

# Rationally Inattentive Savers and Monetary Policy Changes: A Laboratory Experiment

Andrea Civelli\*      Cary Deck†      Antonella Tutino‡

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## Abstract

We study the response of consumption and saving decisions of rationally inattentive individuals to changes in monetary policy in the laboratory. First, we theoretically characterize the choices of a rationally inattentive agent processing information about the interest rate. Then, we design an experiment with induced inattention to test for the predictions of the model, contrasting them to the full information case. Consistent with the predictions, experimental subjects (a) increase attention when utility gains exceed cognitive costs of tracking the policy rate and decrease savings when their perceived economic outlook deteriorates; (b) respond to Delphic, but not Odyssean, forms of forward guidance. These findings agree with recent empirical evidence on monetary policy effects on consumption behavior in U.S. and internationally.

**Keywords:** Rational Inattention, Experimental Evidence, Information Processing Capacity, Consumption

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\*University of Arkansas, Walton College of Business, Department of Economics, Business Building 402, Fayetteville, AR 72701. Email: andrea.civelli@gmail.com

†University of Alabama and Chapman University

‡Federal Reserve Bank of Dallas.

# 1 Introduction

The way the private sector's economic decisions respond to changes in monetary policy and to the communication of such changes is of primary interest for policy makers and economists. In standard economic theory based on rational expectations, agents optimally and promptly react to any change in the economic environment. In reality, however, the responses of private agents' consumption and investment to policy changes may vary greatly, depending on how much attention people pay to the monetary policy environment. For instance, in periods of relative stability, agents may delay or not respond at all to policy changes that are deemed small or unimportant to them. By contrast, in turbulent times, more of their attention may be devoted to tracking changes in the monetary policy environment, and erratic behavioral responses of consumption and investment can be observed while agents parse information about economic conditions.

These behavioral patterns can be captured by models in which agents exhibit limited cognitive ability to process information about the economic environment, as in the Rational Inattention theory introduced by Sims (2006, 2003). In contrast with the rational expectations paradigm, the rational inattention structure is less concerned about how much information should, or should not, be released by the policy maker to the public, but rather focuses on whether and when the information released elicits significant behavioral reactions. Rational inattention encompasses full-information as the limiting case in which agents have infinite information processing capacity.

This paper explores the response of consumption and saving decisions of individuals to changes in monetary policy in a laboratory experiment. We first propose a model where rationally inattentive agents face monetary policy changes, and we derive testable implications of consumption and investment choices in response to them. We then design a laboratory experiment with induced inattention to test these implications in a controlled environment, contrasting the predictions of our rational inattention model to those derived under full information. We find strong support for the rational inattention model from the experimental evidence.

Building on the rational inattention literature, we develop a 2-period model where an agent receives an endowment in the first period and decides how to allocate it between consumption and savings. Savings are invested in a one-period bond, which pays a return in the second period given by the prevailing short-term interest rate set by the monetary policy authority. The agent is rationally inattentive and the interest rate is not fully observed because she has limited cognitive capacity to process information about it and her prior

is uninformative over possible realization of the interest rate. The decision problem of the agent amounts to choosing how much information she wants to process about the interest rate functional to her choice of consumption and investment (savings) in the asset.

We postulate a quadratic functional form for the agent’s utility. This assumption implies a subdued response to changes in the interest rate, as these have limited impact on lifetime utility.<sup>1</sup> With quadratic utility, and given distributional assumptions for the interest rate, we can fully characterize the closed-form solution of the model and derive a set of theoretical predictions to be taken to the laboratory and tested against the full-information outcome.

We trace a tight mapping between the theoretical framework and the experimental design. The experimental subjects receive a fixed endowment and choose among lotteries with uncertain outcomes – which depend on the realization of the policy rate. These lotteries match the lifetime utility profiles of the theoretical model under uncertainty about the investment returns (interest rates). Subjects begin the task with a uniform prior on the lottery payoffs, but can reduce uncertainty about the outcomes by solving real-effort cognitive tasks. Different difficulty levels of these tasks capture the increasing cognitive effort required by the subjects to acquire more informative signals and process more information about the interest rate.<sup>2</sup>

Three main findings emerge from our analysis. First, we show that the behavior of the subjects in our experiment is generally consistent with the predictions of limited attention to interest rate tracking and the consumption choices of the rational inattentive (RI) representative agent. More importantly, the experimental data allows us to formally compare the fit of the rationally inattentive model to the model in which agents make decisions under full information (FI). FI predictions are generally statistically rejected by subjects’ consumption choices, but the RI predictions are not. Participants behave as if they have limited information processing capacity rather than full information, which would make them rapidly and precisely react to changes in the economic environment, as postulated by rational expectations models with infinite processing capacity.

The rationale for the RI theoretical prediction is that utility gains from processing more information do not provide a sufficient compensation for the cognitive effort of precisely tracking the interest rate. The agents prefer to increase consumption in the first period –

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<sup>1</sup>While invoked mainly for analytical tractability, this assumption is backed by the empirical findings of Bachmann *et al.* (2015) and Roth and Wohlfart (2019), for instance, who show muted behavioral responses of households to changes in monetary policy.

<sup>2</sup>Given that Rational Inattention theory is based on cognitive effort rather than time spent executing a number of tasks, these cognitive tasks are more suitable to gauge the difficulty subjects overcome in gathering and processing information (as shown in Civelli and Deck, 2018).

which requires little information on interest rate – and reduce savings. This is true even if, on average, a more informed subject receives a higher utility reward. This result has a stark monetary policy implication: if people’s utility functions make deviations of interest rates policy unimportant to them, interest rate changes are unlikely to elicit significant behavioral reactions. Moreover, both the theoretical and the experimental findings corroborate the empirical evidence in U.S. and international data of a relatively small impact of monetary policy on households’ decisions (as pointed out by Roth and Wohlfart, 2019).

Second, we investigate the effectiveness of forward guidance in affecting behavioral choices. Following Campbell *et al.* (2012), we identify two forms of forward guidance: Delphic and Odyssean forward guidance.<sup>3</sup> In the experiment we implement Delphic forward guidance as a reduction in the volatility of the interest rate, while we model Odyssean forward guidance as a commitment by the central bank to provide a more predictable path of the interest rate.

As noted by Campbell *et al.* (2012), interpreting Delphic forward guidance as reduction in the interest rate volatility would be consistent with the solution for the policy rate of an optimal control problem with a quadratic loss function as in Taylor (1993), where the volatility of the interest rate directly influences private sector’s welfare.<sup>4</sup> In our framework, this policy lowers the cognitive cost associated with the tracking of the interest rate. As a consequence, the RI representative agent makes more deliberate and precise consumption and investment decisions in response to changes in the monetary policy stance, which also lead to a material welfare improvement relative to the full-information case.

We find experimental subjects respond to this treatment as predicted by the theory, enjoying higher utility when this form of forward guidance is adopted. Subjects’ behavior in the laboratory is measurably closer to the predictions of the RI model than the prediction of the FI model in this case as well.

On the contrary, for the Odyssean forward guidance, we find that a commitment by the central bank to provide a predictable path of the interest rate via a 90% accurate signal on the policy stance has no material effect on consumption and information choices of both the RI representative agent and the experiment subjects. As a result, the effect on welfare from this policy is negligible.

These theoretical and experimental results on the efficacy of Delphic and Odyssean

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<sup>3</sup>As described in Campbell *et al.* (2012), Delphic forward guidance refers to communication of the central bank about the economic outlook, whereas Odyssean forward guidance refers to a commitment of the central bank to keep rates stable, see Eggertsson and Woodford (2003).

<sup>4</sup>Among the papers that implement this type of Delphic forward guidance, see Gaballo (2016), Melosi (2016) and Ehrmann *et al.* (2019).

forward guidance are also strongly supported by the empirical literature that uses U.S. and cross-country data on aggregate consumption and investment (Andrade and Ferroni, 2018; McKay *et al.*, 2016; Campbell *et al.*, 2019; Ehrmann *et al.*, 2019). To the best of our knowledge, this is the first paper to provide theoretical and laboratory evidence consistent with these empirical findings.

As a third result, we show that a deterioration in the public perception of the economic outlook given by a higher time discount factor dampens investment – i.e., increases consumption in the first period – for a given information precision in both the RI theory and the experimental data. This finding also agrees with the empirical evidence of, for instance, Roth and Wohlfart (2019), Bachmann *et al.* (2015) and, more recently, Yagan (2019). The implication of this finding is that the influence of monetary policy on private sector’s behavior not only depends on the size of the change in the policy instrument, but also on the timing of the change along the business cycle.

The rest of the paper is organized as follows. After discussing related literature in the second part of this section, Section 2 formally presents the theoretical decision problem under rational inattention. It discusses the properties of the solution of the problem and lays out the testable predictions. Section 3 introduces the experimental setting and the treatments implemented to verify the theoretical predictions. A mapping between experimental set-up and the theoretical model is formally established. Section 4 shows the congruence of the experimental results with the theoretical predictions. Finally, Section 5 offers some concluding remarks. Additional details and robustness checks are left to the Appendix.

## 1.1 Related Literature

This paper relates to two broadly defined areas of research. The first strand concerns the importance of cognitive limits on economic decisions. While there is an extensive literature documenting attention limits in economics,<sup>5</sup> there has been significantly less research on testing models of limited attention, and especially rational inattention, in an experimental setting. Among the papers that empirically test attention limits, Caplin and Dean (2011) tests a sequential search models where agents face a large number of alternatives. The key difference between their paper and ours is that our subjects choose higher information precision by solving progressively more difficult tasks so that the number of alternatives is tightly linked to their cognitive effort.

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<sup>5</sup>See, for instance, in the context of consumer choices: Chetty *et al.* (2009), Allcott and Taubinsky (2015), Santos *et al.* (2012)

Other papers study models of information acquisition and their impact on choices in strategic settings when agents are not fully rational. In the experimental literature, Gabaix *et al.* (2006), Khaw *et al.* (2016), and Goecke *et al.* (2013) study dynamic models of information acquisition without assuming that subjects are rational. These papers focus mostly on information acquisition, while our paper is centered around information processing, explicitly connecting the acquisition of information to the cognitive cost of mapping that information into behavioral choices.

The set of papers closest to our paper (Pinkofskiy, 2009; Cheremukhin *et al.*, 2015; Dean and Neligh, 2017; Civelli *et al.*, 2018)) all use Shannon’s entropy costs as the basis of their experimental analysis. Cheremukhin *et al.* (2015) exposes subjects to gambles in the lab to estimate the cost of information processing as well as attitude to risk. Dean and Neligh (2017) empirically tests the validity of rational inattention models under different specifications of the information cost based on Shannon’s mutual information. Civelli *et al.* (2018) is the closest to our paper as it employs cognitive tasks to explicitly map information acquisition into consumption choices of risk averse subjects.

In contrast with the previous literature, in this paper, we abstract from considering risk attitude and testing for alternative specifications of the rational inattention models. Instead, we propose a model where monetary policy changes are the primary stimuli to the economic environment that trigger changes in information processing. We encode the complexity of deciphering monetary policy changes our experimental subjects face by associating progressively more demanding cognitive tasks to signals providing sharper information. In this context, we focus on how rationally inattentive subjects react to monetary policy variations, and measure their information processing and consumption choices.

The second broad strand of the literature this paper relates to is on information frictions and the signaling channel of monetary policy.<sup>6</sup> In particular, a number of recent papers empirically document the interaction between information rigidities, inflation expectations, and monetary policy. Evidence based on surveys of firms (Kumar *et al.*, 2015; Coibion *et al.*, 2019) show mixed effects of monetary policy on economic outcomes. With respect to households’ expectations, Easaw *et al.* (2013), Roth and Wohlfart (2019), Bachmann *et al.* (2015), Binder (2017), and Khaw *et al.* (2017) find changes in information acquisition that relate to changes in behavioral choices.

In this paper, we track subjects’ information acquisition and processing directly together

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<sup>6</sup>See Baeriswyl and Cornand (2010) and Melosi (2016) for examples of how interest rates serve as communication tools from monetary policy to firms.

with consumption choices. This way we are able to disentangle whether a particular change in monetary policy trigger changes in information acquisition and consumption behavior.

Finally, the paper also relates to the recent debate on the relative effectiveness of Delphic vs. Odyssean forward guidance of monetary policy.<sup>7</sup> McKay *et al.* (2016) and Campbell *et al.* (2019) both warn on the limits of forward guidance in affecting private sector’s behavior, with Delphic forward guidance being more effective than Odyssean forward guidance in nudging behavior when private sector expectations are not rational (as in Eusepi and Preston, 2018) or firms are rationally inattentive (as in Gaballo, 2016).<sup>8</sup>

This paper provides experimental support for the theoretical findings of these papers by showing that, while a central bank signal on the monetary policy stance (a form of Odyssean forward guidance) is generally ineffective in influencing participants’ behavior in terms of consumption and savings, a less volatile interest rate used as a tool of Delphic forward guidance would modify consumption choices.

## 2 Theoretical Framework

This section introduces the theoretical framework of the RI model which provides the structure for the experimental design and delivers the predictions we test in the laboratory. We sketch the representative agent problem in the first part of this section, leaving more details to Appendix A, while in the second part we specialize to a closed-form solution of the general problem with quadratic utility. From this specification, we derive the model’s predictions.

### 2.1 The Model

The model is a two-period consumption-saving optimization program which features a rationally inattentive agent. In period 1, the agent receives an endowment of 1 unit of a good, which can be either consumed or saved through investment in a one-period bond for consumption in period 2. Let the bond return be defined by the interest rate  $r$ , and  $c_1$  and  $c_2$  denote consumption in the two periods respectively. We can express consumption in period 2 as:  $c_2 = r(1 - c_1)$ .

