Diagnostic Global Game: Theory and Experiment*

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Abstract

This paper introduces diagnostic expectations into a standard coordination game with incomplete information. I solve the diagnostic global game model and provide conditions for uniqueness of the equilibrium. I find that comparative statics analysis with respect to the signal precision shows different patterns depending on the level of the cost parameter when compared with the Bayesian global game model. I propose a novel experimental design to test the existence and persistence of diagnostic expectations in an individual belief updating task. I build on this design to propose an experimental way to test the predictions of the diagnostic global game that I solved.

JEL Classifications: C91, D83, D84

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1 Introduction

Individuals' expectations about economic outcomes are central to economic analyses. Since Muth (1961) proposed a common approach to capturing market participants' expectations in macroeconomic and finance models, the rational expectations hypothesis (REH) has been a standard assumption in various fields of economics. The REH often provides tractability of economic models by dictating agents' expectations in models, but there have been numerous empirical findings which contradicts the REH. Although the usefulness of the REH in economic models as a benchmark is still effective, the gap between theoretical predictions and empirical data raises serious questions on the empirical plausibility of the REH. The forward guidance puzzle (Del Negro et al., 2012) posed by the standard New Keynesian model is a typical example that shows this gap.

Recently, there are growing interests in understanding the empirical features of expectations formation. These studies have been supported by the increasing availability of data on expectations from surveys of decision makers. There are generally three strands of research on expectations. The first branch of work focuses on measurement of expectations and empirical analyses of expectations. Another branch of work attempts to develop empirically founded, portable models of beliefs. The last branch of work aims to incorporate these alternative models into economic analyses. While each strand of work is actively interacting with one another, the literature has not yet reached a consensus on the most plausible explanation for expectation.

The literature on expectation formation is especially fast growing in the fields of macroeconomics and finance. These studies keep accumulating evidence that expectations can be meaningfully measured using surveys and they have explanatory power for economic outcomes. As this evidence points to violation of the REH, various models deviating from the FIRE (Full Information Rational Expectations) assumption have been proposed. Many models emphasize deviation from the FIRE due to information rigidities while maintaining the assumption of rational expectations. Among others, sticky information model (Mankiew and Reis, 2007), noisy information model (Woodford, 2003), and rational inattention model (Sims, 2003; Maćkowiak and Wiederhold, 2009) are typical examples of this approach.

Since empirical regularities such as overreaction to new information which is documented in Afrouzi et al. (2022) and Bordalo et al. (2020) also require relaxation of the rational expectations, models with bounded rationality have been proposed. This approach includes models with sparse max operator or cognitive discounting (Gabaix, 2014; Gabaix, 2020) and natural expectations (Fuster et al., 2010). Among others, diagnostic expectations (DE) proposed in Bordalo et al. (2018) have been found to account for crucial empirical features of expectations data in macroeconomics and finance (Bordalo et al., 2020). Furthermore, they have firm microfoundation based on psychological heuristics (Tversky and Kahneman, 1983), which makes the model of DE survive the Lucas critique (Lucas, 1976).

Even though there are increasingly many applications of DE coming out in macroeconomics and finance, a question whether DE models best explain empirical findings on expectations is still an open question. Rather, a large experimental study on expectations by Afrouzi et al. (2022) finds that the pattern of overreaction to new information is better explained by models with expectations formation with costly processing of past information than models with DE. However, this result does not mean that DE has failed since its microfoundation is not directly tested. To establish firm empirical facts on DE, we need to test the underlying mechanism of DE. In particular, DE models in a natural belief updating setup need to be tested since it is the common environment for DE.

The goal of this paper is to bridge this gap between empirical regularities and theoretical predictions of diagnostic belief updating. To capture the influence of DE in a natural belief updating setup in macroeconomics and finance, this paper introduce DE into a model of global games, which are coordination games with incomplete information. I adopt global games as the benchmark setup for the analysis because they offer a unique framework to study belief updating on the economy's fundamentals. I solve the global game model, provide conditions for uniqueness of the equilibrium, and compare the equilibrium with that of the benchmark global game model with standard Bayesian belief updating. To provide empirical support for this DE mechanism, I propose a novel experimental design to test the existence of DE in an individual belief updating problem and test the theoretical predictions of the global game model with DE.

This paper contributes to a large literature on expectation formation. Specifically, the rule of forming beliefs of this paper is related to one general theme in the expectations data: extrapolation of recent shocks and trends. Macroeconomic expectations typically show these patterns of overreaction to recent news, which are documented in Bordalo et al. (2020), Afrouzi et al. (2022), and Angeletos et al. (2021). Financial variables also show these patterns well (Piannesi abd Schneider, 2013; Greenwood and Shleifer, 2014; Gennaioli et al., 2016; De Stefani, 2018; Richter and Zimmermann, 2019). This paper adds to this literature by providing theoretical predictions of microfounded extrapolative expectations in a global game model and testing these overextrapolating features experimentally.

This paper builds upon the literature on DE by applying it to a global game model which has macro-financial interpretations. DE has provided plausible explanations for various financial phenomena including features of (real) credit cycles (Bordalo et al., 2018; Bordalo et al., 2021), dynamics of stock returns (Bordalo et al., 2019), and formation of asset price bubbles (Bordalo et al., 2021). Moreover, business cycle facts have also been shown to be well explained by incorporating DE in the standard New Keynesian models (Bianchi et al., 2022; L'Huillier et al., 2022). In addition, this paper builds upon the literature on probabilistic judgments based on psychological mechanisms by providing a novel experimental design to test the microfoundation of DE, which is based on the representativeness heuristic (Tversky and Kahneman, 1983). I base my experiment on previous experimental evidence on the memory channel in Bordalo et al. (2021) and Bordalo et al. (2022).

