | 0.0253*** | 0.0369*** |
| | | | | | | | | (0.00472) | (0.00474) | (0.0128) |
| Constant | 0.831*** | 0.938*** | 0.747*** | 2.074** | 0.697*** | 0.542** | 1.783** | 0.704** | 0.685** | 1.570* |
| | (0.188) | (0.126) | (0.128) | (0.835) | (0.210) | (0.210) | (0.778) | (0.308) | (0.303) | (0.922) |
| Observations | 265 | 249 | 252 | 249 | 258 | 261 | 258 | 1,290 | 1,305 | 1,290 |
| R-squared | 0.128 | 0.838 | 0.835 | 0.129 | 0.526 | 0.532 | 0.090 | 0.358 | 0.360 | 0.073 |

*This table reports the results from OLS and pooled OLS regressions of EGB on treatments. Columns (1) - (4) report OLS estimates from regressing $Bias_{35,10}$ on Step, Feedback-N, Feedback-G and Forecast with respect to Baseline. Columns (5) - (7) report OLS estimates from regressing $Bias_{35,10}$ on Feedback-N, Feedback-G and Forecast with respect to Step. Columns (8) - (10) report the pooled OLS regression estimates of Bias on Feedback-N, Feedback-G and Forecast with respect to Step. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. Columns (8) - (10) additionally control for Day and cluster standard errors at the individual level. The standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * p<0.10, ** p<0.05, *** p<0.01*

*Table A5: Effect of Treatment on Investment*

| | ***(Comparison Treatment: Baseline)*** | | | | ***(Comparison Treatment: Step)*** | | | ***(Comparison Treatment: Step)*** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | **$\text{Invest}_{35}$** | | | | **$\text{Invest}_{35}$** | | | **Invest** | | |
| | (1) Step | (2) Feedback-N | (3) Feedback-G | (4) Forecast | (5) Feedback-N | (6) Feedback-G | (7) Forecast | (8) Feedback-N | (9) Feedback-G | (10) Forecast |
| **Treatment** | -14.80*** | -28.74*** | -30.35*** | -26.00*** | -13.71*** | -15.76*** | -12.21*** | -7.566*** | -7.975*** | -11.30*** |
| | (1.585) | (1.396) | (1.456) | (1.650) | (1.906) | (1.953) | (2.079) | (1.535) | (1.545) | (1.627) |
| Income | -0.0538 | 0.185 | -0.359 | -0.0527 | -0.109 | -0.607* | -0.230 | -0.0179 | -0.249 | 0.368 |
| | (0.288) | (0.263) | (0.263) | (0.311) | (0.363) | (0.364) | (0.392) | (0.308) | (0.285) | (0.321) |
| Education | -0.151 | 0.490 | -0.609 | -1.359 | 0.785 | -1.064 | -0.825 | 0.138 | -1.417 | -0.295 |
| | (1.302) | (1.145) | (1.205) | (1.511) | (1.437) | (1.496) | (1.724) | (1.143) | (1.205) | (1.284) |
| Health | -0.503 | 1.574* | 0.202 | 1.221 | 0.895 | -0.549 | 0.585 | 0.953 | 0.194 | 0.00952 |
| | (0.920) | (0.926) | (0.954) | (0.990) | (1.150) | (1.154) | (1.164) | (0.950) | (0.922) | (0.933) |
| Religion | -1.051 | 0.202 | 0.374 | 0.173 | -1.256 | -0.542 | -0.755 | -0.211 | -0.346 | 0.0255 |
| | (1.005) | (0.870) | (0.930) | (1.126) | (1.212) | (1.277) | (1.404) | (0.914) | (0.932) | (1.095) |
| Caste | -0.658 | 0.126 | -0.110 | -0.547 | -0.867 | -1.143 | -1.400* | -0.297 | -0.600 | -0.645 |
| | (0.568) | (0.495) | (0.506) | (0.578) | (0.692) | (0.708) | (0.750) | (0.537) | (0.546) | (0.575) |
| ContainmentZone | -0.415 | 0.704 | 1.499** | 0.463 | -0.736 | 0.118 | -0.894 | -0.591 | -0.483 | -0.465 |
| | (0.791) | (0.682) | (0.698) | (0.791) | (0.957) | (0.965) | (1.028) | (0.753) | (0.746) | (0.766) |
| RiskPreference | 0.341 | 0.562** | 0.490* | 0.446 | 0.896** | 0.882** | 0.723* | 0.762*** | 0.650** | 0.439 |
| | (0.303) | (0.260) | (0.284) | (0.316) | (0.354) | (0.392) | (0.406) | (0.292) | (0.328) | (0.349) |
| Female | 1.042 | -1.016 | 2.967* | 1.673 | -2.064 | 1.575 | 0.708 | -0.560 | 1.721 | 1.984 |
| | (1.783) | (1.516) | (1.564) | (1.823) | (2.101) | (2.120) | (2.307) | (1.675) | (1.700) | (1.821) |
| Age | -0.276*** | -0.0932 | -0.0299 | -0.151 | -0.294*** | -0.175* | -0.343*** | -0.241** | -0.182** | -0.310*** |
| | (0.0956) | (0.0930) | (0.0798) | (0.118) | (0.109) | (0.0983) | (0.127) | (0.0957) | (0.0837) | (0.110) |
| Day | | | | | | | | -0.680*** | -0.808*** | -0.264*** |
| | | | | | | | | (0.0741) | (0.0798) | (0.0776) |
| Constant | 60.08*** | 34.11*** | 41.91*** | 46.71*** | 36.21*** | 43.39*** | 45.69*** | 51.73*** | 63.84*** | 47.46*** |
| | (6.908) | (6.547) | (6.787) | (7.983) | (8.273) | (8.527) | (9.373) | (7.626) | (6.589) | (7.872) |
| Observations | 265 | 249 | 252 | 249 | 258 | 261 | 258 | 1,032 | 1,044 | 1,032 |
| R-squared | 0.286 | 0.663 | 0.660 | 0.536 | 0.259 | 0.255 | 0.183 | 0.157 | 0.157 | 0.147 |