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<sup>7</sup>As described in Campbell *et al.* (2012), Delphic forward guidance refers to communication of the central bank about the outlook, whereas Odyssean forward guidance refers to a commitment of the central bank to keep rates stable, see Eggertsson and Woodford (2003).

<sup>8</sup>Gaballo (2016) develops a Rational Inattention model with Delphic forward guidance in central banks may be successful in changing firms’ pricing behavior.

We postulate that the bond return is set by the monetary policy authority, but the agent has limited information-processing capacity to process information about the interest rate. The assumption of limited-information processing capacity is the core of the RI model. In turn, it implies that before processing information about  $r$ , the agent considers  $c_1$  and  $c_2$  as random variables since different realizations of the interest rate give rise to different consumption options. Moreover, the RI framework implies that the decision of how much information to process comes from the trade-off between the benefit of having more precise information about  $r$  functional to consumption choices and the cognitive cost necessary to process more information. The optimal balance between cost and benefit of information processing that maximizes agent's lifetime utility constitutes the solution of the RI model.

Following Tutino (2013) and Civelli *et al.* (2018), we assume the agent starts period 1 with a prior on distribution of the interest rate,  $g(r)$ , and can reduce uncertainty about this prior by acquiring signals on the interest rate, which mutually reduces uncertainty about her consumption possibilities in period 1 and, implicitly, period 2.

The randomness of consumption and interest rate and their intertwined relation make the relevant choice variable of the optimization problem under RI the joint probability distribution of consumption and interest rate:  $p(c_1, r)$ . This joint distribution makes explicit the mutual dependence that  $c_1$  and  $r$  have in the mind of the agent when she chooses how much information to process to maximize her utility. Using Bayes' rule, the choice of the joint distribution can be thought of as a choice of the signal about  $r$  for a given  $c_1$ .<sup>9</sup>

The optimal choice of  $p^*(c_1, r)$  depends on the information processing capacity of the agent. This aspect is embedded in the model by using principles of information theory. Specifically, we assume that the mutual information flow between  $r$  and  $c_1$ ,  $I(p(c_1, r))$ , is bounded by a number,  $\kappa$ , which represents the maximum amount of information that can be extracted from  $c_1$  about  $r$ . In practice,  $\kappa$  corresponds to the amount of information that the agent can process about consumption and interest rate, and poses a limit on the informational content of the signals that the agent can choose.<sup>10</sup>

Let  $u(c_i)$  be standard twice continuously differentiable utility of the agent at periods  $i = (1, 2)$ , and  $0 < \beta < 1$  the period 2 discount factor. The formal optimization program

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<sup>9</sup>That is, the conditional distribution  $p(r|c_1) = \frac{p(c_1, r)}{\int p(c_1, r) dr}$ .

<sup>10</sup>In information theory,  $\kappa$  is defined as the Shannon's channel capacity and the reduction of uncertainty about the interest rate obtained by processing a signal corresponds to the change in the entropy of its distribution. See Appendix A for a more detailed explanation of Shannon's theory and its relation to entropy reduction.



reads:

$$\max_{p(r, c_1)} \mathbb{E} \left\{ \int [u(c_1) + \beta u(c_2)] p(c_t, w_t) \mu(dc_1, dr) | \mathcal{I}_1 \right\} \quad (1)$$

$$\text{s.t.} \quad \kappa = I(p(c_1, r)) \quad (2)$$

$$c_2 = r(1 - c_1) \quad (3)$$

for a given prior  $g(r)$  and with  $p(c_1, r) \in \mathcal{D}(w, c)$ , where  $\mathcal{D}(r, c)$  denotes the set of proper distributions. In equation (1),  $\mathbb{E}$  is the conditional expectation defined with respect to the  $\sigma$ -algebra generated by  $\mathcal{I}_1$ , while  $\mu(\cdot)$  accounts for potential discreteness in the optimal choice of  $p(c, r)$ . The interpretation of the information processing constraint in equation (2), which equates mutual information and  $\kappa$ , is that, for a given shadow cost of processing information,<sup>11</sup> the agent chooses the amount of information she wants to process. This specification of information processing constraint is known as *elastic capacity*: fixing the marginal (shadow) cost, the quantity of information  $\kappa$  acquired varies according to the needs of the agent.

This is a well-posed convex problem, with infinite-dimensional state and control variables. However, given potential discreteness in the optimal distribution, without restrictive assumptions on the shape of the utility and prior distribution, it rarely admits a fully analytical characterization. In general, the solution of the program (1)-(3) is the equilibrium distribution  $p^*(c_1, r)$  which, from Bayes' rule, can be represented as:

$$p^*(c_1, r) = p^*(c_1|r)g(r),$$

where the marginal interest rate distribution is equal to the prior,  $\int p^*(c_1, r) dc_1 = g(r)$ , to satisfy model's internal consistency. The conditional distribution  $p^*(c_1|r)$  embeds the effects of more accurate information about interest rate provided by the selected signal to sharpen consumption choices.

## 2.2 A Useful Closed-Form Solution

To build intuition on the character of the solution and derive testable predictions from the model, we specialize the theoretical framework by assuming a uniform distribution for  $g(r)$  and a quadratic utility function, which are directly conducive to the experimental setting.

The prior on the interest rate is uniformly distributed over the interval  $R = [\underline{r}, \bar{r}]$ , where

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<sup>11</sup>That is, for a given Lagrange multiplier associated with constraint (2).

$r < \beta^{-1} < \bar{r}$ . Moreover, to facilitate the implementation of the experimental design, we assume the signals on interest rates available to the agent partition the interest rate space into sub-intervals of equivalent length, proportional to the precision of the signal. The distribution implied by the signals is also piece-wise uniform within each partition. Let  $R_i$  indicate a generic partition of  $R$  determined by the signal of precision  $i$ , such that  $R_i = [r_i, \bar{r}_i]$ . Then, the solution of the problem in terms of consumption can be compactly written as:

$$\beta^{-1}u'(c_1) = \mathbb{E}_{R_i} \{ru'(r(1 - c_1))\} \quad (4)$$

where  $u'(\cdot)$  is the derivative of utility with respect to consumption, and the expectation  $\mathbb{E}_{R_i}$  is taken with respect to the information provided by the optimal signal  $p^*(r|c_1)$  for the interval  $R_i$ .

To further characterize the solution, let us assume that the utility  $u(c)$  takes on the form:

$$u(c) = \begin{cases} \alpha(c - \bar{c})^2 & c < \bar{c} \\ 0 & c \geq \bar{c} \end{cases}, \quad \bar{c} \gg \bar{r}$$

which postulates that the satiation point  $\bar{c}$  is much higher than the maximum amount that could be consumed by saving all the endowment in the first period, even in the case of the highest possible realization of interest rate,  $r = \bar{r}$ .

The joint assumption of quadratic utility and uniform prior allows us to invoke the certainty equivalent principle and divide the decision problem into information choice and consumption selection given the information acquired. Defining the expectation operator  $\mathbb{E}_{R_i}$  and of the corresponding variance  $\mathbb{V}_{R_i}$ , the RI consumption choice for this case is:

$$c_1 = \frac{\bar{c} + \beta (\mathbb{E}_{R_i}(r^2) - \mathbb{E}_{R_i}(r)\bar{c})}{1 + \beta \mathbb{E}_{R_i}(r^2)} = \frac{\bar{c} + \beta (\mathbb{E}_{R_i}^2(r) + \mathbb{V}_{R_i}(r) - \mathbb{E}_{R_i}(r)\bar{c})}{1 + \beta (\mathbb{E}_{R_i}^2(r) + \mathbb{V}_{R_i}(r))} \quad (5)$$

The benchmark against which we compare the RI model's solution in (5) is the full information (FI) model. The FI problem is simply to maximize the above quadratic utility subject to (3) and its solution is:

$$c_1 = \frac{(\bar{c} + \beta (r^2 - r\bar{c}))}{1 + \beta r^2}. \quad (6)$$

We see that, in (5), the certain value of the perfectly observed interest rate  $r$  is replaced by its expected value within the interval  $R_i$ , revealed by the signal chosen by the agent.

## 2.3 Testable Predictions

We use equation (5) to further characterize four predictions of the model that can be tested in our laboratory experiment. A caveat worth mentioning is that the validity of the closed-form solution in eq. (5) relies on the assumption of quadratic functional form of the utility, and that this specification implies a relatively flat slope of the utility. Moreover, this functional form implies that agent typically devote little attention to monetary policy news in making consumption choices. Such an assumption is corroborated by the empirical evidence on households and firms (see, among the others, Coibion *et al.*, 2019; Kumar *et al.*, 2015; Roth and Wohlfart, 2019; Easaw *et al.*, 2013).

In invoking this assumption to obtain a closed-form solution, we favor sharper and more direct implications of the theory on consumption behavior over a more prominent role of the information processing choices.

### 2.3.1 Testable Prediction 1

Consumption in period 1 decreases as the expected interest rate increases. However, as implied by equation (5), the utility benefit of processing more information about the interest rate is bounded. The first part of the prediction follows immediately from  $\frac{\partial c_1}{\partial \mathbb{E}_{R_i}(r)} < 0$ , while the second part of the prediction clearly stems from the assumed utility functional form.

### 2.3.2 Testable Prediction 2

Consumption in period 1 increases as the perceived volatility of the interest rate increases. This prediction stems from  $\frac{\partial c_1}{\partial \mathbb{V}_{R_i}(r)} > 0$ . In our model, where the interest rate is perceived as a random variable by agents, consumption in period 1 can be interpreted as the “safe” asset. Viceversa, a decrease in volatility of the stochastic interest rate would make returns to saving more predictable and, hence, safer. Moreover, a reduction in interest rate volatility reduces the information required to precisely track the interest rate. As a result, the RI consumption outcomes would be closer to the FI information outcome in this case.

### 2.3.3 Testable Prediction 3

A decrease in the discount rate  $\beta$ , lowers consumption  $c_1$  and makes information processing less valuable. This prediction stems from  $\frac{\partial c_1}{\partial \beta} < 0$ . A decrease in the discount rate can be interpreted as a deterioration of the outlook from the agents’ perspective. With less confidence in future earnings, agents retreat to the safety of  $c_1$ . The decision of consuming

more today also implies that there is even less incentive to process information about tomorrow's return on savings, i.e. about the interest rate.

### 2.3.4 Testable Prediction 4

Enhanced predictability of the interest rate path does not affect consumption behavior. This theoretical result stems from the fact that rationally inattentive agents optimally choose their signal on the interest rate taking into account their information-processing capacity as well as their utility. As a result, a public signal that contains less information than what is optimally chosen would be mostly disregarded as agents rely on their own richer information set to learn about the interest rate. Likewise, a public signal that contains more information than what they would have optimally chosen would be processed with noise: had the agents had sufficient information processing capacity or more interest in processing information as commanded by their utility, they would have already optimally chosen a more informative signal about the interest rate. Thus, a commitment from the monetary authority to provide an accurate path of the monetary policy stance would have limited material impact on consumption.

## 3 Experimental Design and Implementation

This section lays out details of our within-subject experimental design, including a description of the tasks designed to implement the model in Section 2 as well as the four treatments.

### 3.1 Experimental Task

The basic idea of the experiment is to create a decision problem in which one decides how much to consume and how much to save when the interest rate is uncertain. To simplify the task, subjects select one among 11 lotteries with well-specified payoffs for each of 32 equally likely possible states of the world. The 11 lotteries correspond to different levels of period 1 consumption and the 32 states of the world correspond to possible interest rate realizations. Because period 1 consumption and the interest rate determine period 2 consumption per equation (3), these two values are enough to fully determine the discounted expected utility, which gives the payoff of a given lottery in a given state (see equation 1). In the experiment, the payoffs are described to subjects as prizes, the lottery choice is described as selecting

one of 11 prize cards, and the realized state is described as drawing a numbered ball (from 1-32) from a computerized bingo cage.

The prize number (interest rate) is actually drawn before a subject makes her prize card (consumption/savings) choice, but this realization is not revealed to the subject. Consistent with the model’s assumption, the subjects have an uninformative (uniform) prior over all the possible realizations of the interest rate, denoted by  $g(r)$  in Section 2. Before making consumption/savings decisions, subjects can reduce uncertainty about the interest rate by acquiring a signal through solving cognitively challenging puzzles. Signals identify narrower ranges over which the realized state of the world is uniformly distributed. We provide subjects with an array of signals widths; longer intervals are associated with easier puzzles, while more precise signals require solving more difficult puzzles. More details about signals, intervals, and cognitive puzzles are discussed below in Section 3.2. With the introduction of these signals, the subject’s problem becomes how much information to acquire before selecting a prize card. The interval of possible prizes revealed to the subject after acquiring a signal defines the corresponding optimal conditional distribution in the theoretical framework,  $p^*(c_1|r)$ .

The experiment is deployed in the laboratory using the interface shown in Figure 1. The possible prizes – the cells in the table – follow the quadratic surface of the lifetime utility in Section 2. The possible prize numbers are represented by the columns of the table and the rows of the table denote the prize cards. The payoffs in red font provide the full information benchmark of the optimal  $c_1$  associated with each possible interest rate.

Signal selection in the experiment is done by clicking on one of the boxes in the lower left corner of the figure. If a subject successfully obtains a signal then some prize numbers are grayed out for every row, thus reducing the number of possible outcomes and hence payoffs. A signal with level 1 precision reduces the number of possible states of the world by half, and either side of the payoff table could be revealed as containing the true realization of  $r$ . In the figure, this case is illustrated by going from the full space enclosed by the yellow, solid-line box to the reduced space enclosed by the green dashed-line box on the right side of the table corresponding to  $p^*(c_1|r)$ .