I also contribute to the literature on the global game literature. As defined by Carlsson and van Damme (1993), a global game is a coordination game with incomplete information which perturbs private information in such a way that common knowledge of the structure of the game is no longer retained and a unique equilibrium is selected. A variety of coordination problems in economics have utilized global games including speculative attacks (Morris and Shin, 1998; Angeletos and Werning, 2006), bank runs (Goldstein and Pauzner, 2005), debt runs (Morris and Shin, 2004; He and Xiong, 2012), and business cycles and the Great Recession (Chamley, 1999; Schaal and Taschereau-Dumouchel, 2015). This rich applicability of the global game models is based on the understanding of conditions for the uniqueness result, to which this paper adds new insight by introducing non-Bayesian belief updating rule in the model.

I build upon the experiment literature on global games. Since the seminal work of Heinemann et al. (2004), many papers have attempted to test the predictions of global games in the context of laboratory experiments. See, for example, Cornand (2006), Cabrales et al. (2007), Duffy and Ochs (2012), and Shurchkov (2013). However, deviation from the theoretical predictions has been reported in the literature. For instance, Szkup and Trevino (2020) reports experimental results with the comparative statics of equilibrium thresholds and signal precision reversed. This deviation could be interpreted as either failure of the global game models, which could be failure of the equilibrium concept or that of the belief updating rule, or inefficiency of the experimental design, given that all of the previous experiments on global games share a common experimental design where participants update their beliefs based on mathematical information. The experiment of this paper contributes to the literature by testing predictions of the global game model with relaxed belief updating assumptions in a novel way which involves the memory of participants on visual information.

The rest of this paper is organized as follows: In Section 2, I give definitions of DE and the global game setup which I will use as the experimental benchmark. In Section 3, I solve the global game model under the DE assumption and provide the uniqueness conditions of the equilibrium. I also provide simulation results for the comparative statics of the equilibrium. In Section 4, I present a new experimental design to test the existence of DE and to test the DE implications of the global game models. In Section 5, I discuss the current status of my research and delineate the plan.

2 Diagnostic Global Game

I incorporate a belief formation rule called diagnostic expectations proposed by Bordalo et al. (2018) into a global game model. Since there is no single component of the model changed other than the belief updating rule, I call my model of global games the diagnostic global game model. In this section, I introduce diagnostic expectations and a standard global game model.

2.1 Diagnostic Expectations

In this subsection, I review previous studies on diagnostic expectations and its microfoundation first proposed by Bordalo et al. (2018). Diagnostic expectations base their mechanism on Kahneman and Tversky's representativeness heuristic, which they define as follows: "an attribute is representative of a class if it is very diagnostic; that is, the relative frequency of this attribute is much higher in that class than in the relevant reference class" (Tversky and Kahneman (1983, p. 296)). They argue that individuals often make probabilistic judgments by representativeness and present a great deal of experimental evidence to support the claim. I briefly discuss the conceptual framework of DE here.

As a primer of DE, I first define the concept of representativeness. A decision maker judges the distribution of trait T in group G. Gennaioli and Shleifer (2010) define the representativeness of trait $T = t$ for group G as

$$\frac{\pi(T = t|G)}{\pi(T = t| - G)},$$

where $-G$ is a relevant comparison group. Gennaioli and Shleifer (2010) assume that representative types are easier to recall. Due to limited working memory, an agent overweighs these types in his assessment. For example, the trait $t =$ red hair is representative of $G =$ Irish compared to $-G =$ rest of the world and so is overestimated. This pattern is markedly shown in the context of stereotypes as in Bordalo et al. (2016). In other words, individuals' memory restrictions cause the agent to inflate the likelihood of types whose objective probability rises the most in G relative to the reference context $-G$, which is summarized in the relative ranking of representativeness of types.

Bordalo et al. (2018) extend this logic of agents' overreaction to representative types to a rule of agents' expectation formation on aggregate economics conditions. Consider the discrete time framework $\{t : t = 0, 1, \dots\}$. Assume that the state of the economy at t is a random variable ω_t that follows an AR(1) process

$$\omega_t = b\omega_{t-1} + \epsilon_t,$$

where $\epsilon_t \sim \mathcal{N}(0, \sigma^2)$ and $b \in [0, 1]$. When making a forecast for the state of the economy in the future, agents assess the distribution of each state variable in the future, say $\widehat{\omega}_{t+1}$, using the information on the realized current states $\omega_t = \widehat{\omega}_t$. While the rational agent who updates one's belief using Bayes' rule would solve the problem by evaluating the true conditional distribution of ω_{t+1} given $\omega_t = \widehat{\omega}_t$, $\pi(\omega_{t+1}|\omega_t = \widehat{\omega}_t)$, an agent suffering the representativeness heuristic would selectively retrieve this true conditional distribution and naturally overestimates realizations of ω_{t+1} that are representative of $G \equiv \{\omega_t = \widehat{\omega}_t\}$ relative to the background context $-G$. Here, the trait and the group of interest correspond to the future state and the information set up until now, respectively.

In a dynamic context which Bordalo et al. (2018) adopt, the background context would be the information set in which the most recent information is not yet incorporated. Assuming that agents update their information every period, the context group is $-G \equiv \{\omega_t = b\widehat{\omega}_{t-1}\}$ under the AR(1) economy. Then, I can apply the same logic as before, that is, a certain future state $\widehat{\omega}_{t+1}$ is more representative at t if it exhibits the largest increase in its likelihood based on recent news, or equivalently, the largest increase in representativeness which is given by

$$\frac{\pi(\widehat{\omega}_{t+1}|\omega_t = \widehat{\omega}_t)}{\pi(\widehat{\omega}_{t+1}|\omega_t = b\widehat{\omega}_{t-1})}.$$

Note that agents have the true conditional distribution $\pi(\widehat{\omega}_{t+1}|\omega_t = \widehat{\omega}_t)$ deep in their mind. Since the most representative states come to the mind and hardly go out of it after observing current news $\Omega_t = \omega_t$, memory restrictions lead to oversampling of states from agents' memory database $\pi(\widehat{\omega}_{t+1}|\omega_t = \widehat{\omega}_t)$. In this way, agents form beliefs inflating the probability of more representative states and deflating the probability of less representative states.