*This table reports the results from OLS and pooled OLS regressions of investment on treatments. Columns (1) - (4) report OLS estimates from regressing* $\text{Invest}_{35}$ *on Step, Feedback-N, Feedback-G and Forecast with respect to Baseline. Columns (5) - (7) report OLS estimates from regressing* $\text{Invest}_{35}$ *on Feedback-N, Feedback-G and Forecast with respect to Step. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. Columns (8) - (10) report the pooled OLS regression estimates of Invest on Feedback-N, Feedback-G and Forecast with respect to Step. Columns (8) - (10) control for Day in addition to the above controls and cluster standard errors at the individual levels. The standard errors are reported in the parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

Table A6: *Effect of Treatment on Current Situation Index (CSI)*

| | ***(Comparison Treatment: Baseline)*** | | | | ***(Comparison Treatment: Step)*** | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | **CSI** | | | | | | |
| | (1) Step | (2) FeedbackN | (3) FeedbackG | (4) Forecast | (5) FeedbackN | (6) FeedbackG | (7) Forecast |
| **Treatment** | -0.593* | -0.552* | -0.909*** | -0.690** | 0.0128 | -0.378 | -0.222 |
| | (0.309) | (0.300) | (0.304) | (0.303) | (0.304) | (0.304) | (0.305) |
| Income | 0.0448 | 0.0246 | 0.00618 | -0.0525 | 0.0733 | 0.0264 | 0.0116 |
| | (0.0562) | (0.0563) | (0.0549) | (0.0570) | (0.0578) | (0.0567) | (0.0574) |
| Education | 0.140 | 0.292 | 0.237 | 0.283 | 0.0444 | -0.00404 | 0.0107 |
| | (0.254) | (0.246) | (0.252) | (0.277) | (0.229) | (0.233) | (0.253) |
| Health | 0.210 | 0.255 | -0.0125 | 0.503*** | 0.259 | 0.00931 | 0.335* |
| | (0.180) | (0.199) | (0.199) | (0.182) | (0.183) | (0.180) | (0.171) |
| Religion | -0.250 | -0.0875 | -0.100 | 0.211 | -0.274 | -0.200 | -0.00949 |
| | (0.196) | (0.187) | (0.194) | (0.206) | (0.193) | (0.199) | (0.206) |
| Caste | 0.0160 | 0.271** | 0.191* | -0.000554 | 0.126 | 0.0368 | -0.112 |
| | (0.111) | (0.106) | (0.106) | (0.106) | (0.110) | (0.110) | (0.110) |
| Containmentzone | -0.395** | -0.291** | -0.210 | -0.189 | -0.474*** | -0.343** | -0.301** |
| | (0.154) | (0.146) | (0.146) | (0.145) | (0.153) | (0.150) | (0.151) |
| RiskPreference | 0.0443 | 0.187*** | 0.191*** | 0.0418 | 0.127** | 0.112* | -0.00410 |
| | (0.0590) | (0.0557) | (0.0592) | (0.0579) | (0.0564) | (0.0610) | (0.0594) |
| Female | -0.190 | -0.150 | -0.0887 | 0.344 | -0.316 | -0.374 | 0.258 |
| | (0.348) | (0.325) | (0.327) | (0.334) | (0.335) | (0.330) | (0.338) |
| Age | -0.0807*** | -0.0896*** | -0.0782*** | -0.112*** | -0.0550*** | -0.0567*** | -0.0678*** |
| | (0.0186) | (0.0199) | (0.0167) | (0.0217) | (0.0174) | (0.0153) | (0.0186) |
| Constant | 101.1*** | 98.68*** | 99.76*** | 99.14*** | 99.15*** | 100.5*** | 99.92*** |
| | (1.348) | (1.405) | (1.417) | (1.464) | (1.318) | (1.326) | (1.373) |
| Observations | 265 | 249 | 252 | 249 | 258 | 261 | 258 |
| R-squared | 0.151 | 0.238 | 0.216 | 0.191 | 0.142 | 0.124 | 0.096 |

*This table shows the results from OLS regressions of CSI on the treatments. Columns (1) - (4) report OLS estimates from regressing CSI on Step, Feedback-N, Feedback-G and Forecast with respect to Baseline. Columns (5) - (7) report OLS estimates from regressing CSI on Feedback-N, Feedback-G and Forecast with respect to Step. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The robust standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