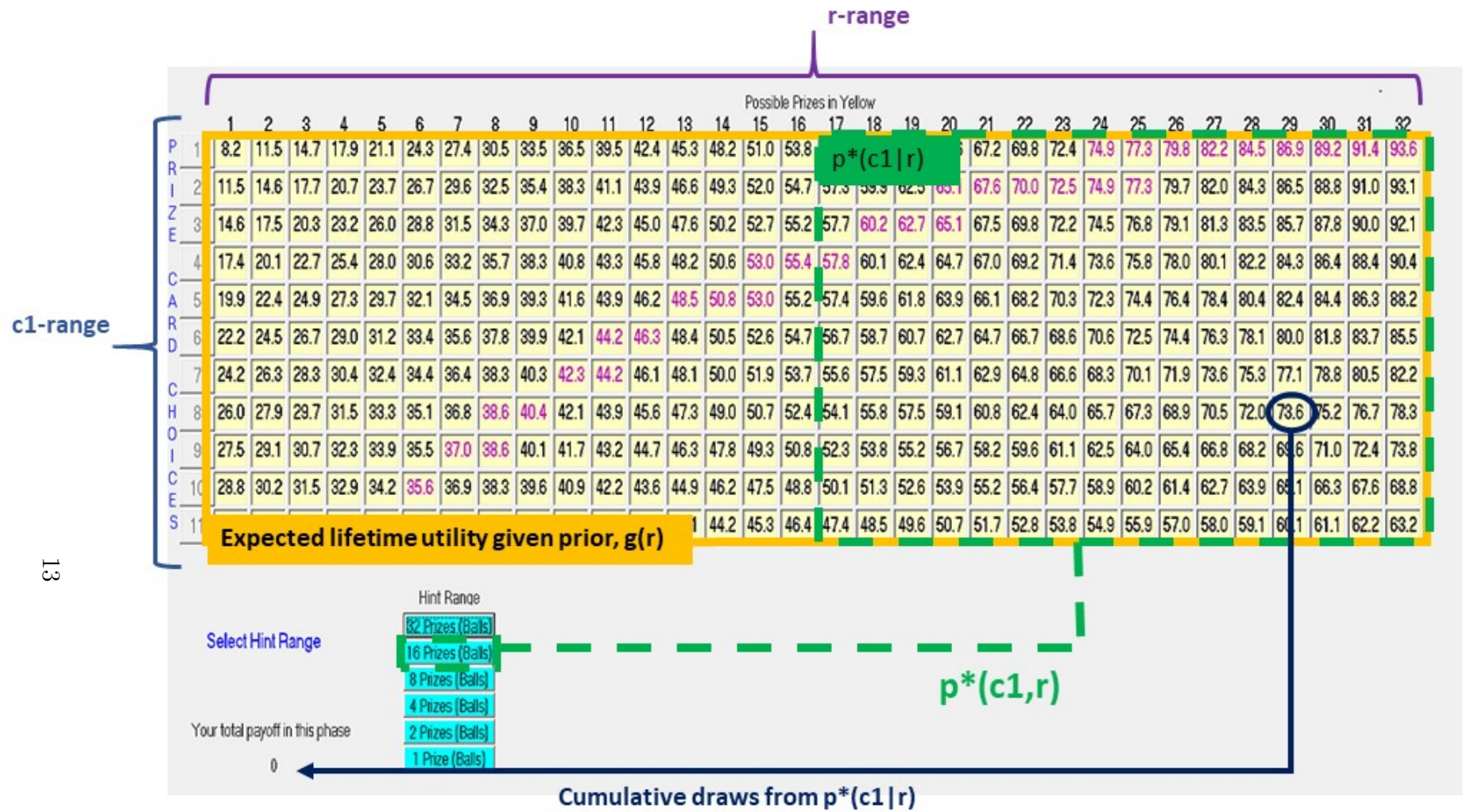


Figure 1: Mapping the theory to the experiment: A screenshot of the experimental interface with elements of the theoretical framework superimposed. The matrix of lottery payoffs in the yellow box are a function of the  $r$  drawn in the column (32 possibilities) and the consumption choice of the subject in the row (11 options). Red payoffs indicate the full information optimum for a given  $r$ . Subjects select a signal by clicking on one of the cyan buttons on the SW corner of the interface, which reveals a subset of columns containing the true realization of  $r$  (the green dashed box, which corresponds to the theoretical conditional distribution of consumption  $p^*(c_1|r)$ ). In the example, the second signal precision is selected and the right side of the  $r$  support is revealed. Signal selection and restricted support jointly correspond to the choice of the optimal distribution  $p^*(c_1, r)$ .

Once a signal is revealed, the subjects chooses a row which would then be highlighted in green. This is equivalent to drawing a particular realization of  $c_1$  from the optimal distribution conditional on the signal,  $p^*(c_1|r)$ . Next the column of the prize number is revealed and highlighted in blue.<sup>12</sup> The intersection of the row and column determines the payoff for subject and this amount is added to the subject’s cumulative payoff. Again looking at Figure 1, if row 8 is chosen and column 29 is drawn, the subject would earn a payoff of 73.6.

### 3.2 Signal Characteristics and Cognitive Tasks

In the model, we postulate that the representative agent is limited in her ability to process information about interest rate variations. In the experiment, we encode this limit through the structure of the precision level of the signals. This section describes the characteristics and information content of these signals.

Subjects have six levels of signal precision available, ranging from uninformative (level 0) to fully informative (level 5). We measure the informativeness of the signal as amount of information (in bits) contained in the signal. Letting  $j \in (0, 5)$  indicate the precision level, a signal identifies one of the  $2^j$  intervals containing  $2^{5-j}$  draws into which the full support of draws is partitioned. Since the signals presented to the subjects all have uniform distribution, our signals have the property that the change in entropy is constant from one precision level to the next, and equal to 0.3 bits. This structure means that, once a signal is revealed, the expectation  $\mathbb{E}_{R_i}$  and the corresponding variance  $\mathbb{V}_{R_i}$  in the optimal choice of which lottery to play described in equation (5) in Section 2.2 are taken with respect to the updated prior on the states of the world as it emerges from the signal.

The actual logic puzzles are based on a visual task developed by Civelli and Deck (2018). These puzzles take on the form of a  $(3 \times 3)$  graphical matrix in which eight images are provided and one is omitted. Subjects must identify the missing image among a set of alternatives, after analyzing how the images are similar or different along each of several dimensions. A puzzle’s level of difficulty is based on the number of dimensions along which images vary.<sup>13</sup> An example puzzle is illustrated in Appendix C.

Given the puzzle calibration exercises conducted by Civelli and Deck (2018), we are able to create tasks of a desired cognitive difficulty by requiring someone to solve a series of

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<sup>12</sup>In the experiment, the subject must confirm the row choice before the outcome is revealed.

<sup>13</sup>The puzzles are similar to the well-known Raven’s Progressive Matrices. We opt to use these puzzles rather than Raven’s Progressive Matrices because the level of difficulty can be controlled and there are potentially a very large number of puzzles of any given difficulty level.

Precision Level	Logic Puzzle Attributes	% Task Correct
0	1 puzzle: level 0	99%
1	2 puzzles: level 1 and level 1	80%
2	2 puzzles: level 1 and level 2	65%
3	2 puzzles: level 2 and level 2	50%
4	2 puzzles: level 3 and level 3	35%
5	2 puzzles: level 4 and level 5	20%

Table 1: Signal structure: precision level, logic puzzle attributes, and expected success rate of cognitive tasks. Note: a level  $k$  puzzle has  $k$  attribute changes.

puzzles. Acquiring a signal requires correctly solving two puzzles, with the exception of precision level 0 which requires solving one trivial puzzle.<sup>14</sup> Table 1 shows the precision level of the signal (first column), number of attributes changed in each puzzle that forms the task (second column), and the calibrated probability that a subject successfully acquires a signal (third column). In the experiment, a subject could try as many times as she wishes to acquire a signal. A subject could attempt to acquire a more precise signal after obtaining a less precise signal, but could not attempt to acquire a less precise signal after acquiring a more precise signal.<sup>15</sup>

### 3.3 Experimental Implementation

The experiment uses a within-subject design and is broken into several parts. First the subjects read general instructions about how to interpret the prize table and go through 10 unpaid practice periods where they select a price card and observe the outcome for a randomly drawn prize number.<sup>16</sup> Second, subjects read additional instructions on signal acquisition and logic puzzles before completing a 10 minutes unpaid practice phase. Next, subjects re-read the main instructions and then began the paid portion of the experiment.<sup>17</sup>

<sup>14</sup>Subjects do not have to solve the puzzle correctly to receive a precision level 0 signal since it is completely uninformative. Subjects do have to go through the motions of acquiring a level 0 signal to maintain consistency.

<sup>15</sup>This assumption encoded in the experimental setting captures the well-known principle in information theory that information cannot be forgotten. In order to avoid subjects having to rely on cognitive effort to remember the more informative signals, we prevent them from choosing signals with lower precision than one already successfully obtained.

<sup>16</sup>In the experiment, the term period refers to the process of acquiring a signal, selecting a prize card, and receiving a payoff. This should not be confused with the notion of period 1 and period 2 consumption as described in the model as these notions were never introduced to subjects.

<sup>17</sup>The instructions before and after the practice phase differed slightly due to the subject being at different points in the study, but the two sets of instructions did not differ materially.



Subject instructions are available in Appendix C.

The paid portion of the experiment consisted of four phases. Each paid phase was associated with one of the four treatments described in the next subsection. The order of the treatments was randomized for each subject to control for learning and sequence effects. Subjects knew that there were four paid phases, but did not know anything about a given phase until reaching that point in the study. Each phase was preceded by brief phase-specific instructions. Each of the four practice phases lasted approximately 10 minutes. In each phase, subjects face an indefinite number of periods during which they can try to earn as much money as possible. The unspecified ending time is designed to mitigate end of game effects on behavior. A cap on the number of periods that could be completed during a phase was intended to discourage subjects from opting to always solve easy puzzles and race through the task.<sup>18</sup> Once a subject confirmed their prize card choice and received the payoff for that period, the subject automatically proceeded to the next period.

The experiment was conducted at The Interactive Decision Experiment (TIDE) Lab at The University of Alabama. Subjects were recruited from the lab’s standing subject pool.<sup>19</sup> A total of 51 subjects participated in the experiment over the course of 3 sessions during October 2019. Average subject payment, including a \$5 participation payment, was \$24.16 USD. The salient portion of a subject’s earnings was the sum of her cumulative earnings in the four paid phases. All prize payoffs displayed to the subjects were in cents and final payments were rounded up to the next quarter. Each session lasted approximately 90 minutes, which included working through the instructions, the practice phases, and participating in the actual experiment.

### 3.4 Experimental Treatments

Up to this point the description of the task has focused on the baseline (Treatment 1). In Treatment 2, which we dub the *Delphic forward guidance treatment*, the interest rate is drawn randomly from a uniform distribution whose support,  $[0.7 \ 1.0]$ , is lower than the

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<sup>18</sup>For this reason, there was also a one-minute time penalty for subjects who made decisions without obtaining a signal precision above 0. This feature of the experimental design exemplifies the case in which a representative agent incurs in a fee for investing her savings in an asset without any information about the potential returns or losses of the investment. This cost is codified in the assumed functional form of the utility for which a zero consumption returns the maximum loss of  $\bar{c}^2$ . In the experiment, few subjects reached the cap of 10 periods, but several opted to incur the time penalty from making a decision with a completely uninformed prior.

<sup>19</sup>The subject pool primarily consists of undergraduate students from across campus, but graduate students comprise a small percentage of the subject pool.

	(1) Range of $r \in [r_1, \dots, r_{32}]$	(2) Discount factor $\beta$	(3) Utility function parameters $[\bar{c}; \alpha]$	(4) Subjects' information set before treatment
Treatment 1 (T1) <i>Baseline</i>	[0.4 1.3]	0.90	[1.5; 10]	General Instructions
Treatment 2 (T2) <i>Delphic Forward Guidance</i>	[0.7 1.0]	0.90	[1.5; 10]	General Instructions
Treatment 3 (T3) <i>Outlook Deterioration</i>	[0.4 1.3]	0.75	[1.5; 10]	General Instructions
Treatment 4 (T4) <i>Odyssean Forward Guidance</i>	[0.4 1.3]	0.90	[1.5; 10]	$r$ in top/bottom half of range, correct with prob. .9

Table 2: Parametric characterization of each treatment. Column (3) specifies the parameter used in the utility function described in Section 2.2, where  $\bar{c}$  is the satiation level and  $\alpha$  the multiplicative constant. Column (4) states which information participants are given at the beginning of each treatment. Payoffs are displayed in Figure 1.

support, [0.4 1.3], of the baseline. The shrinkage of the support in a uniform distribution implies that the volatility associated to the interest rate is reduced. As a result, the degree of uncertainty about the economic environment and the level of risk in investing (savings) are both diminished. This treatment combines the testable predictions of Subsections 2.3.1 and 2.3.2.

In Treatment 3, dubbed the *outlook deterioration treatment*, we decrease the appeal of savings by decreasing the discount factor  $\beta$  in (1) from  $\beta = .9$  in Treatment 1 to  $\beta = .75$ . This corresponds to a situation where the agent becomes less optimistic about future investment prospects. This treatment encompasses the testable prediction in Subsection 2.3.3.

Finally, in Treatment 4, the *Odyssean forward guidance treatment*, we retain the same values of the lottery and range of interest rates as in the Treatment 1 but the realized draw becomes more predictable. Specifically, subjects are provided with a noisy clue as to whether the realized outcome is in the first half of the possible outcomes or the second half. This signal is correct with a 90% probability, which is known to the subject. We use this treatment to test the prediction in Subsection 2.3.4.