The idea of alternative belief formation due to memory restrictions can be further extended to a general model of probabilistic judgments based on two established regularities of selective recall: similarity and interference. Bordalo et al. (2021) present a model of probabilistic assessments which are context dependent. Based on the argument of memory research (Kahana, 2012), their model captures that similarity between the cued data d and a hypothesis h to evaluate drives recall of a hypothesis h and the recall is subject to interference. Here, the hypothesis and the cued data correspond to the trait and the group in the previous models, respectively. While this model reflects representativeness which decision makers suffer, Bordalo et al. (2022) generalized the model so that it can reconciles a variety of empirical findings related to biases in probabilistic judgments such as the availability heuristic, the representativeness heuristic, and conjunction and disjunction fallacies. This generalized model specifies biases due to interference from the alternative hypothesis as well as from the irrelevant data.

In my global game model in the next subsection, I adopt the concept of DE in Bordalo et al. (2018) as the basic belief updating rule in the model. Note that incorporating the generalized model of probabilistic judgment needs additional modeling work, such as adopting an irrelevant economy, and this involves modification of the global game model, which goes beyond the original purpose. Thus, I incorporate the original DE in the global game model for the purpose of analyzing theoretical implications. On the other hand, in the experimental design, I base the predictions for proposed experimental hypotheses on the generalized model of Bordalo et al. (2022) since I intend to check whether the memory-based microfoundation of DE is empirically plausible and so we can generally adopt DE models.

I conclude this subsection by formalizing the concept of DE which I will use in my analysis for the global game model. Suppose that the memory database is described by a probability space with event space Ω and probability measure P, which summarizes a person's experiences including their frequencies. The decision maker assesses the probability of hypothesis $h \in H$ given data $d \in D$, where H and D are two random variables representing the hypotheses and data.

Definition 1. For a given $\theta \in [0, +\infty)$ which measures the level of severity that agents suffer representativeness, the diagnostic probability is defined by

$$P^{\theta}(h|d) = P(h|d)\left[\frac{P(h|d)}{P(h|-d)}\right]^{\theta} Z, \tag{2.1}$$

where $-d$ is the decoy or irrelevant data and Z is a constant ensuring that the assessed density integrates to 1.

Note that the decoy or irrelevant data in the case of Gennaioli and Shleifer (2010) and Bordalo et al. (2016) is the relevant comparison group $-G$, while it is information up to period $t-1$ in the case of Bordalo et al. (2018). In the static global game model discussed in the next subsection, I interpret information about the prior distribution as the decoy or irrelevant data of the above definition.

2.2 A Global Game Model

In this subsection, I introduce a standard coordination game with incomplete information. We formulate the model so that I can incorporate the DE framework into it and test implications of DE in a canonical belief updating setup. To this end, I adopt global game models with effective prior information on the fundamental parameter, which is not agnostic *Laplacian*. Thus, I consider a standard model of regime change, where players update their belief on the fundamental of the economy, as in Morris and Shin (1998) and Angeletos and Werning (2006). This model of regime change is especially suitable for macroeconomic and financial interpretation. Specifically, I choose the basic model with exogenous information of Angeletos and Werning (2006) as the benchmark model since the normality assumption of prior information and noise is especially suited for DE analysis.[1]

Assume that there is a continuum of agents of measure 1, each of whom is indexed by i and uniformly distributed over [0,1]. Agents move simultaneously, choosing between two actions: they can either attack the status quo or refrain from attacking. Let $x \in \mathbb{R}$ denote the exogenous fundamental representing the strength of the status quo. Furthermore, A denotes the mass of agents of attacking and $c \in (0,1)$ is a parameter representing the cost of attacking. The payoff from not attacking ($a_i = 0$) is $1 - c > 0$ if the status quo is abandoned ($R = 1$) and $-c < 0$ otherwise ($R = 0$). Agent i's payoff can be summarized as

$$U(a_i, A, x) = a_i(1_{A>x} - c),$$

and the payoff structure is given in Table 1.

Table 1: Payoff Table

	Regime Change ($A \geq x$)	Status Quo ($A < x$)
Attack ($a_i = 1$)	$1 - c$	$-c$
Not Attack ($a_i = 0$)	0	0

Note that the payoff structure induces a coordination motive since $U(1, A, x) - U(0, A, x)$ is increasing in A. In other words, an agent's incentive to attack increases with the aggregate size of attack, which implies that agents' actions are strategic complements. If x was common knowledge to all agents, the equilibrium of the game would become evident: for $x \in (0, 1]$, there would exist two pure-strategy equilibria, one in which all agents attack and the status quo is abandoned ($A = 1 \geq x$), and the other in which no agent attacks and the status quo is maintained ($A = 0 < x$). Thus, the size of the attack would determine the regime outcome.

However, information about the fundamental is imperfect and asymmetric, which breaks the common knowledge about x among agents. Nature first draws x from a normal distribution $\mathcal{N}(z, \sigma_x^2)$ with $z \in \mathbb{R}$, $\sigma_x > 0$, which defines the initial common prior about x. Each agent then receives a private signal $s_i = x + \epsilon_i$, where $\epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon^2)$ with $\sigma_\epsilon > 0$ is a noise term which is independent and identically distributed across agents, and independent of x. For the convenience of notation, I define precision parameters corresponding to variance parameters as follows: $\sigma_x^2 = 1/\alpha$ and $\sigma_\epsilon^2 = 1/\beta$.

This stylized model of global game admits various interpretations and possible applications. One of the most widely used examples is self-fulfilling currency crises as in

[1]Proposition 1 of Bordalo et al. (2018) show that if X_{t+1} is conditionally normal, the diagnostic distribution of beliefs is also normal.