*Table A7: Effect of Treatment on FEI*

| | *(Comparison Treatment: Baseline)* | | | | *(Comparison Treatment: Step)* | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | **FEI** | | | | | | |
| | (1) Step | (2) FeedbackN | (3) FeedbackG | (4) Forecast | (5) FeedbackN | (6) FeedbackG | (7) Forecast |
| **Treatment** | -2.013*** | -2.892*** | -2.953*** | -2.624*** | -0.800*** | -0.910*** | -0.654** |
| | (0.251) | (0.236) | (0.242) | (0.250) | (0.264) | (0.265) | (0.269) |
| Income | 0.0675 | 0.0635 | 0.0911** | 0.0557 | 0.0902* | 0.117** | 0.102** |
| | (0.0456) | (0.0444) | (0.0436) | (0.0471) | (0.0502) | (0.0493) | (0.0507) |
| Education | -0.0904 | 0.101 | -0.0449 | -0.0428 | 0.122 | -0.0720 | 0.00354 |
| | (0.206) | (0.194) | (0.200) | (0.229) | (0.199) | (0.203) | (0.223) |
| Health | 0.0312 | -0.0796 | -0.209 | 0.255* | 0.186 | -0.0209 | 0.317** |
| | (0.146) | (0.157) | (0.158) | (0.150) | (0.159) | (0.156) | (0.151) |
| Religion | 0.0485 | 0.185 | 0.174 | 0.0580 | 0.0602 | 0.167 | -0.00851 |
| | (0.159) | (0.147) | (0.154) | (0.170) | (0.168) | (0.173) | (0.182) |
| Caste | -0.0148 | 0.0989 | 0.133 | -0.00809 | -0.0486 | 0.0263 | -0.0870 |
| | (0.0900) | (0.0837) | (0.0839) | (0.0875) | (0.0957) | (0.0959) | (0.0970) |
| Containmentzone | -0.196 | -0.165 | -0.0379 | -0.0267 | -0.312** | -0.178 | -0.180 |
| | (0.125) | (0.115) | (0.116) | (0.120) | (0.132) | (0.131) | (0.133) |
| RiskPreference | 0.0596 | 0.213*** | 0.149*** | 0.0491 | 0.154*** | 0.0667 | 0.00459 |
| | (0.0479) | (0.0439) | (0.0471) | (0.0478) | (0.0489) | (0.0531) | (0.0525) |
| Female | 0.0321 | 0.320 | -0.158 | -0.128 | -0.300 | -0.813*** | -0.680** |
| | (0.282) | (0.256) | (0.260) | (0.276) | (0.291) | (0.287) | (0.298) |
| Age | -0.0390** | -0.0295* | -0.0289** | -0.0303* | -0.0335** | -0.0332** | -0.0396** |
| | (0.0151) | (0.0157) | (0.0132) | (0.0179) | (0.0151) | (0.0133) | (0.0164) |
| Constant | 101.9*** | 99.72*** | 100.9*** | 100.3*** | 98.00*** | 99.36*** | 99.08*** |
| | (1.094) | (1.107) | (1.126) | (1.208) | (1.144) | (1.155) | (1.212) |
| Observations | 265 | 249 | 252 | 249 | 258 | 261 | 258 |
| R-squared | 0.243 | 0.458 | 0.445 | 0.357 | 0.172 | 0.158 | 0.116 |

*This table shows the results from OLS regressions of FEI on the treatments. Columns (1) - (4) report OLS estimates from regressing FEI on Step, Feedback-N, Feedback-G and Forecast, with respect to Baseline. Columns (5) - (7) report OLS estimates from regressing FEI on Feedback-N, Feedback-G and Forecast, with respect to Step. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The robust standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * p<0.10, ** p<0.05, *** p<0.01*

*Table A8: Effect of Treatment on $GrUn_6$*

| | *(Comparison Treatment: Baseline)* | | | | *(Comparison Treatment: Step)* | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | | | | $GrUn_6$ | | | |
| | (1) Step | (2) FeedbackN | (3) FeedbackG | (4) Forecast | (5) FeedbackN | (6) FeedbackG | (7) Forecast |
| Treatment | -0.710** | -0.985*** | -1.533*** | -2.653*** | -0.235 | -0.798** | -1.932*** |
| | (0.311) | (0.309) | (0.289) | (0.298) | (0.335) | (0.311) | (0.315) |
| Income | -0.0272 | 0.0452 | -0.0925* | -0.0310 | 0.000601 | -0.129** | -0.0692 |
| | (0.0565) | (0.0582) | (0.0522) | (0.0562) | (0.0638) | (0.0580) | (0.0593) |
| Education | 0.348 | -0.210 | 0.108 | -0.0962 | 0.125 | 0.329 | 0.287 |
| | (0.255) | (0.254) | (0.240) | (0.273) | (0.253) | (0.238) | (0.261) |
| Health | 0.303* | 0.264 | -0.106 | 0.453** | 0.324 | 0.0455 | 0.360** |
| | (0.181) | (0.205) | (0.190) | (0.179) | (0.202) | (0.184) | (0.176) |
| Religion | -0.318 | 0.0840 | -0.0279 | -0.129 | -0.305 | -0.355* | -0.608*** |
| | (0.197) | (0.193) | (0.185) | (0.203) | (0.213) | (0.203) | (0.212) |
| Caste | 0.157 | 0.340*** | 0.247** | 0.0989 | 0.195 | 0.0839 | 0.0496 |
| | (0.112) | (0.110) | (0.101) | (0.104) | (0.122) | (0.113) | (0.114) |
| Containmentzone | -0.129 | -0.202 | -0.140 | -0.0922 | -0.109 | -0.00141 | 0.0614 |
| | (0.155) | (0.151) | (0.139) | (0.143) | (0.168) | (0.154) | (0.156) |
| RiskPreference | 0.194*** | 0.350*** | 0.322*** | 0.128** | 0.343*** | 0.312*** | 0.159** |
| | (0.0593) | (0.0576) | (0.0563) | (0.0570) | (0.0622) | (0.0624) | (0.0614) |
| Female | 0.195 | 0.423 | 0.654** | 0.185 | -0.457 | -0.212 | -0.679* |
| | (0.350) | (0.336) | (0.311) | (0.329) | (0.369) | (0.338) | (0.349) |
| Age | -0.0538*** | -0.0777*** | -0.0408** | -0.0662*** | -0.0530*** | -0.0214 | -0.0327* |
| | (0.0187) | (0.0206) | (0.0159) | (0.0213) | (0.0192) | (0.0157) | (0.0192) |
| Constant | 4.883*** | 4.903*** | 5.375*** | 6.088*** | 3.782*** | 4.159*** | 4.804*** |
| | (1.355) | (1.451) | (1.349) | (1.442) | (1.454) | (1.359) | (1.418) |
| Observations | 265 | 249 | 252 | 249 | 258 | 261 | 258 |
| R-squared | 0.175 | 0.318 | 0.285 | 0.338 | 0.222 | 0.184 | 0.244 |