Table 2 summarizes the specific calibration for each treatment. The first column shows the range of the interest rate, while the second column the discount factor. In column 3, we encode the parametrization of the utility function as described in Section 2.2, with  $\bar{c}$  indicating the satiation level and  $\alpha$  the multiplicative constant. Column 4 describes the clues the participants are given on the treatments they are about to play in the experiment, which characterizes their information set before making their signal and consumption choices.

## 4 Results

In this section we compare theoretical predictions to empirical observations. We start by illustrating the implications of the model assumptions laid out in Section 2 on the empirical setting and outcomes. We formally test how consumption choices of the representative rational inattentive (RI) agent compare with the choices selected by subjects, and whether the behavior predicted by the RI model describes the empirical behavior better than the model with full information (FI).

We proceed by formally testing the main theoretical predictions of the model in Section 2 against the empirical choices of participants in the laboratory experiment. First, we explore the value of information processing in observed consumption choices, and contrast empirical consumption outcomes with the theoretical optimum expressed in equation (5) of Section 2. This allows us to gauge the consistency between the empirical distribution of consumption and the theoretical predictions in Subsection 2.3.1. Second, we test the effectiveness on both theoretical and empirical consumption outcomes of two kinds of forward guidance in the lab: Delphic and Odyssean forward guidance corresponding to the testable predictions in Subsection 2.3.2 and 2.3.4, respectively. Finally, we test whether consumption choices with a deterioration of the outlook as defined in Subsection 2.3.3 are aligned with their empirical counterparts.

### 4.1 Theoretical Assumptions and Empirical Outcomes

The closed-form theoretical solution of the model in equation (5) relies on the assumption of quadratic utility of the agents. Translating this assumption into the empirical model results in a rather flat profile of expected gains, as evident from the payoff matrix in Figure 1. Moreover, in the model with fixed lifetime endowment, consumption in period 1 is akin to investing in an asset with certain return as opposite to the uncertain-return asset represented by savings and consuming in period 2, implied by the stochasticity of the interest rate. In this environment, the theory predicts that when the utility gains of processing more information do not provide a sufficient compensation for the cognitive effort of precisely tracking the interest rate, the agent would prefer to experiment with changes in the behavioral variable rather than varying signal acquisition.

Figures 2 and 3 suggest this is the case in the experiment as well. The figures plot individual (blue) and average (red) choices in the experiment across treatments for period 1 consumption (Figure 2) and precision (Figure 3). The laboratory evidence reveals that

subjects prefer to exercise a relatively modest cognitive effort in processing information, represented by low and flat signal precision, while they are more willing to adjust the behavioral variable in response to different interest rate scenarios.

In general, the period 1 consumption behavior predicted by the model captures rather closely the average subject choices across treatments, as the black (representative agent) and red (experimental average) lines in Figure 2 show. This result has a stark monetary policy implication: when changes in interest rates policy are unimportant for people’s utility, these changes are unlikely to elicit strong behavioral reactions in attention allocation.

## 4.2 Value of Information, Model Validation, and Consumption Outcomes

We first establish how information about interest rate movements impact agents’ total profits (lifetime utility) by comparing the laboratory outcomes with the full information benchmark for the baseline (Treatment 1: T1). Figure 4 illustrates the loss in lifetime utility calculated as the difference between full information profits and realized total profits as a percentage of full information profits (y-axis), plotted against the precision level of the signals acquired (x-axis). Each dot in the figure represents the average precision acquired by one subject and her average percentage profit loss in T1. From our experimental design, the participants can choose among six progressively higher precision levels, with 0 being the uninformative signal and 5 corresponding to the full information. It is immediate to see lower signal precision are associated with higher utility losses. We formalize this graphical intuition by estimating a kernel regression between the average loss and the average signal precision. The choice of a kernel regression is motivated by the possibility of a non-linear relationship between the two variables.<sup>20</sup>

Figure 4 also shows that there are diminishing returns to information processing for the quadratic utility specification assumed in Section 2.2. In fact, the flatness of the quadratic utility at high values of consumption provides minimal gains to information processing beyond signal precision 3, whereas for signals with precision less than or equal to 2 the lifetime utility gains from increasing information processing are more substantial. Departures from the full-information benchmark also depends on the heterogeneity in risk attitude of the subjects. As an example, consider the dots of Figure 4 corresponding to precision 1. Subjects that gather little information differ widely with respect to payoff losses according

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<sup>20</sup>We use a local linear kernel with Nadaraya-Watson estimator and apply a bandwidth of 0.58, estimated following Bowman and Azzalini (1997).

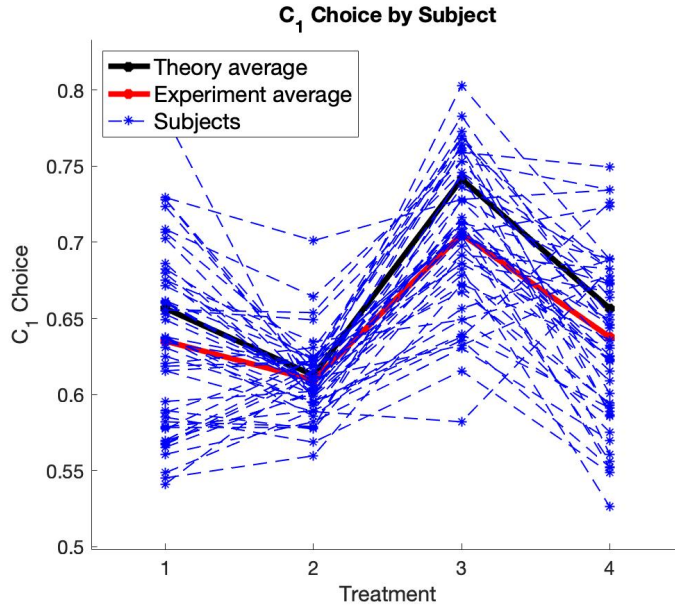


Figure 2: Consumption choices for the first period of the model ( $c_1$ ) across treatments for the subjects in the experiment. Individual average  $c_1$  choices are given by the thin, dashed blue lines, overall subjects average by the thick red line, and the representative agent choice by the thick black line. Treatments defined in Table 2

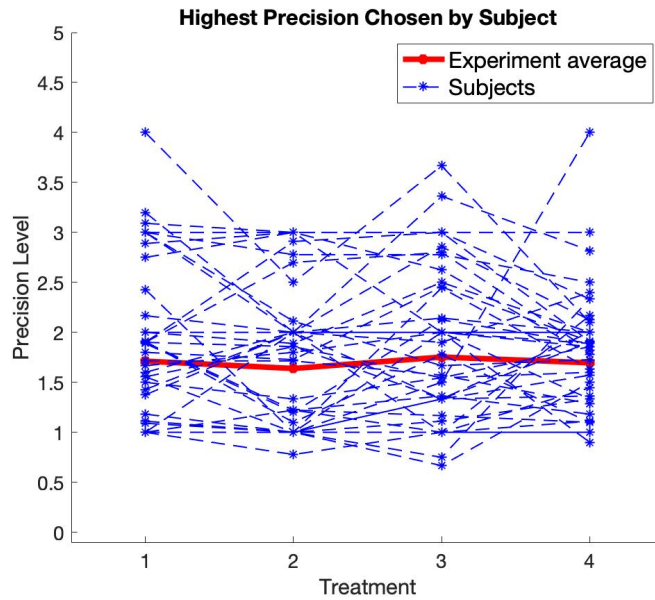


Figure 3: Highest signal precision level chosen by the subjects in the experiment before making their consumption choice across treatments. Individual average precision is given by the thin, dashed blue lines, while the overall subjects average by the thick red line. Treatments defined in Table 2

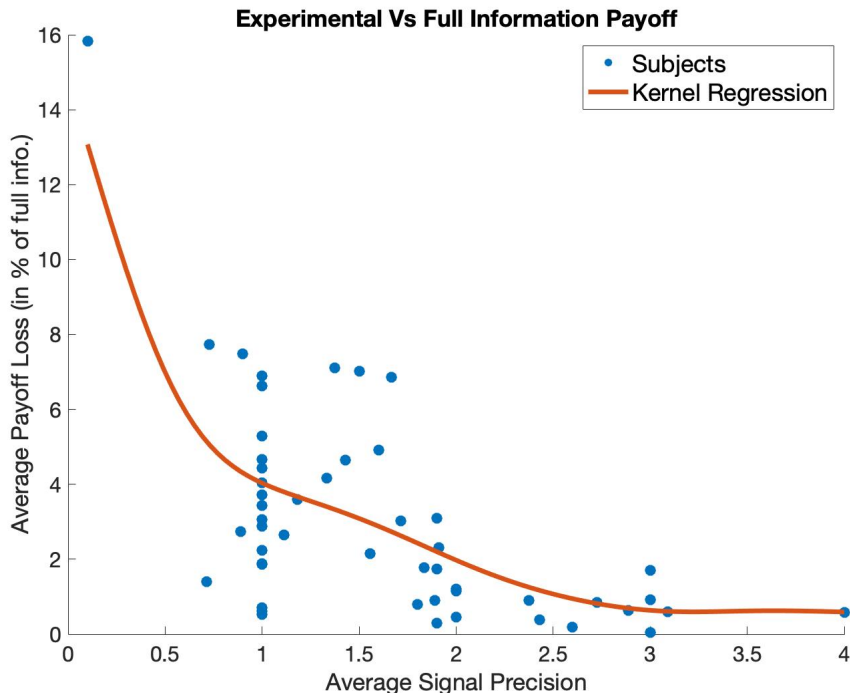


Figure 4: Average difference between full information and realized total payoffs (lifetime utility) as percentage of full information total payoffs plotted against average signal precision. The averages are taken within subjects. Each dot represents the average outcomes of one subject in the course of the baseline treatment. The red line corresponds to the local linear kernel regression with Nadaraya-Watson estimator.

to whether they are over- or under-confident. In the first case, they make riskier bets on the interest rate and trade off consumption today for a better payoff tomorrow while retreat to the safe asset ( $c_1$ ) in lieu of exercising more effort to track the interest rate.

Next, we evaluate the congruence of the subjects' behavior with that of the representative agent from the RI model. Furthermore, we assess whether the consumption behavior predicted in the RI model describes the experimental consumption choices better than the FI model.

Figure 5 presents a scatter plot of the consumption choices  $c_1$  of the RI representative agent (y-axis) against the experimental choices of the subjects (x-axis). For both theoretical and experimental data the  $c_1$  outcomes are de-meanned, and each dot represents an observation of the triplet [Theoretical RI  $c_1$ , Experimental  $c_1$ , Signal Precision].<sup>21</sup> The color of the dot indicates the precision chosen by each subject according to the scale on the upper right

<sup>21</sup>For the baseline treatment, T1, the mean for the theoretical RI  $c_1$  is 0.65 whereas the experimental average is 0.63

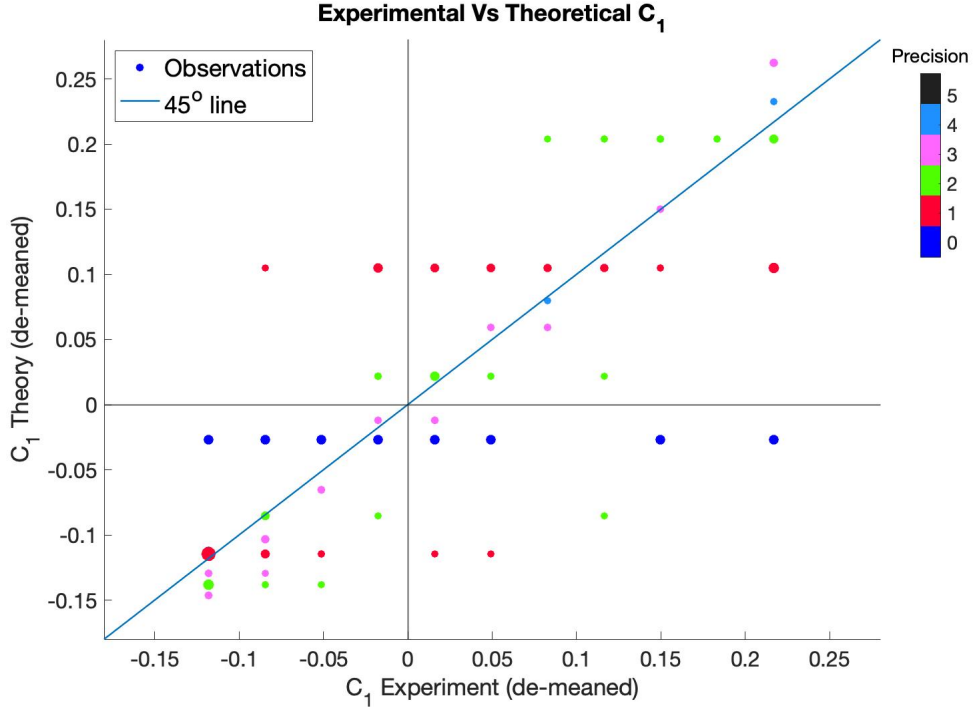


Figure 5: Scatter plot of theoretical and experimental consumption choices,  $c_1$ . Observations are de-meaned and each dot represents a subject. The color of the dots indicates the precision selected by the subject according to the legend in the upper-east corner of the figure. The size of the dot is proportional to the sample frequency of a given triplet (precision, theoretical  $c_1$ , experimental  $c_1$ ).

corner of the figure. The size of the dot is proportional to the sample frequency of each triplet. There are two main take-aways from this figure.

First, for higher precision levels (i.e., level 4) the experimental choices of  $c_1$  are very close to both the FI model and the RI representative agent choices. This observational equivalence between the FI model, the RI model, and observed behavior arises in our setting because of the length of the interval revealed by the signal for high precision compounded with the flatness of the utility function assumed in the theoretical model. Thus, the more informative cases in terms of congruence of model predictions and experimental choices occur at lower precision levels, where the width of the interval is substantial and the sample much more sizeable.