Obstfeld (1986), Obstfeld (1996), and Morris and Shin (1998), where a sufficient amount of speculators can force the central bank to abandon its peg. Likewise, we can think of a scenario where a large number of depositors induce the banking system to suspend payments by withdrawing their deposits simultaneously as in Rochet and Vives (2004) and Goldstein and Pauzner (2005). Other interpretations include investment complementarities (Dasgupta, 2007) and debt runs (Morris and Shin, 2004; He and Xiong, 2012), among others.

I adopt any of these common interpretations of global games for the theoretical predictions since I mainly focus on the DE implications for equilibrium analysis. However, I consider a different way of interpretation in the experimental design since I plan to newly include a component which serves as irrelevant data. Thus, the global game interpretation will have to adapt to this change. In particular, I will adopt interpretation similar to that of global games modeling financial contagion as in Dasgupta (2004), Goldstein and Pauzner (2004), and Trevino (2020). Note that I only adopt their "interpretation" of the model where irrelevant data could affect agents' belief about the relevant fundamental parameter of the model. Since the irrelevant data in the experimental design are not correlated with the relevant data, I do not not revisit the model of global games.

3 Theoretical Predictions

In the diagnostic global game model, I assume that agents update their belief using diagnostic expectations rather than Bayes' rule. Here, I also consider a standard global game model with Bayesian updating as a benchmark. In other words, I consider two types of agents in each global game model with the same structure: one with Bayesian belief updating and the other with diagnostic belief updating. Since I consider Nash equilibria as the equilibrium concept, I implicitly assume that agents know that other agents are also Bayesian (diagnostic). In this section, I characterize the unique Bayesian (diagnostic) Nash equilibrium and provide conditions for its uniqueness. Furthermore, I present comparative statics with respect to the private signal precision. Throughout this section, the focus is on how these conditions change when I adopt DE instead of Bayes' rule.

3.1 Equilibrium Analysis

Here, I initially focus on *monotone* equilibria and later show that the unique monotone equilibrium is actually the unique equilibrium. Indeed, it is natural to concentrate on *monotone* Bayesian (diagnostic) Nash equilibria in which agents' strategy is nonincreasing in the private signal s since the posterior cumulative distribution function of agents' belief about the fundamental x is decreasing in s. Moreover, it is strictly dominant to attack for sufficiently low signals, or for $s < \underline{s}$, and not to attack for sufficiently high signals, or for $s > \overline{s}$, where $\underline{s}$ solves $P(x \leq 0|\underline{s}) = c$ and $\overline{s}$ solves $P(x \leq 1|\overline{s}) = c$.

Suppose there is a threshold $\widehat{s} \in \mathbb{R}$ such that each agent attacks if and only if $s_i \leq \widehat{s}$ for all i. Since the measure of all agents is 1, the measure of agents attacking is then decreasing in x and is given by

$$A(x) = P\left(s_i \leq \widehat{s}|x\right) = \Phi\left(\sqrt{\beta}\left(\widehat{s} - x\right)\right), \tag{3.1}$$

where Φ denotes the cumulative distribution function of a standard normal random variable. Then, the status quo is abandoned if and only if $x \leq \widehat{x}$, where $\widehat{x}$ solves $\widehat{x} = A(\widehat{x})$, or equivalently,

$$\widehat{x} = \Phi\left(\sqrt{\beta}\left(\widehat{s} - \widehat{x}\right)\right). \tag{3.2}$$

To begin with, consider a global game with Bayesian players. By standard Gaussian updating, agent i's posterior belief about x conditional on his private signal s_i is normal with the following mean and precision:

$$x|s_i \sim \mathcal{N}\left(\frac{\alpha z + \beta s_i}{\alpha + \beta}, \frac{1}{\alpha + \beta}\right). \tag{3.3}$$

It follows that agent i's posterior probability of regime change is given by

$$\begin{aligned} P(R = 1|s_i) &= P(x \leq \widehat{x}|s_i) \\ &= 1 - \Phi\left(\sqrt{\alpha + \beta}\left(\frac{\alpha z + \beta s_i}{\alpha + \beta} - \widehat{x}\right)\right). \end{aligned}$$

Since the probability is decreasing in s_i, it is optimal for agent i to attack if and only if $s_i \leq \widehat{s}$, where $\widehat{s}$ solves $P(x \leq \widehat{x}|\widehat{s}) = c$, or equivalently,

$$1 - \Phi\left(\sqrt{\alpha + \beta}\left(\frac{\alpha z + \beta \widehat{s}}{\alpha + \beta} - \widehat{x}\right)\right) = c. \tag{3.4}$$

A monotone equilibrium is thus characterized by a joint solution $(\widehat{s}, \widehat{x})$ to (3.2) and (3.4). Such a solution always exists and is unique for all z if and only if $\alpha \leq \sqrt{2\pi\beta}$. In addition, the unique monotone equilibrium is the only equilibrium by the standard argument of iterated deletion of strictly dominated strategies.

Proposition 1. *In the global game of regime change with Bayesian agents, the equilibrium is unique if and only if $\alpha \leq \sqrt{2\pi\beta}$ and is in monotone strategies.*

Next, consider a global game with players who are subject to DE. By definition of diagnostic updating, the posterior about x conditional on the private signal s_i is normal with the following mean and precision:

$$x^\theta|s_i \sim \mathcal{N}\left(\frac{\alpha z + \beta(1+\theta) s_i}{\alpha + \beta(1+\theta)}, \frac{1}{\alpha + \beta(1+\theta)}\right). \tag{3.5}$$

It follows that agent i's posterior probability of regime change is given by

$$P^\theta(R=1|s_i) = P^\theta(x \leq \widehat{x}|s_i)$$
$$= 1 - \Phi\left(\sqrt{\alpha+\beta(1+\theta)}\left(\frac{\alpha z+\beta(1+\theta)s_i}{\alpha+\beta(1+\theta)} - \widehat{x}\right)\right)$$