*This table reports the results from OLS regressions of $GrUn_6$ on the treatments. Columns (1) - (4) report OLS estimates from regressing $GrUn_6$ on Step, Feedback-N, Feedback-G and Forecast, with respect to Baseline. Columns (5) - (7) report OLS estimates from regressing $GrUn_6$ on Feedback-N, Feedback-G and Forecast, with respect to Step. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The robust standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

Table A9: Effect of Treatment on $GrUn_{12}$

| | *(Comparison Treatment: Baseline)* | | | | *(Comparison Treatment: Step)* | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | $GrUn_{12}$ | | | | | | |
| | (1) Step | (2) FeedbackN | (3) FeedbackG | (4) Forecast | (5) FeedbackN | (6) FeedbackG | (7) Forecast |
| **Treatment** | -1.221*** | -1.358*** | -2.487*** | -3.658*** | -0.0514 | -1.223*** | -2.473*** |
| | (0.270) | (0.257) | (0.249) | (0.206) | (0.316) | (0.302) | (0.278) |
| Income | 0.0672 | 0.0913* | -0.00499 | 0.0398 | -2.20e-05 | -0.0931* | -0.0320 |
| | (0.0491) | (0.0484) | (0.0450) | (0.0388) | (0.0601) | (0.0564) | (0.0523) |
| Education | 0.122 | -0.109 | -0.0207 | -0.0452 | -0.0264 | -0.0797 | -0.00237 |
| | (0.222) | (0.211) | (0.206) | (0.189) | (0.238) | (0.232) | (0.230) |
| Health | 0.275* | 0.251 | 0.0168 | 0.176 | 0.332* | 0.106 | 0.206 |
| | (0.157) | (0.171) | (0.163) | (0.124) | (0.190) | (0.179) | (0.155) |
| Religion | -0.0349 | 0.257 | -0.0295 | 0.0905 | -0.113 | -0.306 | -0.257 |
| | (0.171) | (0.160) | (0.159) | (0.141) | (0.201) | (0.198) | (0.187) |
| Caste | 0.0937 | 0.258*** | 0.111 | 0.0707 | 0.0758 | -0.0589 | 0.00249 |
| | (0.0970) | (0.0913) | (0.0866) | (0.0722) | (0.115) | (0.110) | (0.100) |
| Containmentzone | -0.0356 | 0.0246 | 0.136 | -0.0772 | -0.0327 | 0.0959 | -0.0746 |
| | (0.135) | (0.126) | (0.120) | (0.0988) | (0.158) | (0.149) | (0.137) |
| RiskPreference | 0.149*** | 0.284*** | 0.177*** | 0.106*** | 0.320*** | 0.227*** | 0.155*** |
| | (0.0516) | (0.0479) | (0.0486) | (0.0394) | (0.0586) | (0.0607) | (0.0542) |
| Female | 0.204 | 0.342 | 0.413 | 0.561** | -0.391 | -0.276 | -0.132 |
| | (0.304) | (0.279) | (0.268) | (0.228) | (0.348) | (0.328) | (0.308) |
| Age | -0.0411** | -0.0501*** | -0.0188 | -0.0443*** | -0.0396** | -0.0105 | -0.0276 |
| | (0.0163) | (0.0171) | (0.0137) | (0.0147) | (0.0181) | (0.0152) | (0.0170) |
| Constant | 5.513*** | 4.395*** | 6.084*** | 6.660*** | 4.170*** | 5.923*** | 5.931*** |
| | (1.178) | (1.207) | (1.162) | (0.997) | (1.370) | (1.320) | (1.252) |
| Observations | 265 | 249 | 252 | 249 | 258 | 261 | 258 |
| R-squared | 0.189 | 0.346 | 0.358 | 0.610 | 0.194 | 0.152 | 0.298 |