Second, with respect to informative precision levels ranging from 1 to 3, Figure 5 shows a remarkable consistency of the experimental outcomes with the behavior predicted by the RI model for the cases with higher sample frequency (i.e., bigger dots). This finding places

the average consumption choice per subject strikingly close to the RI representative agent outcome in each precision level.

We corroborate this visual insight by formally testing the fit of the RI model in describing the experimental data and its performance in comparison to the FI outcomes. To this end, we run linear regressions of individual subjects' experimental  $c_1$  choices on the RI representative agent behavior predicted by the model. We first run these regressions individually for the three informative precision levels, precision 1 to 3, observed in the baseline treatment of the experiment, T1.<sup>22</sup> We then estimate two pooled models, again for the T1 observations: one including fixed effects and one without fixed effects but using weights proportional to the length of the signal intervals.<sup>23,24</sup> We run this battery of regressions of the experimental  $c_1$ 's on the full information solution as well, and we formally contrast the regressions outcomes from the RI and the FI models to assess their relative performance in explaining the experimental data. The results of this analysis are in Table 3.

The first three models of Table 3 present the estimates of an OLS regression of the experimental consumption,  $c_1$ , on either the rational inattention prediction of consumption,  $c_{RI}$  in the table, or the full information outcome of consumption,  $c_{FI}$ , conditional on the precision levels of the signal. In all the regressions we use robust standard errors clustered by subjects. We take the evidence from these three models as the baseline in our analysis. If a theoretical model is a good fit for the data, we would expect the slope associated to the consumption choice predicted by the model to be close to one and the constant of the regression to be close to zero. As the table illustrates, the coefficients associated to  $c_{RI}$  are systematically bigger and closer to 1 than those associated to  $c_{FI}$ . A t-test of the slope of the regression cannot reject the hypothesis that the slope of the regression for the model is, in fact, one for precision 1 but not for the other two. Similarly the constant terms are also smaller in the RI case, and not significantly different from zero for precision 1.

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<sup>22</sup>We omit precision level 0, the uninformative signal, since the theoretical prediction for this particular signal corresponding to a zero-capacity Shannon's channel is just a random draw from the uniform distribution of the interest rate.

<sup>23</sup>The F.E. model excludes precision 4, since only one subject chooses this signal in the experiment and only 4 observations are available at this precision.

<sup>24</sup>The F.E. model controls for the systematic bias in the distribution of consumption at different precision levels. For instance, both RI models and the data display leptokurtic and left-skewed distributions as opposite to the uniform updated prior revealed by the signals. The weighted model is meant to capture the fact that subjects face more freedom in the choice of  $c_1$  for lower precision signals. The probability of a choice being close to the RI model simply because of chance is therefore smaller the larger the interval.



Table 3: **Model validation** – Estimation of the regression of Experimental consumption choices,  $c_1$ , on the consumption predicted by the Rational Inattention model,  $c_{RI}$ , and by the Full Information model,  $c_{FI}$ . OLS estimation, with standard errors clustered by subject reported in parentheses. Significance of estimated coefficients at 1%, 5%, and 10% level is respectively indicated by \*, \*\*, and \*\*\*. Models (1)-(3) are estimated by precision level of the selected signal as indicated in the Table. Model (4) uses precision fixed effects, with precision 0 as baseline and excluding precision 4. Model (5) is a weighted pooled model, with weights proportional to the length of the signal intervals. <sup>(a)</sup> T-Test of the null hypothesis that coefficient on either  $c_{RI}$  or  $c_{FI}$  is equal to one (p-values reported); <sup>(b)</sup> BIC statistic computed using N. Obs.; <sup>(c)</sup> Non-nested model coparison tests (p-values reported). J-Test correspond to the Davidson-McKinnon test. The alternative hypothesis  $M_{FI} \succ M_{RI}$  always rejected (omitted).

	(1) Precision 1		(2) Precision 2		(3) Precision 3		(4) F.E.		(5) Weighted	
	RI	FI	RI	FI	RI	FI	RI	FI	RI	FI
$c_{RI}$	0.91 (0.08)***		0.88 (0.03)***		0.84 (0.01)***		0.88 (0.04)***		0.89 (0.05)***	
$c_{FI}$		0.59 (0.06)***		0.79 (0.03)***		0.78 (0.02)***		0.66 (0.04)***		0.57 (0.06)***
Const.	0.04 (0.04)	0.24 (0.03)***	0.06 (0.02)***	0.12 (0.02)***	0.09 (0.01)***	0.13 (0.01)***	0.06 (0.05)	0.18 (0.05)***	0.05 (0.03)	0.26 (0.03)***
$prec_1$							-0.01 (0.04)	0.02 (0.05)		
$prec_2$							0.00 (0.04)	0.03 (0.05)		
$prec_3$							0.00 (0.04)	0.03 (0.05)		
N. Obs.	229	229	122	122	72	72	449	449	453	453
$Slope = 1^{(a)}$	.24	.00	.00	.00	.00	.00	.00	.00	.06	.00
BIC <sup>(b)</sup>	-570.4	-432.8	-489.1	-374.3	-414.6	-346.9	-1232.8	-956.2	-1080	-838
$M_{RI} \succ M_{FI}^{(c)}$										
J-Test		.34		.03		.99		.24		.54
Cox-Pesaran		.17		.03		.49		.08		.00

These results are confirmed by the other two models in Table 3. Model (4) presents the results of the linear regression for unconditional  $c_1$ , estimated with precision fixed effects to account for systematic biases within precision. Model (5) presents the results for the unconditional  $c_1$ , where the observations are weighted proportionally to the length of the precision interval. This weighting scheme accounts for the fact that a larger interval revealed by the signal is relatively more informative of the goodness of fit of the *RI* model than a smaller one. The slope of the regression is not significantly different than one only for the RI case in Model (5), however the constant is not significantly different than zero for both the RI regressions, but substantially larger and significant for the two FI models. Interestingly, the fixed-effect models show there is little, if no, heterogeneity in the pooled regression across precision levels.

The last rows of the table formally test whether the rational inattention model does a better job in predicting the experimental data than the full information model, thereby testing the assumption of capacity constrained individuals. The BIC statistics show that in the pairwise comparison within each regression group, the RI model exhibits a better fit than the FI model and it would always be strongly selected by the criterion.<sup>25</sup> The Davidson-McKinnon (J-test) and Cox-Pesaran tests for non-nested model comparison favor the rational inattention model over the full information model across the board as well. At the same time, the alternative hypothesis that the the FI model is preferable is strongly rejected in each case (not reported in the Table). Thus, we can reject the hypothesis that individuals behave according to the full information model and we find robust evidence that our subjects display a degree of rational inattention in their consumption choices.

### 4.3 Forward Guidance Outcomes

We explore the effects on consumption and information processing of two dimensions of forward guidance. First, we study whether a monetary authority that commits to lower volatility of the policy instruments succeeds in affecting consumption behavior of the agents as well as in modifying their attention to monetary policy. This treatment can be considered as a form of *Delphic Forward Guidance*.<sup>26</sup> We test the theoretical prediction in Subsections 2.3.1 and 2.3.2 in the laboratory experiment by giving to the subject a significantly lower range of possible realizations of the interest rate, thereby reducing the variance of the

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<sup>25</sup>The AIC results are similar, thus we omit them from Table 3 for sake of brevity.

<sup>26</sup>Campbell *et al.* (2012) defines Delphic forward guidance as using interest rate to stabilize the economic outlook, while Odyssean forward guidance is a commitment to undertake policy actions in the future, like “keeping rates lower for longer” when inflation and GDP rise.

(uniform) interest rate distribution. The results of this stimulus are in Subsection 4.3.1.

Second, we study whether an enhanced predictability of the interest rate policy may provide enough stimulus to the subject to change their behavior toward consumption and information processing. This treatment can be considered as a form of *Odyssean Forward Guidance*.<sup>27</sup> We test this assumption by having the monetary authority announcing whether the monetary policy stance would be accommodative (low interest rate) or tight (high interest rate) during the current period and committing to the announcement 90% of the time while deviating from that commitment with probability 10%. The results of this treatment are in Subsection 4.3.2.

### 4.3.1 *Delphic forward guidance*

A monetary policy that makes the interest rate path less volatile and, as a result, more stable by, e.g., providing forward guidance via Fed officials' communication and regular release of the Summary of Economic Projection (SEP) forecasts, requires less effort from the representative agents to track the policy instrument closely. This occurs because the predictability of the interest rate path implies a lower cognitive burden to the tracking of the interest rates for the agents. As a result, agents are more confident in their estimate of the monetary policy stance when making consumption and investment decisions.

The RI model's prediction in Subsection 2.3.2 calls for a  $c_1$  choice which is closer to the FI benchmark when the volatility of the interest rate is reduced. This prediction stems from the fact that a lower volatility reduces the effort necessary to precisely track the policy rate, so that the RI agent's consumption choices are, on average, more deliberate and, as a result, her welfare computed as lifetime utility is closer to that of the FI agent. Combining the theoretical predictions of Subsections 2.3.2 and 2.3.1, the model predicts a decreasing and flatter  $c_1$  profile as a function of the interest rate expected by the RI agent. An illustration of this prediction is provided in Appendix B, while we focus on the welfare implications here.

We implement this scenario with a reduction of the interest rate volatility to about one tenth of the baseline one, as explained in Section 3.4. This treatment captures the monetary policy's aim to stimulate private sector's investment by providing a stable economic environment for households and lower their cognitive effort of tracking the interest rate.<sup>28</sup>

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<sup>27</sup>We see this treatment as a form of Odyssean forward guidance in that, at least in principle, providing a signal on the monetary policy stance and committing to a high accuracy of the signal is a guidance to the private sector on the behavior of the interest rate that may foster a more predictable environment in which to consume and allocate attention.

<sup>28</sup>Under our distributional assumption on the interest rate, a reduction in its variance implies that fewer

We evaluate the effectiveness of this policy by comparing deviations, in terms of losses, of lifetime utility from the full information benchmark as a percentage of full information values in this scenario relative to the baseline. As standard for evaluating monetary policy changes in the literature, we use lifetime utility as a proxy for agents' welfare, measured by the mean total profits of each subject in the experiment. Figure 6 illustrates the kernel estimates of the aggregate distributions of the welfare losses for the rational inattention theory (top panel) and the experimental data (bottom panel). In both panels, blue dashed lines indicate the baseline (T1) whereas the red solid lines represent the Delphic forward guidance treatment (T2). The densities are estimated using a Gaussian kernel.

Four main observations emerge from this figure. First, the experimental data is strongly consistent with the RI theoretical predictions. The main difference between experimental and theoretical cases is a longer tale for the experimental distributions. Second, welfare losses are largely smaller under T2 than they are under T1. The T2 density is much more concentrated than the T1 one: the empirical density displays a clear, sizeable peak around 0.15%, while the distribution of losses in T1 is spread out over the support 0-10% with a peak around 1.25%. More importantly, the standard deviation of the distribution of losses is dramatically reduced from 2.6% in T1 to 0.7% in T2. The T2 distribution is leptokurtic and left-skewed.

Third, the difference between RI theoretical outcomes and experimental data can likely be attributed to risk aversion. The representative RI agent displays modest risk tolerance consistent with the quadratic utility, whereas experimental subjects appear more risk averse. However, note that the average subject in the experiment modestly lowers her attention to the interest rate (decrease signal precision, as evident from Figure 3) and moderately increase investment (lowers  $c_1$  consumption with respect to T1 as shown by Figure 2). With respect to  $c_1$  and investment decisions, the representative RI agent and the average experimental subjects appear aligned as per Figure 2.

Finally, in the RI theory as well as in the experimental data, the decrease in both the magnitude and the volatility of welfare losses are consistent with behavioral choices that are more deliberate and attune to an economic environment with reduced uncertainty with respect to the baseline. The monetary policy implication of the comparison between T2 and the baseline is that the form of Delphic forward guidance considered appears to be effective in reducing the welfare loss in a world where agents are rationally inattentive.

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bits of information are needed to accurately track the interest rate with respect to the baseline.

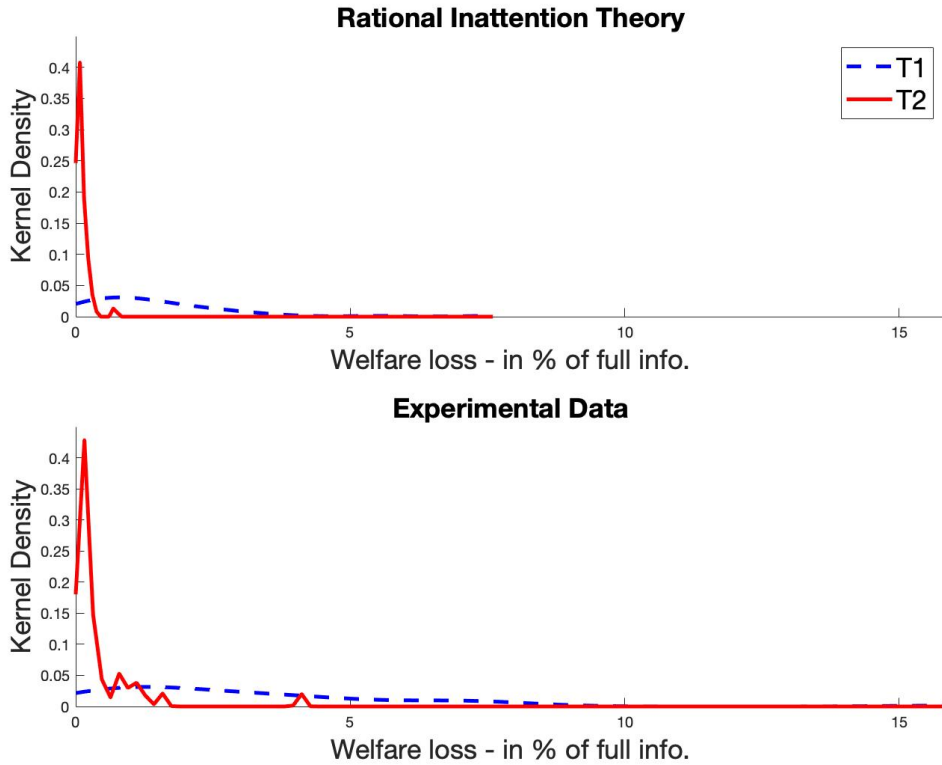


Figure 6: Aggregate density distribution of welfare losses as percentage of full information under the *Delphic forward guidance treatment* (T2) in red solid line and the baseline (T1) in blue dashed line. The aggregate densities are estimated using a Gaussian kernel. The top panel shows the density for the representative RI agent, whereas the bottom panel displays the density for the average aggregate experimental data. For the data, welfare losses are computed as mean deviations per subject of total profits from full information profits.