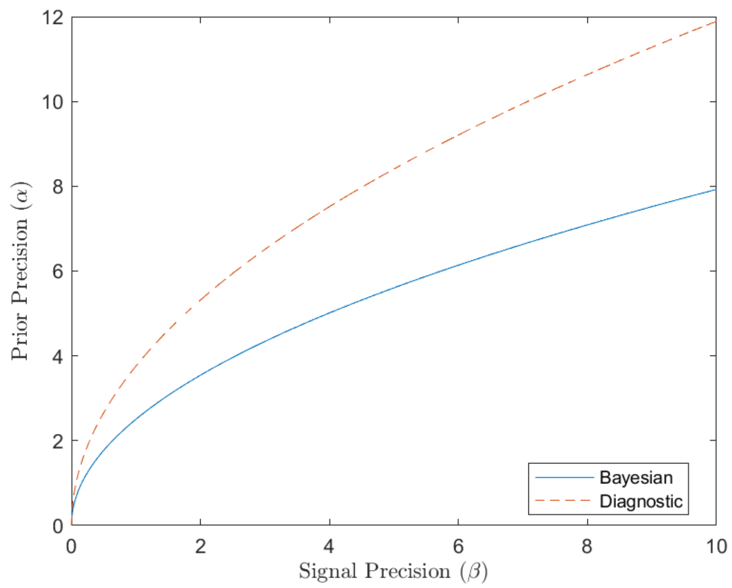
As in the case of Bayesian global game, it is optimal for agent i to attack if and only if $s_i \leq \widehat{s}$, where $\widehat{s}$ solves $P^\theta(x \leq \widehat{x}|\widehat{s}) = c$, or equivalently,

$$1 - \Phi\left(\sqrt{\alpha+\beta(1+\theta)}\left(\frac{\alpha z+\beta(1+\theta)\widehat{s}}{\alpha+\beta(1+\theta)} - \widehat{x}\right)\right) = c. \tag{3.6}$$

A monotone equilibrium is thus characterized by a joint solution $(\widehat{s}, \widehat{x})$ to (3.2) and (3.6). Such a solution always exists and is unique for all z if and only if $\alpha \leq (1+\theta)\sqrt{2\pi\beta}$. In addition, the unique monotone equilibrium is the only equilibrium by the logic of iterated deletion of strictly dominated strategies.

Proposition 2. *In the global game of regime change with diagnostic agents, the equilibrium is unique if and only if $\alpha \leq (1+\theta)\sqrt{2\pi\beta}$ and is in monotone strategies.*

Figure 1: Uniqueness Region



Note. For descriptive purpose, I use the diagnosticity parameter $\theta = 0.5$, which belongs to the range of $[0.5, 1.5]$ reported in the previous literature. The uniqueness region for the Bayesian global game is below the blue lined curve and that for the diagnostic global game is below the orange dashed curve.

The uniqueness region for the diagnostic global game is larger than the Bayesian counterpart as Figure 1 illustrates. Intuitively, this can be attributed to increased posterior precision, that is, $\alpha + \beta(1+\theta) > \alpha + \beta$. In other words, diagnostic players systematically overreact to recent news in a sense that they are more attentive to more representative states, and thus they think that other players are also diagnostic and are more confident about their behaviors. Thus, strategic uncertainty faced by diagnostic learners becomes smaller, which leads to more frequent uniqueness results.

3.2 Comparative Statics

One common comparative statics exercise in the global game literature is to investigate the limiting behavior as the private signal precision β becomes large. This exercise makes it available to evaluate the role of information in the global game. When the prior precision α goes to infinity, the uniqueness condition breaks and so I only focus on the equilibrium behavior with respect to the private signal precision β. Building upon this result, I can implement another comparative statics exercise by changing the payoffs of the game. In particular, I change the relative cost of action c, which leads to different limit results with respect to the private signal precision β.

Limit Results

As the precision of the private signal becomes greater, individual agents tend to anchor their belief on the signal while ignoring the prior information. Since private information is heterogeneous among agents, this increases strategic uncertainty by making it difficult to predict others' actions. The uniqueness condition in Proposition 1 and 2 imply that if this effect is strong enough, then there is a unique equilibrium. In the limit of $\beta \to \infty$, individuals cease to use the prior information and thus the equilibrium dependence on the prior uncertainty σ_x disappears. This argument holds for both global games with different types of learners as the following proposition shows.

Proposition 3. *In the limit as private information becomes infinitely precise, where $\beta \to \infty$ ($\sigma_\epsilon \to 0$) for given $\alpha < \infty$ ($\sigma_x > 0$), the probability of regime change converges to 1 for all $x < x_\infty$ and to 0 for all $x > x_\infty$, where*

1. $x_\infty \equiv 1 - c$ *for the Bayesian global game*
2. $x_\infty \equiv \Phi\left(\dfrac{\Phi^{-1}(1-c)}{\sqrt{1+\theta}}\right)$ *for the diagnostic global game.*

Hence, a small variation in x can trigger an abrupt change in the size of attack and the regime outcome when the noise of private information is small enough and x is in the neighborhood of x_∞. While the regime outcome is dictated only by the fundamental x and the exogenous cost c in the Bayesian global game, the diagnosticity parameter θ

kicks in the equilibrium result under the DE framework. From this result, I can derive a lesson that a "belief channel", which is characterized by the diagnosticity parameter θ here, is fundamental to the global game's equilibrium result even when agents essentially process only their private information.

Proposition 3 suggests that the equilibrium threshold under DE can deviate from the one under Bayesian updating differently depending on the value of c.

Corollary 1. *The following holds for the equilibrium thresholds in the limit as private information becomes infinitely precise:*

1. *When* $c > \frac{1}{2}$, $x_\infty^{Bayesian} < x_\infty^{Diagnostic}$.
2. *When* $c < \frac{1}{2}$, $x_\infty^{Bayesian} > x_\infty^{Diagnostic}$.

Intuitively, this result is also attributed to the fact that diagnostic players hold more confidence about their belief on others' action. When the relative cost of action is high (low), players of the game are less (more) likely to attack and so lower (raise) the level of the threshold of attacking. Since the perceived strategic uncertainty of diagnostic players is lower than that of Bayesian players, diagnostic agents overestimate the marginal cost (benefit) of decreasing (increasing) their own thresholds. Therefore, the equilibrium threshold for the diagnostic global game is formed at a higher (lower) level.