*This table shows the results from OLS regressions of $GrUn_{12}$ on the treatments. Columns (1) - (4) report OLS estimates from regressing $GrUn_{12}$ on Step, Feedback-N, Feedback-G and Forecast, with respect to Baseline. Columns (5) - (7) report OLS estimates from regressing $GrUn_{12}$ on Feedback-N, Feedback-G and Forecast, with respect to Step. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The robust standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

*Table A10: Effect of Treatment on $IncJob_6$*

| | (Comparison Treatment: Baseline) | | | | (Comparison Treatment: Step) | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | $\mathbf{IncJob_6}$ | | | | | | |
| | (1) Step | (2) FeedbackN | (3) FeedbackG | (4) Forecast | (5) FeedbackN | (6) FeedbackG | (7) Forecast |
| **Treatment** | 0.190 | 1.137*** | 0.316 | 1.856*** | 1.130*** | 0.249 | 1.756*** |
| | (0.304) | (0.276) | (0.314) | (0.263) | (0.280) | (0.313) | (0.271) |
| Income | -0.0109 | -0.00822 | -0.0527 | -0.00960 | 0.0378 | 0.0113 | 0.0482 |
| | (0.0553) | (0.0519) | (0.0567) | (0.0496) | (0.0534) | (0.0584) | (0.0510) |
| Education | -0.0730 | 0.130 | 0.189 | -0.00396 | 0.200 | 0.248 | 0.207 |
| | (0.250) | (0.226) | (0.260) | (0.241) | (0.211) | (0.240) | (0.225) |
| Health | 0.374** | 0.136 | 0.134 | 0.304* | 0.348** | 0.300 | 0.321** |
| | (0.177) | (0.183) | (0.206) | (0.158) | (0.169) | (0.185) | (0.152) |
| Religion | -0.129 | 0.0581 | -0.0303 | 0.281 | -0.458** | -0.532*** | -0.220 |
| | (0.193) | (0.172) | (0.201) | (0.180) | (0.178) | (0.205) | (0.183) |
| Caste | 0.0758 | 0.106 | 0.0686 | 0.0480 | -0.00227 | -0.0312 | -0.0550 |
| | (0.109) | (0.0979) | (0.109) | (0.0923) | (0.102) | (0.113) | (0.0978) |
| Containmentzone | -0.000362 | -0.229* | -0.138 | 0.0634 | -0.186 | -0.0598 | 0.148 |
| | (0.152) | (0.135) | (0.151) | (0.126) | (0.141) | (0.155) | (0.134) |
| RiskPreference | 0.206*** | 0.200*** | 0.133** | 0.131** | 0.215*** | 0.177*** | 0.150*** |
| | (0.0580) | (0.0514) | (0.0612) | (0.0504) | (0.0520) | (0.0628) | (0.0529) |
| Female | -0.245 | 0.0625 | -0.141 | -0.0284 | -0.498 | -0.605* | -0.574* |
| | (0.342) | (0.300) | (0.338) | (0.291) | (0.309) | (0.340) | (0.301) |
| Age | -0.0162 | 0.00147 | -0.0265 | -0.00198 | -0.0155 | -0.0298* | -0.0165 |
| | (0.0183) | (0.0184) | (0.0172) | (0.0189) | (0.0161) | (0.0157) | (0.0166) |
| Constant | 4.055*** | 3.594*** | 5.147*** | 2.905** | 4.548*** | 5.472*** | 3.997*** |
| | (1.325) | (1.295) | (1.465) | (1.274) | (1.216) | (1.367) | (1.221) |
| Observations | 265 | 249 | 252 | 249 | 258 | 261 | 258 |
| R-squared | 0.113 | 0.145 | 0.063 | 0.215 | 0.178 | 0.117 | 0.219 |

*The table reports the results from OLS regressions of $IncJob_6$ on the treatments. Columns (1) - (4) report OLS estimates from regressing $IncJob_6$ on Step, Feedback-N, Feedback-G and Forecast, with respect to Baseline. Columns (5) - (7) report OLS estimates from regressing $IncJob_6$ on Feedback-N, Feedback-G and Forecast, with respect to Step. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The robust standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * p<0.10, ** p<0.05, *** p<0.01*