### 4.3.2 *Odyssean* forward guidance

An announcement of future paths of interest rate constitutes an attempt from the monetary authority to keep monetary policy predictable and, as a result, enhancing the predictability of the economic environment. Examples of this form of forward guidance in the U.S. are in several FOMC's statements and speeches signalling whether the monetary policy stance is loose or tight. The literature has labelled this kind of forward guidance as *Odyssean*.

For this scenario, we assume that the central bank announces to the public whether the monetary policy stance in the current period would be accommodative (low interest rate) or tight (high interest rate). The monetary authority commits to deliver a signal on the monetary policy stance that is 90% accurate. For this case, the model predicts no change

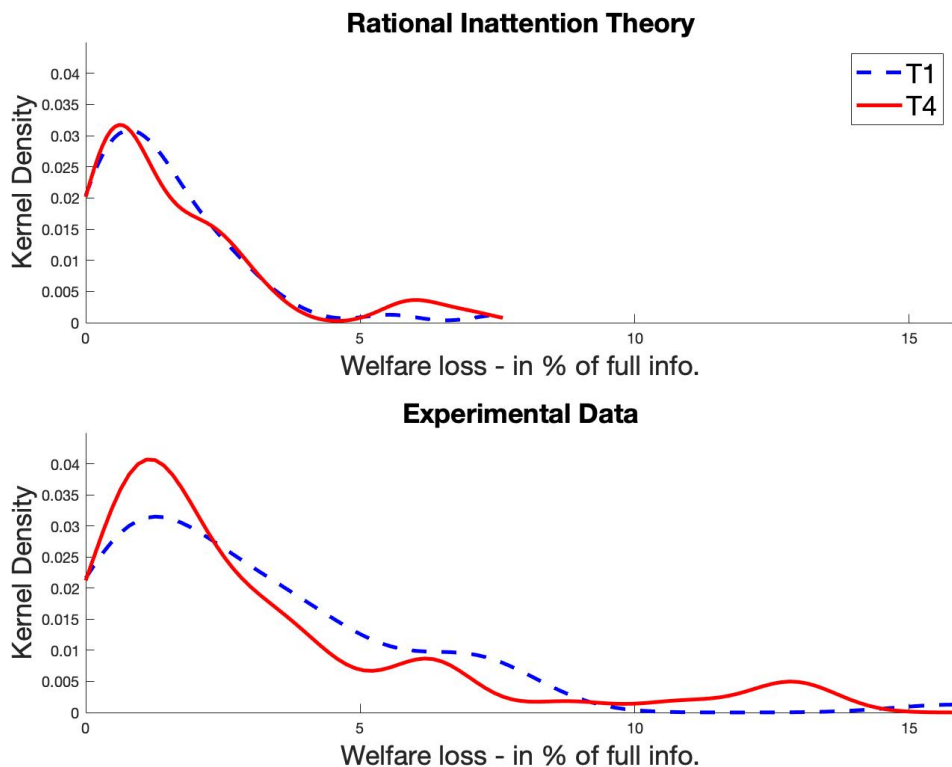


Figure 7: Aggregate density distribution of welfare losses as percentage of full information under the *Odyssean forward guidance treatment* (T4) in red-dashed line and the baseline (T1) in blue solid line. The aggregate densities are estimated using a Gaussian kernel. The top panel shows the density for the representative RI agent, whereas the bottom panel displays the density for the average aggregate experimental data. For the data, welfare losses are computed as average mean deviations per subject of total profits from full information profits.

in consumption behavior with respect to the baseline. The rationale behind this theoretical finding stems from the fact that, conditional on the signal acquired, the optimal choice in equation (5) remains unchanged under this scenario with respect to the baseline. An illustration of this prediction is in Appendix B.

We implement this scenario by giving the subjects the announcement on the monetary policy stance at the beginning of each period of this treatment, as explained in Section 3.4. This treatment is meant to replicate the commitment of the monetary authority to make the interest rate more predictable. This policy’s goal is that interest rate rigidity may foster investment while lowering the cognitive burden of keeping track of the policy rate. As we did for the previous form of forward guidance, we assess the effectiveness of

this policy experiment on private sector’s welfare by studying the percentage deviations of lifetime utility from the full information benchmark in this treatment in comparison to the baseline.

The estimated aggregate kernel densities of these deviations are reported in Figure 7 for the rational inattention theory (top panel) and the experimental data (bottom panel). As above, blue dashed lines indicate the baseline (T1), whereas the red solid lines represent the Odyssean forward guidance treatment (T4). We use the same estimation methodology to derive this figure as we did for Figure 6.

From Figure 7 it is clear that the theoretical and experimental distributions are once again strongly consistent with each other. It is also immediate to note that the distributions of welfare losses are remarkably similar under T1 and T4. We formally test for the equivalence between these two distributions by using the two-sample Kolmogorov-Smirnov (KS) test. The null hypothesis tested is that the two vectors of welfare losses from the two treatments are from the same continuous distribution, evaluated against the alternative hypothesis that the data are from different distributions.<sup>29</sup> The null hypothesis is not rejected at very high level of confidence (p-value of .95), while the same test conducted to compare the distributions of T1 and T2 strongly rejects the null (p-value of .00). Further robustness checks on subsamples of the distributions broken down by precision also confirm the equivalence of the distributions for T1 and T4. The results of this analysis are in Appendix B.

Both graphical inspection and quantitative results are in agreement in concluding that the welfare gains of going from T1 to T4 are statistically negligible. The stark monetary policy implication of this treatment is that the Odyssean forward guidance is not effective in affecting behavior and reducing welfare losses with an economy populated by rationally inattentive agents.

#### 4.4 Deterioration of Outlook and Consumption Outcomes

From the optimal theoretical solution in equation (5), dimming economic prospects captured by an increase in impatience of the private sector – a drop in  $\beta$  – makes investment a less appealing option for the agents than consuming right away. This change in private sector sentiment may occur, for instance, after a prolonged expansion when consumers and businesses sense a slowdown in economic activity. In this case, the model implies that agents

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<sup>29</sup>The Kolmogorov-Smirnov test is a nonparametric method which compares the cumulative distribution functions of two data vectors and is based on the maximum absolute distance between the empirical distributions of the two samples. It is sensitive to both location and shape of the distributions.

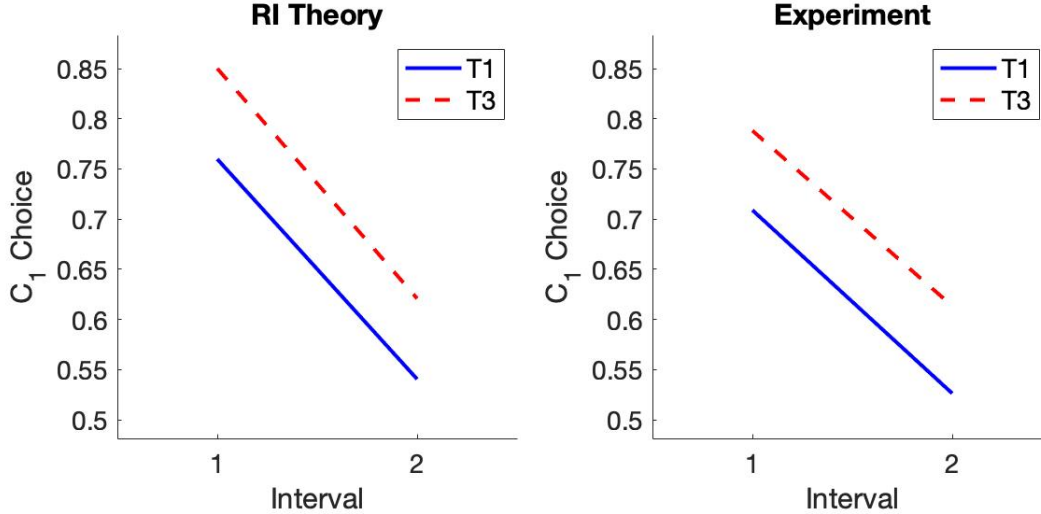


Figure 8: Comparison between the *outlook deterioration treatment* (T3) and the baseline (T1) consumption choices for the first period of the model ( $c_1$ ) made by the theoretical RI representative agent (left-panel) and by the subjects of the experiment on average (right-panel), when signal precision 1 is selected. Signal precision 1 identifies a partition of the  $r$  space in two intervals of 16 columns each, as exemplified in Figure 1. Intervals 1 and 2 then correspond to the left-hand side and right-hand side of the partition of the payoff space respectively.

will increase period 1 consumption relative to the baseline case, while keeping a similar watch on movements of the interest rate.

We implement this scenario by lowering the discount factor in the computation of the lifetime utility payoff as explained in Section 3.4. Figure 8 compares the representative agent’s choice of consumption as predicted by the RI theory with the corresponding average choice across subjects in the experiment. We report the data for signal precision 1, which identifies a partition of the  $r$  space into two 16-element intervals.

The figure illustrates a remarkable agreement between theory and experiment on the prediction that a deterioration of the outlook is associated with an increase in *precautionary consumption* with respect to risky investment from both the theoretical representative agent and the average participant. Moreover, as predicted by the theory, participants worried for future prospects still pay attention to the economic conditions and, specifically, to the interest rate. As Figure 3 shows, optimal signal precision for this treatment is at least as high as that for the baseline, on average.



## 5 Concluding Remarks

This paper presents a model in which a rationally inattentive representative agent chooses consumption and savings under uncertainty about the interest rate applied to savings. A central bank can persuade agents to change consumption behavior in response to changes in monetary policy.

We consider two changes in policy that relate to forward guidance: a reduction in the volatility of the interest rate (a form of Delphic forward guidance) and a commitment to provide an accurate signal on the monetary policy stance (a form of Odyssean forward guidance). The model predicts that the rationally inattentive agent is not responsive to Odyssean forward guidance, while Delphic forward guidance offers enough incentive to modify her consumption behavior. The model also predicts that a deterioration of the outlook from the agent's perspective, which may be caused by variations in *fiscal* rather than monetary policy, is extremely effective in inducing a change in behavior of the rationally inattentive agent, resulting in changes in investment behavior in the future.

These theoretical findings are tested in a laboratory experiment. We find that subjects' choices are consistent with those predicted by the rational inattention model. Moreover, we show that the predictions of the rational inattention model are more accurate in replicating subjects' behavior than those from the full information model, thereby reinforcing the idea that people behaviors and their changes are better described as coming from limited cognitive capacity agents than omniscient full information agents.

The experimental and theoretical results are corroborated by the recent and growing empirical literature on households' reactions to fiscal and monetary policy. To our knowledge, this is the first paper that tests in the laboratory the effectiveness of the two forms of forward guidance as well as of changes in the outlook on the consumption and savings behavior of individuals.

The paper has three stark policy implications. First, people react to changes in policy only insofar as those changes represent significant shifts of their utility. Changes that imply small deviations from the current conditions are not considered worthy of attention or behavioral responses. Second, a central bank concerned about people's welfare is best served by a policy that reduces uncertainty about the interest rate and, as a result, the economic environment than by a commitment to keep rates predictable. In our theory and experiment, the commitment to predictable rates, while it might change people's attention to monetary policy in general, has no effect on people's behavior with respect to an economic environment where this commitment is absent. Third, people's perception of the outlook

as it emerges from material changes in the economic environment or fiscal landscape is the most important trigger of behavioral change.

We believe this last point, especially in light of the difference in attention and behavioral responses to fiscal and monetary policies uncovered by the recent empirical evidence for the U.S., constitutes a promising venue for future research.

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# Online Appendix

## A Further Details About the Model

This Appendix provides some more theoretical details about the RI model used in the main paper.

The rationally inattentive agent of the model has limited information-processing capacity to process information about the interest rate. Thus, the agent must decide how much information to acquire about the interest rate functional to her consumption choices. Specifically, the agent starts out in period 1 with a prior on the interest rate that has distribution  $g(r)$ . She can reduce uncertainty about her prior by acquiring signals on the interest rate as they relate to her consumption possibilities in period 1. As explained in Section 2 of the paper, this choice variable is represented by the joint probability  $p(c_1, r)$ .

The optimal choice of the joint distribution depends on the information processing capacity of the agent. We postulate that the maximum amount of information that she can extract from consumption about the interest rate is limited by the Shannon's channel capacity. Before processing any information, the uncertainty about interest rate can be expressed by the entropy of the prior on  $r$ ,  $\mathcal{H}(r) \equiv -\mathbb{E}[\log_2(g(r))]$ . Since consumption and interest rate are related in the agent's decision, knowledge of consumption in period 1 also provides information about the interest rate. Thus the reduction of uncertainty about the interest rate that can be achieved through knowledge of consumption can be expressed as the conditional entropy of interest rate given consumption,  $\mathcal{H}(r|c_1)$ .