Remark. Proposition 3 indicates a possible reason for one known failure of theoretical predictions of the standard global game model. Szkup and Trevino (2020) find that subjects' behavior tends towards the efficient equilibrium threshold rather than the risk dominant one. Although this finding seems at odds with the prediction of the standard global game model, the diagnostic global game model might provide an alternative explanation for this finding because Proposition 3 implies that the representative heuristic that subjects suffer shifts the limit threshold from the risk dominant one.

Simulation Results

To investigate how effectively the comparative statics analysis holds valid for finite values of β, I perform numerical analysis on how the equilibrium threshold changes as I vary the value of c. Since the equilibrium thresholds do not have analytical solutions, I implement simulation exercises with $\alpha = 0.3$ and $\beta = 0.5$ so that they satisfy the uniqueness condition of Proposition 1 and 2. For the other parameters, let $z = 0$ for computational convenience and $\theta = 0.5$ following the estimation results using survey expectation data in Bordalo et al. (2020).

As expected by Proposition 3 and Corollary 1, equilibrium thresholds differ for Bayesian global games and diagnostic global games. As I change the value of c from 0 to 1, this difference in thresholds becomes narrower, at a point around $c \in [0.5, 0.6]$ their order is reversed, and the gap becomes larger thereafter. Here, I present 3 cases with $c = 0.1, 0.6, 0.9$

which illustrate this property well in Figure 2, 3, and 4, where equilibrium thresholds are the intersections of the inverse of the normal distribution and red lines. In addition, I also implement sensitivity analysis with respect to α and β when $c = 0.1, 0.6, 0.9$. Since the pattern of widening gap at the extreme values of c also appears, I relegate those analyses to the appendix.

Figure 2: Equilibrium thresholds when $c = 0.1$

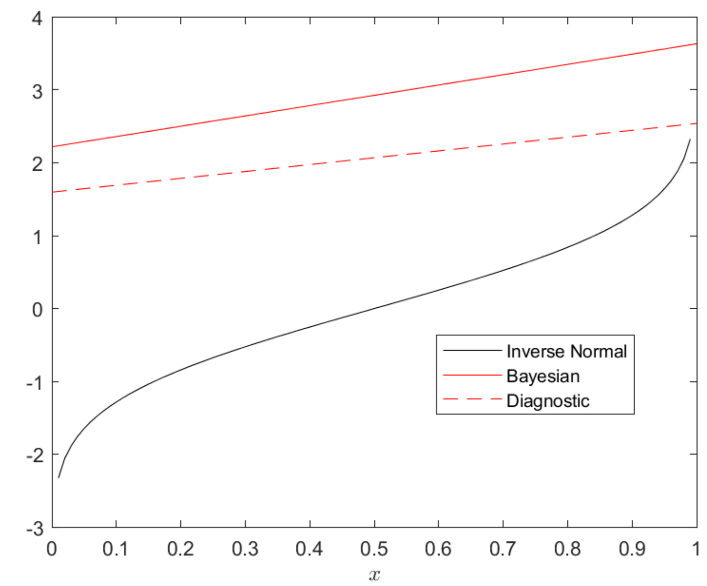


Figure 3: Equilibrium thresholds when $c = 0.6$

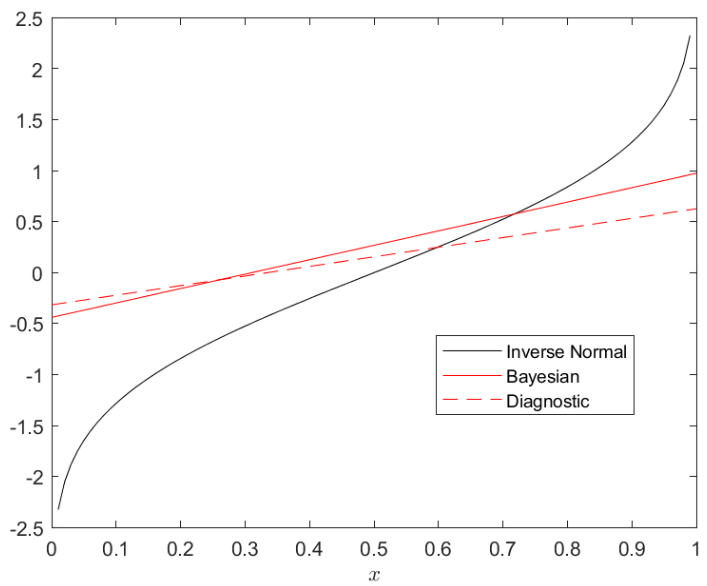
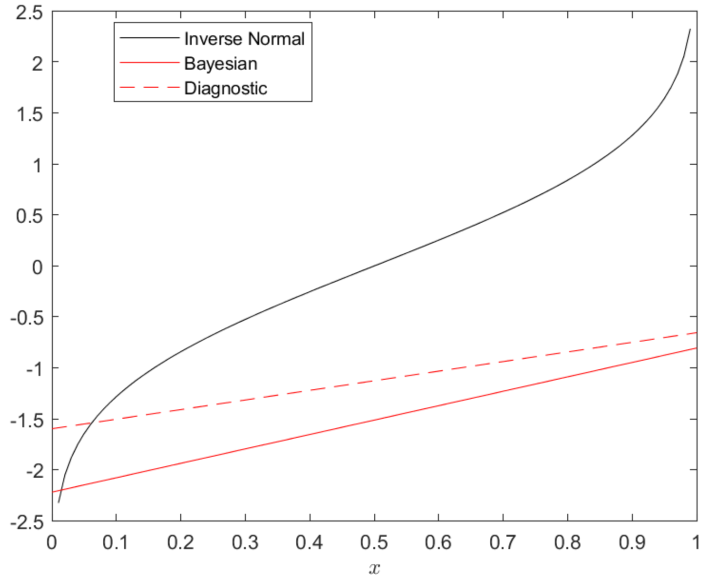


Figure 4: Equilibrium thresholds when $c = 0.9$



4 Experimental Design

As Bordalo et al. (2021) and Bordalo et al. (2022) show in their memory experiments, individuals' conditional probabilistic judgments are subject to interference from irrelevant data when they attempt to recall objects. Based on the previous findings on the mechanism of DE in a simple setup, I propose novel experiments which directly (1) test DE in an individual belief updating setup and (2) test its implications for economic analysis in global games model. Although global games involve belief updating, this belief updating requires forming expectations about other players' action and so it is intrinsically strategic. Then, the strategic structure of the game might further complicate the operation of DE. Thus, I first check whether DE still works in an individual decision making where one needs to update his belief. Then, I proceed to test DE implications in global games based on the best design I can effectively test DE.