*Table A11: Effect of Treatment on TimeJob*

| | ***(Comparison Treatment: Baseline)*** | | | | ***(Comparison Treatment: Step)*** | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | | | | *TimeJob* | | | |
| | (1) Step | (2) FeedbackN | (3) FeedbackG | (4) Forecast | (5) FeedbackN | (6) FeedbackG | (7) Forecast |
| **Treatment** | 1.221*** | 2.522*** | 1.646*** | 1.991*** | 1.401*** | 0.484 | 0.632 |
| | (0.420) | (0.417) | (0.419) | (0.430) | (0.408) | (0.415) | (0.425) |
| Income | 0.0975 | 0.115 | -0.0217 | -0.0324 | 0.153* | -0.00164 | -0.0154 |
| | (0.0763) | (0.0784) | (0.0755) | (0.0810) | (0.0777) | (0.0775) | (0.0801) |
| Education | -0.152 | -0.135 | -0.0977 | -0.128 | 0.143 | 0.121 | 0.253 |
| | (0.345) | (0.342) | (0.346) | (0.394) | (0.308) | (0.318) | (0.353) |
| Health | -0.0100 | -0.168 | -0.341 | 0.256 | 0.0317 | -0.170 | 0.346 |
| | (0.244) | (0.277) | (0.274) | (0.258) | (0.246) | (0.245) | (0.238) |
| Religion | 0.0319 | -0.0314 | 0.0584 | 0.0722 | -0.183 | -0.0576 | -0.132 |
| | (0.266) | (0.260) | (0.267) | (0.293) | (0.260) | (0.272) | (0.287) |
| Caste | 0.0487 | -0.00531 | -0.0738 | -0.125 | 0.130 | -0.0157 | -0.0207 |
| | (0.151) | (0.148) | (0.145) | (0.151) | (0.148) | (0.150) | (0.153) |
| Containmentzone | -0.196 | -0.0196 | 0.314 | 0.319 | -0.433** | -0.0334 | -0.0903 |
| | (0.209) | (0.204) | (0.201) | (0.206) | (0.205) | (0.205) | (0.210) |
| RiskPreference | 0.265*** | 0.122 | 0.172** | 0.105 | 0.195** | 0.261*** | 0.232*** |
| | (0.0801) | (0.0776) | (0.0815) | (0.0822) | (0.0758) | (0.0833) | (0.0830) |
| Female | -0.420 | -0.0221 | -0.0213 | -0.00595 | -0.218 | -0.332 | -0.301 |
| | (0.472) | (0.453) | (0.450) | (0.475) | (0.450) | (0.451) | (0.472) |
| Age | 0.0635** | 0.0148 | 0.00206 | 0.00301 | 0.0343 | 0.0238 | 0.0348 |
| | (0.0253) | (0.0278) | (0.0229) | (0.0308) | (0.0234) | (0.0209) | (0.0260) |
| Constant | 3.675** | 6.539*** | 7.203*** | 5.268** | 5.535*** | 6.463*** | 4.079** |
| | (1.830) | (1.955) | (1.951) | (2.079) | (1.772) | (1.813) | (1.917) |
| Observations | 265 | 249 | 252 | 249 | 258 | 261 | 258 |
| R-squared | 0.096 | 0.151 | 0.087 | 0.101 | 0.102 | 0.048 | 0.056 |

*This table shows the results from OLS regressions of TimeJob on the treatments. Columns (1) - (4) report OLS estimates from regressing TimeJob on Step, Feedback-N, Feedback-G and Forecast, with respect to Baseline. Columns (5) - (7) report OLS estimates from regressing TimeJob on Feedback-N, Feedback-G and Forecast, with respect to Step. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The robust standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

Table A12: *IV estimates from regressing Investment and Economic Expectations on EGB - Instrument w.r.t Baseline*

| | **First Stage** | **Second Stage** | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLES | $Bias_{35,10}$ | $Invest_{35}$ | $CSI$ | $FEI$ | $GrUn_6$ | $GrUn_{12}$ | $IncJob_6$ | $TimeJob$ |
| | | | | ***(A) Treatment: Feedback-N*** | | | | |
| **Treatment** | -0.921*** | | | | | | | |
| | (0.0269) | | | | | | | |
| $\widehat{\textbf{EGB}}$ | | 31.20*** | 0.599*** | 3.139*** | 1.069*** | 1.474*** | -1.234*** | -2.738*** |
| | | (1.289) | (0.316) | (0.268) | (0.323) | (0.265) | (0.299) | (0.454) |
| **Constant** | 0.938*** | 4.835 | 98.12*** | 96.78*** | 3.900*** | 3.012*** | 4.751*** | 9.107*** |
| | (0.126) | (5.560) | (1.361) | (1.156) | (1.392) | (1.145) | (1.291) | (1.960) |
| **Observations** | 265 | 265 | 265 | 265 | 265 | 265 | 265 | 265 |
| | | | | ***(B) Treatment: Feedback-G*** | | | | |
| **Treatment** | -0.936*** | | | | | | | |
| | (0.0275) | | | | | | | |
| $\widehat{\textbf{EGB}}$ | | 32.41*** | 0.970*** | 3.153*** | 1.637*** | 2.656*** | -0.337*** | -1.757*** |
| | | (1.456) | (0.314) | (0.260) | (0.302) | (0.268) | (0.329) | (0.441) |
| **Constant** | 0.747*** | 17.72*** | 99.03*** | 98.50*** | 4.153*** | 4.102*** | 5.399*** | 8.515*** |
| | (0.128) | (6.322) | (1.364) | (1.129) | (1.310) | (1.163) | (1.430) | (1.914) |
| **Observations** | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 |
| | | | | ***(C) Treatment: Forecast*** | | | | |
| **Treatment** | -0.852*** | | | | | | | |
| | (0.173) | | | | | | | |
| $\widehat{\textbf{EGB}}$ | | 30.50*** | 0.809** | 3.079*** | 3.113*** | 4.292*** | -2.178*** | -2.335*** |
| | | (6.396) | (0.383) | (0.670) | (0.699) | (0.872) | (0.544) | (0.704) |
| **Constant** | 2.074** | -16.56 | 97.47*** | 93.94*** | -0.369 | -2.243 | 7.422*** | 10.11*** |
| | (0.835) | (27.84) | (1.667) | (2.917) | (3.042) | (3.794) | (2.366) | (3.064) |
| **Observations** | 249 | 249 | 249 | 249 | 249 | 249 | 249 | 249 |
| **Control** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Note: This table reports the first stage and second stage results from the 2SLS regression estimation of EGB ($Bias_{35,10}$) on investment and economic expectations. Column (1) reports the first stage OLS estimates from regression of EGB on the IV, which in this case is the treatment. The first stage is reported for Feedback-N, Feedback-G, and Forecast in Panels A, B, and C. The reference group is Baseline. The fitted values obtained from the first stage regression, $\widehat{EGB}$, is regressed on $Invest_{35}$, CSI, FEI, $GrUn_6$, $GrUn_{12}$, $IncJob_6$ and $TimeJob$ to obtain the second stage IV estimates reported in Columns (2) to (8). All specifications control for Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The standard errors are reported in parentheses. In Panel A (B/C), observations are included from Baseline and Feedback-N (Feedback-G/Forecast). The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