Shannon's theory posits that the information flow between the random variables  $r$  and  $c_1$ , expressed as  $I(c_1, r)$ , is bounded by a number,  $\kappa$ , which represents the maximum amount of information that can be extracted from  $c_1$  about  $r$ . In formulae:

$$I(c_1, r) = \mathcal{H}(r) - \mathcal{H}(r|c_1) \leq \kappa.$$

The bound  $\kappa$  is expressed as the number of bits of information that the agent can process about consumption and interest rate, and poses a limit on the informational content of the signals that the agent can choose.

We report the optimization program of the RI agent for convenience below:

$$\max_{p(r, c_1)} \mathbb{E} \left\{ \int [u(c_1) + \beta u(c_2)] p(c_t, w_t) \mu(dc_1, dr) | \mathcal{I}_1 \right\} \quad (\text{A1})$$

$$\text{s.t.} \quad \kappa = I(p(c_1, r)) \quad (\text{A2})$$

$$c_2 = r(1 - c_1) \quad (\text{A3})$$

$$p(c_1, r) \in \mathcal{D}(w, c) \quad (\text{A4})$$

$$g(r) \text{ given} \quad (\text{A5})$$

$\mathcal{D}(r, c)$  in constraint (A4) restricts the choice of the agent to be drawn from the set of possible distributions, while  $\mu(\cdot)$  is the Dirac measure that accounts for potential discreteness in the optimal choice of  $p(c, r)$ .

The program in (A1)-(A5) can be solved by Lagrangian methods. Let  $\theta$  indicate the *Lagrange multiplier* associated with constraint (A2), which can be interpreted as the shadow cost of processing information. Then the total cost of choosing a signal of information content  $\kappa$  is given by  $\theta\kappa$ . We postulate an environment with elastic capacity on agents' information-processing. That is, for a given marginal cost of processing information,  $\theta$ , the agent chooses a signal that conveys the optimal amount of information, as determined by the informational content of  $p(c_1, r)$ .

The program in equations (A1)-(A5) is a well-posed convex problem, but with state and control variables that are infinite dimensional. The solution to this specific 2-period model can be characterized analytically as:

$$p^*(c, r) = g(r) \left( e^{(\theta + \frac{u(C)}{\theta}) \ln 2} - 1 \right), \quad (\text{A6})$$

where  $u(C) = u(c_1) + \beta(u(c_2))$  – from which the closed form solution in (5) is then obtained for the utility functional form assumed in the paper.

The optimal joint distribution in (A6) illustrates how the solution depends on the shadow cost of processing information,  $\theta$ , the prior distribution of interest rate,  $g(r)$ , and the functional form of the lifetime utility,  $u(C)$ .

## B Forward Guidance: Further Results and Robustness Checks

### B.1 Consumption in Theory and Experimental Data

#### B.1.1 Delphic Forward Guidance

Figure A1 compares first period consumption choices for the Delphic forward guidance treatment (T2) with the baseline (T1) for the theoretical RI solution described in equation (5) of Section 2 of the paper (left panel) and the experimental average across subjects (right panel). We consider the choices made when signal precision level 1 is selected, for which we have a sufficiently large number of observations to conduct this exercise for an individual precision. As illustrated in Figure 1 of the paper, signal precision 1 identifies a partition of the  $r$  space into two intervals of 16 columns each. Intervals 1 and 2 in the figure then correspond to the left-hand side and right-hand side of the partition of the payoff space respectively.

The figure shows that this form of forward guidance makes subjects more deliberate in their investment decisions when the interest rate drawn is low, as they decrease period 1 consumption with respect to the baseline in interval 1, while they switch to more conservative choices than in the baseline treatment for higher draws of the interest rate in interval 2. Consistent with the theory, by decreasing the volatility of the monetary policy rate, Delphic forward guidance allows the agents to track more precisely the interest rate for a given optimal information choice. As a result, they adjust their consumption/savings in line with the prevailing policy rate.

The change in slope of the profile of  $c_1$  from T1 to T2 in Figure A1 for both RI theory and experimental data reflects the fact that empirically the shrinkage of the volatility from T1 to T2 is implemented by changing the support of the interest rate from  $[0.4 - 1.3]$  to  $[0.7 - 1]$ . As a result, low values of  $r$  correspond to lower values of  $c_1$  in T2 than in T1, since the return to savings when  $r$  is low in T2 are still on average higher than the corresponding return on savings in T1. Likewise, when  $r$  is in the upper side of the interest rate partition, the return to savings are lower in T2 than they are in T1 (the maximum value for T2 is 1 as opposite to 1.3 in T1), which explains why for both the RI theory and experimental data, the slope of  $c_1$  is flatter in T2 than it is in T1 in Interval 2 of the figure.



### B.1.2 Odyssean Forward Guidance

The comparison of consumption choices between an economy with Odyssean forward guidance (T4) and the baseline (T1) is documented in Figure A2 for the theoretical RI representative agent (left panel) and the average subject (right panel) when the precision level 1 signal is selected. The figure shows a remarkable consistency of the theoretical and empirical results. In particular, a commitment of the central bank to announce the policy stance (high vs. low interest rate) with 90% accuracy before agents process more information has no effect on the consumption behavior of either the representative RI agent or the average experimental subject: they both select the consumption they would have chosen without the central bank's signal.

## B.2 Precision and Welfare for the Odyssean Forward Guidance

To shed further light on how the *Odyssean* forward guidance treatment affects subjects' choices and behavior, we look at participants' decisions of precision next. Figure A3 illustrates the scatter plot of the average precision chosen by a subject in T1 vs. T4. For each subject, two averages are calculated. One corresponds to the decisions taken after receiving a central bank clue for tight monetary policy stance ( $r$  in the top half of the support), and is represented by red dots. The second is for the decisions taken after receiving a clue for loose monetary policy ( $r$  in the bottom half of the support), and is denoted by green dots.

Figure A3 illustrates two main observations. First, participants do not systematically modify their information acquisition according to whether the monetary policy stance is tight or loose, as the lack of a clear pattern of changes in information gathering from T1 to T4 in response to high and low interest rates shows.

Second, the figure also suggests that the decision to change information gathering might be triggered by their cognitive ability. Subjects comfortable with processing very little information in T1 (precision  $\leq 1$ ) treat the signal as a new prior where the tracking of the interest rate is made easier by the shrinkage of the support from 32 values to 16 values with 90% probability.<sup>30</sup> For these low-cognitive capacity subjects, the *Odyssean* forward guidance treatment elicits a modest increase in attention and cognitive effort in tracking the monetary policy instrument from T1 to T4.

On the contrary, for people who select relatively more informative signals in T1 (precision

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<sup>30</sup>We chose precision 1 as cut-off point because the central bank's signal conveys information on whether the interest rate is in the top or bottom half of its support, which is effectively equivalent to a signal of precision 1, with 90% probability.

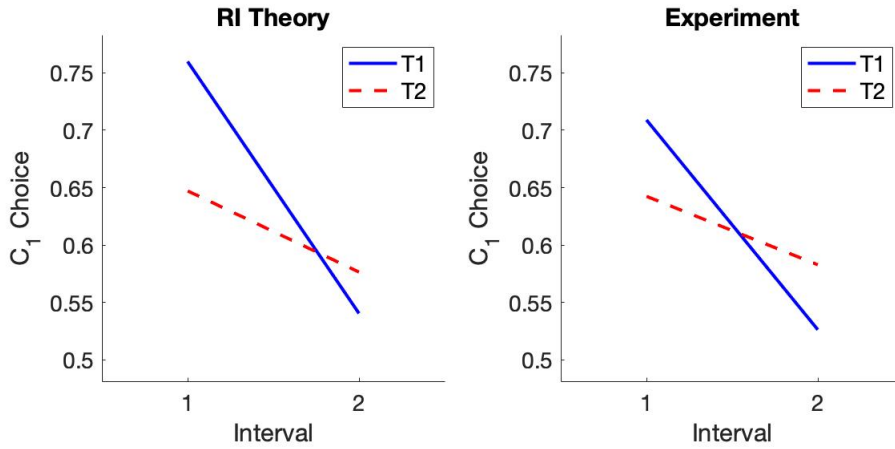


Figure A1: Comparison between the *Delphic* forward guidance treatment, (T2), and the baseline (T1) consumption choices for the first period of the model ( $c_1$ ) made by the theoretical RI representative agent (left-panel) and by the subjects of the experiment on average (right-panel), when signal precision 1 is selected. Signal precision 1 identifies a partition of the  $r$  space in two intervals of 16 columns each, as exemplified in Figure 1 of the paper. Intervals 1 and 2 then correspond to the left-hand side and right-hand side of the partition of the payoff space respectively.

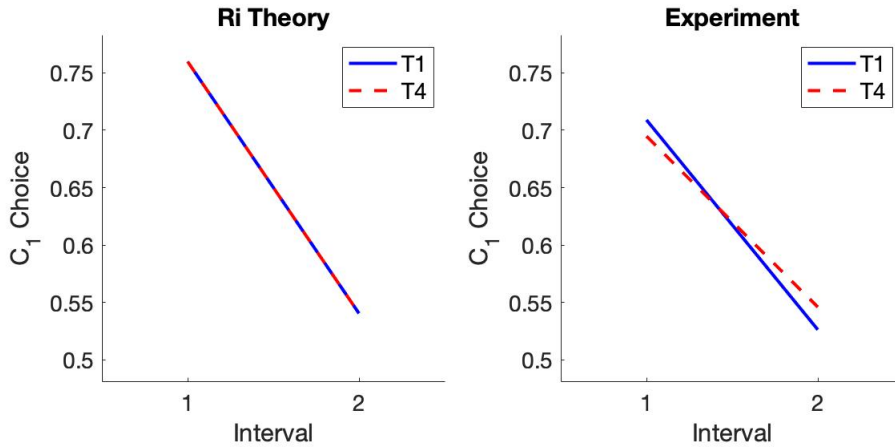


Figure A2: Comparison between the *Odyssean* forward guidance treatment, (T4), and the baseline (T1) consumption choices for the first period of the model ( $c_1$ ) made by the theoretical RI representative agent (left-panel) and by the subjects of the experiment on average (right-panel), when signal precision 1 is selected. Signal precision 1 identifies a partition of the  $r$  space in two intervals of 16 columns each, as exemplified in Figure 1 of the paper. Intervals 1 and 2 then correspond to the left-hand side and right-hand side of the partition of the payoff space respectively.

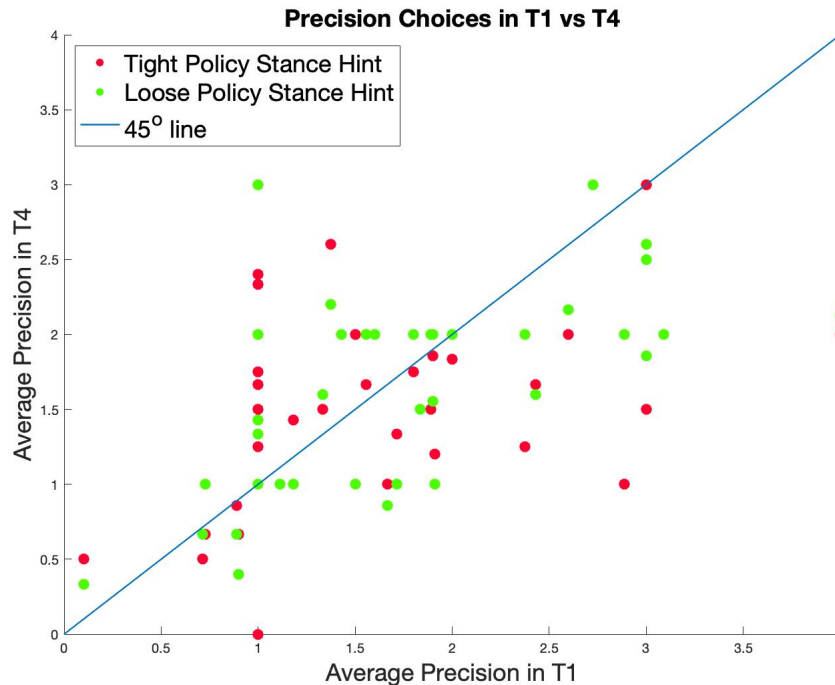


Figure A3: Average precision by subject in T1 vs. T4. Each dot represents the average precision chosen by an individual. For each subject, the average is calculated across realizations of the signal that  $r$  is high (top half of the support of  $r$ ) in red, or low (bottom half of the support of  $r$ ) in green.

$>1$ ), the central bank’s signal on the policy stance provides a mild incentive to lower their attention to the interest rate. While their chosen signal is still more informative than the one provided by the monetary authority, they marginally drop the precision of their optimal signal following the announcement. Since our model’s testable predictions are focused mostly on behavioral outcomes induced by information gathering, rather than the information gathered before the decisions are made per se, we leave a more detailed investigation of these patterns for future research.<sup>31</sup>

The litmus test of whether this form of *Odyssean* forward guidance is successful in modifying the economic behavior of the subjects, however, ultimately rests on the ability of the policy to affect macro aggregates, such as consumption and investment and, as a result, welfare. In Figure A4, hence, we decompose the bottom panel of Figure 7 of the paper by splitting subjects by their precision level acquired in T1. The top panel shows the kernel

<sup>31</sup>These changes in information gathering could also simply be due to some statistical noise. However, evidence on the potential for forward guidance to increase private sector’s uncertainty in the U.S. and cross-country have been recently documented by, among the others, Ehrmann *et al.* (2019).