4.1 Experiment for Testing Diagnostic Expectations

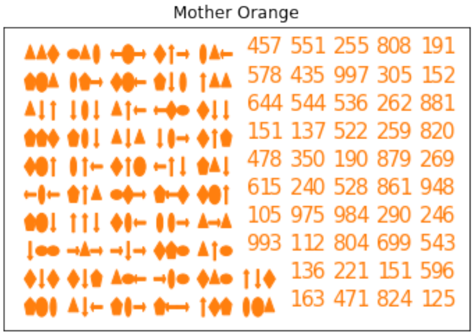
I design an experiment to assess (1) whether DE operates and (2) how persistent it is over time when subjects are given solitary belief updating tasks. To this end, I construct an individual decision making task whose structure inherits that of global games. Specifically, subjects are given a task to guess the true parameter x using the common prior information on x and private information on x. However, this setup is not enough to test DE directly since I have no instrument to use as the main treatment which only affects diagnostic learners. This is because the original diagnostic belief updating in the macro-financial literature takes the prior information as the background context and changing this prior affects Bayesian learners as well. Thus, I need to exploit the underlying mechanism of DE by introducing irrelevant data which interfere with subjects retrieving relevant data.

I introduce two urns with balls: one with orange balls ("Mother Orange") and the other with blue balls ("Mother Blue") as in Figure 5. Each ball in each urn has a shape or a number on it so that there are 4 kinds of balls with 2 characteristics along the color and mark dimensions. I draw 25 balls from each Mother Urn with replacement and make a new urn called "Baby Orange" and "Baby Blue" composed of these 25 balls as in Figure 6. Then, the true parameter x is determined to be the number of one of the 4 kinds: (Orange, Shape), (Orange, Number), (Blue, Shape), (Blue, Number). While information on the proportion of each Mother Urn is public to subjects, they do not observe x which they need to infer in this experiment. To give a hint to subjects, 25 balls are drawn with replacement now from each Baby Urn and these 25 balls separately form "Signal Orange" and "Signal Blue" as in Figure 7. Signal Urns are observable to subjects so that they can infer x using information on Mother Urns and Signal Urns.

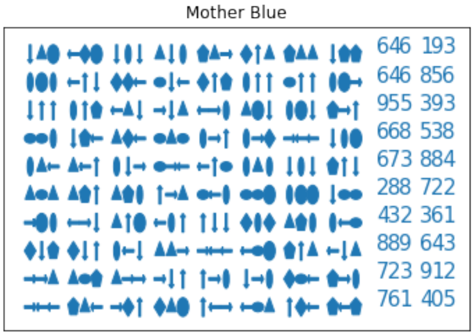
This type of task is implemented individually and repeatedly over 30 rounds. Once x is fixed, say the number of (Orange, Shape), information on blue urns become irrelevant, in which the DE mechanism can operate. Thus, I use the proportion of Mother Urns in each round as the main treatment dimension. Under the "Interference" treatment, the composition of Mother Orange differs from that of Mother Blue, while they coincide with each other under the "No Interference" treatment. For Bayesian learners, these two treatments will make no significant difference in their guessing on the true parameter. On the other hand, diagnostic learners under the influence of the irrelevant data due to memory restrictions will overestimate or underestimate x under the "Interference" treatment while not making biased judgments under the "No Interference" treatment. Of course, all the information subjects observe is available for a certain amount of time to stimulate the memory recall process.

To check the persistence of DE over 30 rounds, I randomize x and randomly shuffle the proportion of Mother Urns among possible candidates for each round. A certain level of randomization is necessary since fixed proportions over each round could induce unwanted learning of subjects. While diversifying proportions of irrelevant Mother Urn, say Mother Blue, is obviously essential for my purpose, changing proportions of relevant Mother Urn, which is Mother Orange, can introduce another interference channel as Bordalo et al. (2022) predict. In a guessing problem of the number of (Orange, Shape) balls, the number of (Orange, Nubmer) balls serves as an alternative hypothesis which can also interfere with inference for the number of (Orange, Shape) balls in a different way. Thus, I pair the "Interference" and "No Interference" treatments in such an order that I can control the effect of interference from the alternative hypothesis.