*Table A13: IV estimates from regressing Investment and Economic Expectations on EGB - Instrument w.r.t Step*

| | **First Stage** | | | **Second Stage** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | (1) $Bias_{35,10}$ | (2) $AverageBias$ | (3) $Bias$ | (4) $Invest_{35}$ | (5) $Invest$ | (6) $CSI$ | (7) $FEI$ | (8) $GrUn_6$ | (9) $GrUn_{12}$ | (10) $IncJob_6$ | (11) $TimeJob$ |
| | | | | | ***(A) Treatment: Feedback-N*** | | | | | | |
| **Treatment** | -0.743*** | -1.104*** | -1.104*** | | | | | | | | |
| | (0.0483) | (0.0710) | (0.0688) | | | | | | | | |
| **$\widehat{EGB}$** | | | | 18.46*** | 5.533*** | -0.0116 | 0.725*** | 0.213*** | 0.0466** | -1.024*** | -1.269*** |
| | | | | (2.458) | (1.072) | (0.270) | (0.236) | (0.294) | (0.279) | (0.264) | (0.380) |
| **Constant** | 0.697*** | 1.356*** | 0.704** | 23.34*** | 24.87*** | 99.17*** | 97.02*** | 3.493** | 4.107*** | 5.937*** | 7.257*** |
| | (0.210) | (0.308) | (0.308) | (7.972) | (6.756) | (1.314) | (1.152) | (1.432) | (1.361) | (1.289) | (1.850) |
| **Observations** | 258 | 258 | 1,290 | 258 | 1,290 | 258 | 258 | 258 | 258 | 258 | 258 |
| | | | | | ***(B) Treatment: Feedback-G*** | | | | | | |
| **Treatment** | -0.755*** | -1.114*** | -1.114*** | | | | | | | | |
| | (0.0481) | (0.0707) | (0.0688) | | | | | | | | |
| **$\widehat{EGB}$** | | | | 20.88*** | 5.778*** | 0.339*** | 0.816*** | 0.716*** | 1.098*** | -0.223*** | -0.434*** |
| | | | | (2.580) | (1.094) | (0.263) | (0.231) | (0.268) | (0.264) | (0.277) | (0.369) |
| **Constant** | 0.542** | 1.318*** | 1.318*** | 32.08*** | 33.36*** | 100.1*** | 98.29*** | 3.215** | 4.476*** | 5.767*** | 7.035*** |
| | (0.210) | (0.309) | (0.302) | (8.509) | (5.800) | (1.300) | (1.141) | (1.326) | (1.305) | (1.370) | (1.820) |
| **Observations** | 261 | 261 | 1,044 | 261 | 1,044 | 261 | 261 | 261 | 261 | 261 | 261 |
| | | | | | ***(C) Treatment: Forecast*** | | | | | | |
| **Treatment** | -0.671*** | -0.966*** | -0.966*** | | | | | | | | |
| | (0.173) | (0.185) | (0.155) | | | | | | | | |
| **$\widehat{EGB}$** | | | | 18.19*** | 10.35*** | 0.230*** | 0.678*** | 2.000*** | 2.560*** | -1.818*** | -0.654*** |
| | | | | (5.488) | (2.220) | (0.309) | (0.296) | (0.473) | (0.534) | (0.452) | (0.463) |
| **Constant** | 1.783** | 2.492*** | 2.492*** | 13.25 | 10.47 | 99.35*** | 97.39*** | -0.180 | -0.449 | 8.528*** | 5.709*** |
| | (0.778) | (0.832) | (0.675) | (18.38) | (9.530) | (1.479) | (1.416) | (2.263) | (2.556) | (2.162) | (2.215) |
| **Observations** | 258 | 258 | 1032 | 258 | 1,032 | 258 | 258 | 258 | 258 | 258 | 258 |
| **Control** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Day** | No | No | Yes | No | Yes | No | No | No | No | No | No |

*Note: The table reports the first and second stage results from 2SLS regression of EGB on investment and economic expectations. Columns (1) - (3) report the first stage estimates from regression of EGB ($Bias_{35,10}$, $AverageBias$, $Bias$) on the IV - treatment. The first stage for Feedback-N, Feedback-G, and Forecast is reported in Panels A, B, and C with Step as a reference. The fitted values of bias, $\widehat{EGB}$, is regressed on $Invest_{35}$, $Invest$, $CSI$, $FEI$, $GrUn_6$, $GrUn_{12}$, $IncJob_6$ and $TimeJob$ to obtain the second stage IV estimates and are reported in Columns (4) to (11). EGB is $Bias_{35,10}$ for Column (4), $Bias$ for Column (5) and $AverageBias$ for Columns (6) - (11). All specifications control for Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. Columns (3) and (5) additionally control for Day and cluster standard errors at the individual level. In Panel A (B/C), observations are from Step and Feedback-N (Feedback-G/Forecast). The standard errors are reported in parentheses. The p-values are adjusted for multiple hypotheses testing based on the Westfall-Young Randomization-t method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