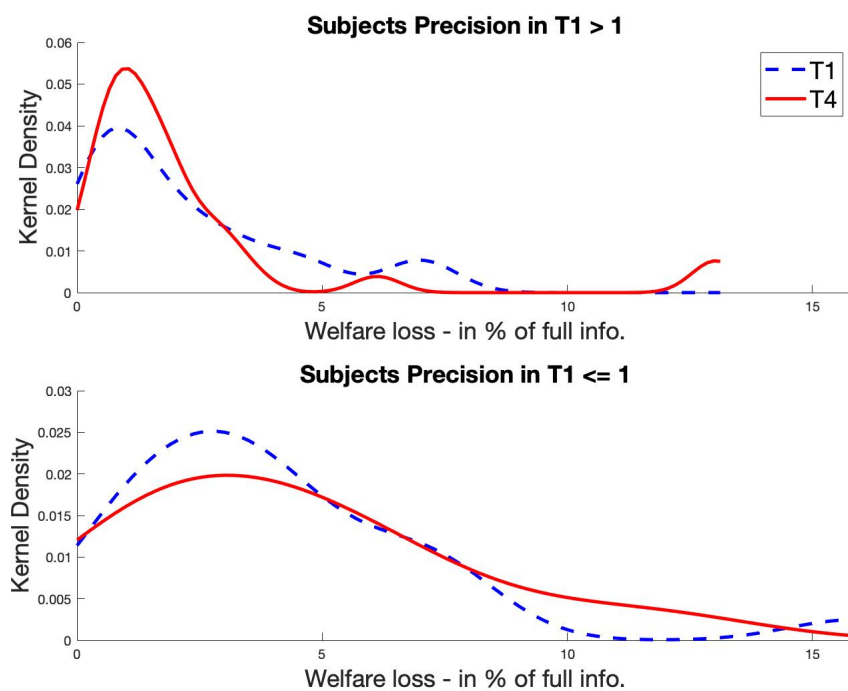


Figure A4: Kernel density estimate of welfare loss as percentage of full information for subjects who chose precision  $> 1$  in T1 (top panel) and subjects who chose precision  $\leq 1$  in T1 (bottom panel). Red-solid lines are for T4, while blue-dashed line are for T1. The aggregate densities are estimated using a Gaussian kernel.

density estimation of welfare loss for subjects with signal precision  $> 1$ , while the bottom panel shows the density for subjects with precision  $\leq 1$ .<sup>32</sup> For both panels, solid red lines indicate the density in T4, whereas dashed blue lines show the corresponding density in T1.

As for the overall case in Figure 7, the differences in the estimated distributions for the two treatments appear quite small for the two sub-groups as well. We corroborate this visual intuition by formally test for the equivalence of the distributions with two-sample KS tests. The KS test shows that the null hypothesis of equality between T1's and T4's distributions cannot be respectively rejected at level of confidence of 76% for subjects whose precision in T1 is  $> 1$  and .99% for those with T1 precision  $\leq 1$ .

Next, we test whether the distributions retain the same variance between the two treatments for each group to make sure that the change in information acquisition, albeit marginal, have not affected the spread of the distributions. To account for non-Gaussianity of the underlying generating process of the data, we use the Levene's test. The null hypothesis of the test is that the two population variances are homoscedastic; the alternative is that they are heteroscedastic. We cannot reject the hypothesis for either group (p-values are .71 for the precision  $> 1$  group and .81 for the precision  $\leq 1$  one, respectively).

Finally, we employ the non-parametric Wilconox's signed-rank test to compare the medians of the distributions. The null hypothesis of this test is that the difference between the paired observations of the T1 and T4 samples for each subgroup follows a symmetric distribution around zero. Once again, we cannot reject the null hypothesis of equality of the median at very high levels of confidence (p-values of .69 for the first group and .66 for the second, respectively).<sup>33</sup>

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<sup>32</sup>The numbers of subjects in the two groups are 30 for precision  $> 1$  and 21 for the precision  $\leq 1$  respectively.

<sup>33</sup>The more commonly used  $F$ - and  $t$ - tests for equality of variance and mean of two samples strongly rely on the assumptions of Gaussianity of the data, which are void in our case.

## C Instructions for the Laboratory Experiment

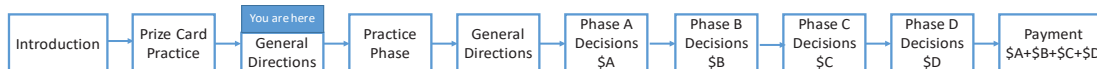
After you read these instructions you will go through a 10 minute practice phase. The practice phase will not impact your payoff at all. It is designed to help you understand the choices you are making before you begin the paid phases of the experiment. After the practice phase you will have a chance to go back through the directions before beginning the paid phases.

If you have a question at any point, please raise your hand, but ...

How you use your time is an important factor in how much money you can earn, so it is best to ask any questions while the instructions are on your screen because the experiment cannot be paused during the active phases of it.

### Phases of the Study

You will complete **4** paid phases that each last *about* **10** minutes. Each phase is a little different and you will read specific instructions before completing each phase. What you do in one phase will have no bearing on what happens in another phase. The amount you will be paid is based on the sum of what you earn in each phase. Monetary amounts in the study are denoted in Lab Dollars which are converted into \$US at the rate 100 Lab Dollars = \$US 1.



### Periods and Payoffs in a Phase

Each paid phase is comprised of a series of periods. In each and every period you will pick a prize card and earn money. Prize cards work exactly like the ones in the practice you just went through.

Your prize each period will be added to the running total for that phase and a new period will begin automatically once your prize is revealed for the previous period.

There is a limit to the number of periods you can complete in a phase, but you do not know what that limit is and it can differ phase to phase. **The more periods you complete, the more opportunities you have to earn money so you do not want to waste time during a phase.**

**NOTE: The only way you earn money is selecting a prize card (clicking on a row heading) and then confirming your choice.**

The prize cards do not change period to period within a phase, but may be different in different phases.

### Hints about what Ball is Drawn

The prize ball is actually drawn before you choose your prize card. But the draw is not revealed to you until after you pick a prize card. However, you can get a hint about the ball that has been drawn.

To get a hint you have to correctly solve logic puzzles. The harder the puzzles you solve, the more accurate the hint you will receive. How logic puzzles work is explained below.

You can narrow the range of balls and thus possible prize amounts to a group of 16 by solving easy puzzles. In this case you would be informed either that the ball drawn is numbered between 1 and 16 or that the ball drawn is numbered between 17 and 32. That is you are told if it is the first group of 16 or the second group of 16. The way the hint is displayed on your screen is that prizes associated with balls in the group that does not contain the drawn ball are grayed out on every prize card. Prizes associated with balls in the group that does contain the ball that was drawn are highlighted in yellow on every prize card.

You can narrow the size of the group down to 8 balls (balls 1-8, balls 9-16, balls 17-24, or balls 25-32) by solving slightly harder puzzles, a group of 4 balls by moderately harder puzzles, a group of 2 balls by solving very hard problems, or even to a single ball by solving really hard puzzles.

As you will see, the puzzles can be time consuming. So you face a tradeoff of

getting a more specific hint so you can increase what you expect to earn the current period &

getting a more vague hint and completing more periods

Returning to the previous example with only 5 prize cards and 8 balls, if you got the hint that the range for the prize ball that was drawn was between 1 and 4 then your screen would look like this:

Possible Prizes in Yellow

	1	2	3	4	5	6	7	8	
Prize Cards	1	1	2	3	4	5	6	7	8
2	2	3	4	5	6	7	8	6	
3	4	5	6	7	7	6	5	4	
4	6	8	7	6	5	4	3	2	
5	8	7	6	5	4	3	2	1	

Notice that the prizes for balls 5 through 8 are grayed out. This is how you know that the ball that has been drawn is not in that range. If you were to pick card 2 your prize is equally likely to be 2, 3, 4, or 5. If you were to pick card 4, your prize is equally likely to be 6, 8, 7, or 6. Notice that card 4 has a higher prize than card 2 for all four of the balls that could be drawn so in this case picking card 4 would always earn you more money than card 2. But card 5 would earn more than card 4 if ball 1 was drawn. In general, the more accurate your hint, the better able you are to pick the card that will pay you the most money that period. But getting more accurate hints takes time and means that you can complete fewer periods

*TIME PENALTY: If you do not get a hint that narrows the number of balls down to something less than 32, then you will have to wait 60 seconds before starting the next period. Keep in mind that you only have about 10 minutes in each phase and that your earnings are the sum of the prizes you earn and you only earn one prize each period.*

*MULTIPLE HINTS: If you successfully get a hint, you can then try to get an even more accurate hint. But you do not have to have to work your way up to a more accurate hint. That is, if you want to narrow the range down to 4 balls, you can go straight to that level rather than first narrowing it down to 16 then 8 then 4. Generally, it is better to decide how accurate of a hint you want and go straight to that option, keeping in mind that more accurate hints are harder to achieve.*







*FAILURE to get HINT: If you have not successfully gotten a hint in the period, it is as if you are just starting the period. You can make a choice without getting a hint, but you would incur the 60 second penalty or you can try to get a hint. If you have already successfully received a hint during the period, but failed to get a more accurate hint, it is as if you just receive the hint you already had. You can either pick a prize card or try to get a more accurate hint.*

### **Logic Puzzles**

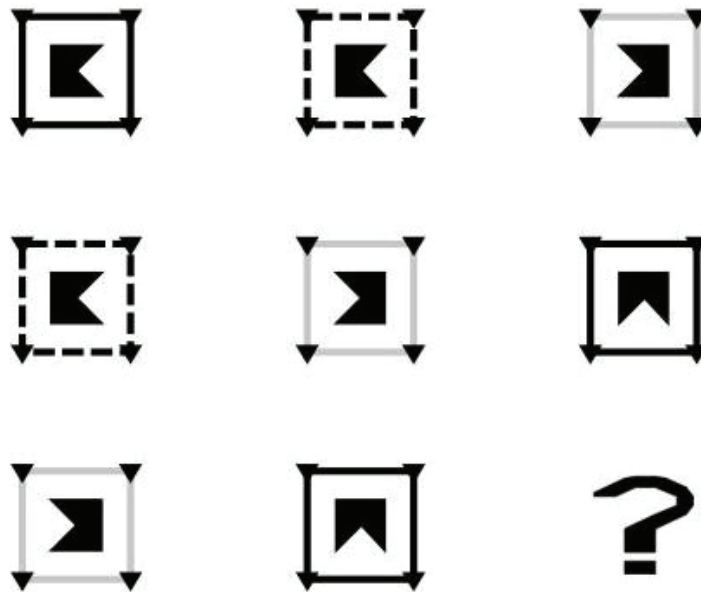
The logic puzzles involve a 3-by-3 table of images, with the image that belongs in the lower right missing. To solve the logic puzzle you have to identify the image that completes the table from the multiple choice options provided.



The images have six characteristics: shape, size, color, orientation, border style, and border

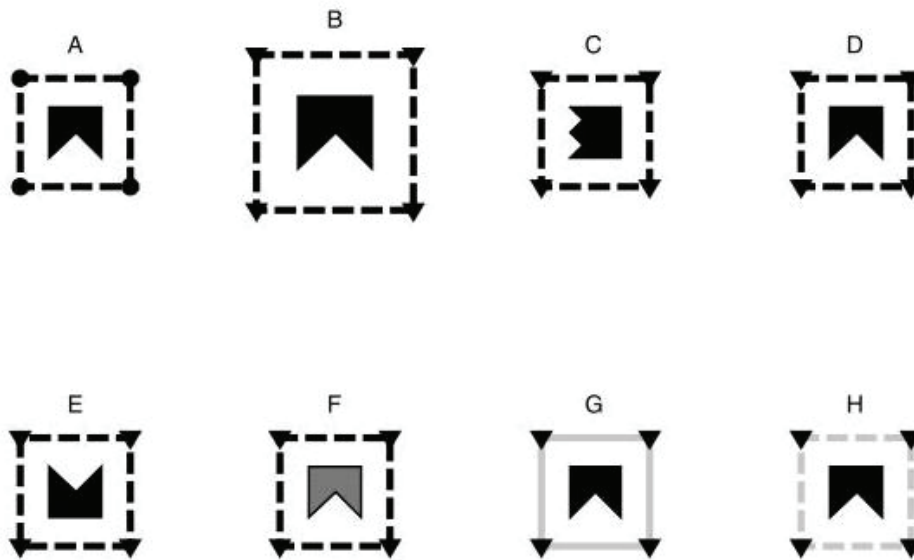
corner style. These characteristics can change by row , column , diagonal , reverse diagonal , corner , or reverse corner .

Below is an example of a logic puzzle.



In this example, the shape is the same in each image as is the color, size, and border corner. But the border changes along the reverse diagonal. The orientation changes with the corner - the image is turned in the same direction for everything in the top left (above the diagonal) of the table.

Given this, the correct answer from the choices below is “D” because it has a dashed border and the correct orientation while all of its other characteristics match those of the other images in the table. Notice that A has circles for border corners. B is the wrong size – it is too large. C has the wrong shape. E is oriented the wrong way. F is the wrong color. G and H both have the wrong border.



### Summary

1. There are 4 paid phases that each last about 10 minutes. You are paid based on the sum of your earnings in all four phases.
2. During a period the computer will draw a prize ball numbered 1 – 32, but you will not observe this draw until after you pick a prize card.
3. You will earn the prize associated with the ball drawn for the prize card you pick.
4. Before you pick a prize card, you can get a hint about what prize ball was drawn by solving logic puzzles.
  - a. A more accurate hint requires you to solve harder puzzles.
  - b. You can select an accuracy level at any point.
5. There is an unknown limit to the number of periods you can complete in a phase, but if you do not successfully get a hint that narrows the range of the drawn ball down to something less than 32, then you will have to wait 60 seconds to start the next period.

If you have any questions, please raise your hand. Otherwise, you can click [Start](#) to go to the ten minute unpaid practice phase. After the practice phase ends you will have a chance to reread the instructions before starting the paid phases.