*Table A14: Difference in the Predicted Number of Cases between Series and Step*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | **$\mathbf{Prediction_{15}}$** | **$\mathbf{Prediction_{20}}$** | **$\mathbf{Prediction_{25}}$** | **$\mathbf{Prediction_{30}}$** | **$\mathbf{Prediction_{35}}$** |
| **Series** | 132.7 | 210.9 | -6,968 | -29,029 | -42,645 |
| | (991.1) | (2,974) | (6,999) | (19,074) | (29,128) |
| Constant | 8,456** | 29,770** | 79,588*** | 138,043* | 222,309* |
| | (4,006) | (12,022) | (28,291) | (77,102) | (117,744) |
| Observations | 207 | 207 | 207 | 207 | 207 |
| R-squared | 0.048 | 0.106 | 0.111 | 0.084 | 0.109 |
| Control | Yes | Yes | Yes | Yes | Yes |

*Note: This table reports the OLS regression estimates of the treatment effect of Series, relative to Step. $Prediction_i$ is the predicted number for Day i. Columns (1) - (5) reports treatment effect on $Prediction_{15}$, $Prediction_{20}$, $Prediction_{25}$, $Prediction_{30}$, and $Prediction_{35}$. Control variables include Income, Education, Health, ContainmentZone, RiskPreference, Female, Age, Caste, and Religion. The robust standard errors are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

# B Multiple Hypotheses Correction - For Online Publication Only

In this section, we present a brief note on the multiple hypotheses correction we perform. Given the number of outcome variables and treatments we analyze, the number of hypothesis we end up testing is rather large. It is important that we make the statistical inference after correcting for multiple hypotheses testing. We follow Young (2019) who formulates an omnibus test for overall experimental significance. The paper uses randomization inference (randomization-t) and bootstrapped standard errors instead of usual standard errors. This helps address concerns with finite sample standard errors being affected by high leverage observations. We use Young's *randcmd* stata code to calculate the adjusted $p$-values. We analyze two sets of outcome variables - EGB, which forms the basis of our proposed mechanism, and Economic Expectations, which is the principle outcome of our interest. We conduct multiple hypotheses correction separately for these two sets of variables. Table B1 reports the number of hypotheses which are being tested. Panel A in Table B1 shows that a total of ten hypotheses are tested for EGB. The significance levels denoted in Table A4 and Figure 2(A), (B) correct for ten multiple hypotheses. Panel B shows that 52 hypotheses are tested for outcomes related to Economic Expectations, including investment. The significance levels denoted in Table A5 to Table A11 and in Figure 2(C), (D) and Figure 3 correct for 52 hypotheses. Likewise, Table A12 and Table A13 reports significance levels which correct for 52 hypotheses (Panel C) and Table A3 reports significance levels which correct for 16 hypotheses (Panel D).

Table B1: *Set of Hypotheses for which Multiple Hypotheses Correction has been done*

| (A) Treatment Effect on EGB | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Comparison Treatment: Baseline | | | | Comparison Treatment: Step | | |
| | Step | Feedback-N | Feedback-G | Forecast | Feedback-N | Feedback-G | Forecast |
| $Bias_{35,10}$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $Bias$ | | | | | Yes | Yes | Yes |
| **(B) Treatment Effect on Economic Outcomes** | | | | | | | |
| | Comparison Treatment: Baseline | | | | Comparison Treatment: Step | | |
| | Step | Feedback-N | Feedback-G | Forecast | Feedback-N | Feedback-G | Forecast |
| $Invest_{35}$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $Invest$ | | | | | Yes | Yes | Yes |
| $CSI$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $FEI$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $GrUn_6$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $GrUn_{12}$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $IncJob_6$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $TimeJob$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **(C) EGB and Economic Outlook - 2SLS** | | | | | | | |
| | Instrument w.r.t Baseline | | | | Instrument w.r.t Step | | |
| | Step | Feedback-N | Feedback-G | Forecast | Feedback-N | Feedback-G | Forecast |
| $Invest_{35}$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $Invest$ | | | | | Yes | Yes | Yes |
| $CSI$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $FEI$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $GrUn_6$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $GrUn_{12}$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $IncJob_6$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $TimeJob$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **(D) EGB and Economic Outlook - OLS** | | | | | | | |
| | Without Treatment as Covariate | | | | With Treatment as Covariate | | |
| $Invest_{35}$ | Yes | | | | Yes | | |
| $Invest$ | Yes | | | | Yes | | |
| $CSI$ | Yes | | | | Yes | | |
| $FEI$ | Yes | | | | Yes | | |
| $GrUn_6$ | Yes | | | | Yes | | |
| $GrUn_{12}$ | Yes | | | | Yes | | |
| $IncJob_6$ | Yes | | | | Yes | | |
| $TimeJob$ | Yes | | | | Yes | | |

# C Experimental Instructions - For Online Publication Only

Please click here for the experimental instructions.