Figure 5: Mother Urns

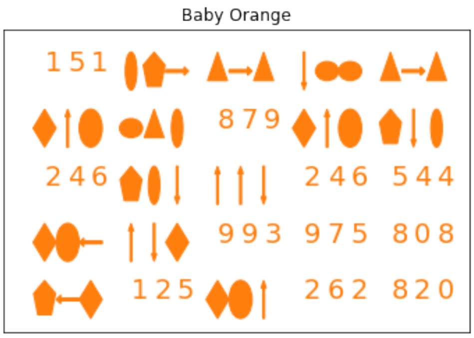


(a) Mother Orange

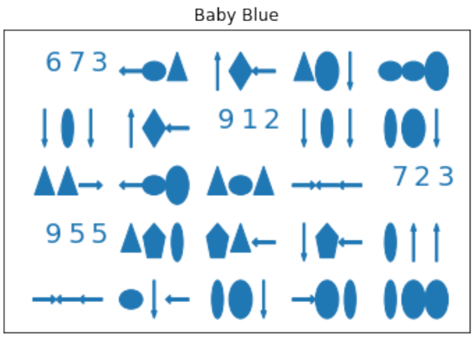


(b) Mother Blue

Figure 6: Baby Urns

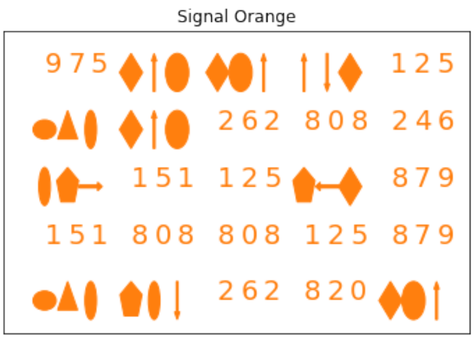


(a) Baby Orange

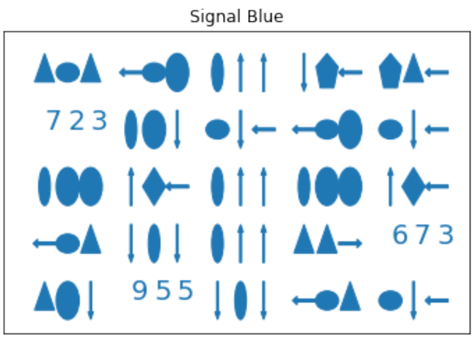


(b) Baby Blue

Figure 7: Signal Urns



(a) Signal Orange



(b) Signal Blue

4.2 Experiment for Testing Diagnostic Global Games

Based on the previous experiment for testing DE, I consider a 2×2 experimental design for testing the diagnostic global game: one dimension differentiating between Bayesian and diagnostic players, and the other dimension affecting both Bayesian and diagnostic players. The first treatment dimension is the existence of interference from irrelevant data as in the above experiment. Specifically, I use the same design as before for fair comparison, that is, with the "Interference" and "No Interference" treatments. In addition, since Corollary 1 predicts that the equilibrium thresholds of Bayesian and diagnostic global games have different orders for different levels of c, I utilize the cost of action as the other treatment dimension. Specifically, I use $c = 0.1$ for the "Low Cost" treatment and $c = 0.9$ for the "High Cost" treatment.

Thus, the experimental procedure for one round of each session can be summarized as follows:

1. Instructions on the general information of the experiment are illustrated to participants, including information on the urns filled with balls and the structure of the global game.

2. The proportion of Mother Orange and Mother Blue is determined and each urn composed of 100 balls is shown to participants.

3. 25 balls are drawn with replacement to compose Baby Orange and Baby Blue from each Mother Urn and the fundamental parameter x of a global game is chosen from the four candidates: # of (Orange, Shape), # of (Orange, Number), # of (Blue, Shape), # of (Blue, Number)

4. For each player, individual Signal Orange and Signal Blue are created by drawing 25 balls with replacement from each Baby Urn and these compositions are privately informed with visual information.

5. Participants choose their action based on their inference on the fundamental parameter x and other participants' action of the given global game.

In order to interpret this experiment as a diagnostic global game introduced in Section 2, I establish normal interpretation of the experiment. Basically, each ball in Mother Urns follows a Bernoulli distribution. Thus, the normal approximation to the binomial distribution, or alternatively, the central limit theorem offers us the normal interpretation of the belief updating problem. Let X_i, $i = 1, \ldots, n$, denote each ball in the relevant Baby Urn. Here, the distribution of each ball in the relevant Mother Urn follows Bernoulli(p) with $p > 0$ and $q \equiv 1 - p$. Then, the fundamental parameter of the global game x is defined as $\sum_{i=1}^{n} X_i \sim \mathcal{N}(np, npq)$. Similarly, I have a similar result for the Signal Urn using the bootstrap central limit theorem.

Thus, I have the following approximation for each stage of Urns:

(1) Mother Urn: $X_i \sim \text{Bernoulli}(p)$

(2) Baby Urn: $\sum_{i=1}^{n} X_i \sim \mathcal{N}(np, npq)$

(3) Signal Urn: $\sum_{i=1}^{n} X_i^* \sim \mathcal{N}(\sum_{i=1}^{n} X_i, npq)$

Finally, I need to interpret the "Interference" and "No Interference" treatments in terms of the original DE represented by one parameter θ. As I have seen in the previous subsection, irrelevant data can interfere with belief updating in such a way that boosts overestimation or underestimation of the fundamental parameter. Although this interference treatment only determines the proportion of Mother Urns, Signal Urns are also affected in a similar way. Thus, the dynamic DE mechanism which is overreaction to recent information will be strengthened under the "Interference" treatment which stimulates overestimation of the fundamental parameter. Therefore, I can interpret the "Interference" treatment in the overestimation (underestimation) domain as an increased (decreased) θ. Hence, the summary of the experimental design is given in Table 2.

Table 2: Experimental design and prediction

	Low cost	High cost
No Interference	$\widehat{x}_{Bayesian} \gg \widehat{x}_{Diagnostic}$	$\widehat{x}_{Bayesian} \ll \widehat{x}_{Diagnostic}$
Interference (Overestimation)	$\widehat{x}_{Bayesian} \ggg \widehat{x}_{Diagnostic}$	$\widehat{x}_{Bayesian} \lll \widehat{x}_{Diagnostic}$
Interference (Underestimation)	$\widehat{x}_{Bayesian} > \widehat{x}_{Diagnostic}$	$\widehat{x}_{Bayesian} < \widehat{x}_{Diagnostic}$

5 Discussion

This paper has developed into a joint project with Professor Syngjoo Choi at Seoul National University and Professor Jeongbin Kim at Florida State University. We are at the final stage of polishing our experimental design. After we determine every detail of our experiments, we will run a couple of pilot sessions for minute adjustments. Then, we plan to run regular sessions in this winter.

A Proofs of Propositions

Proof of Proposition 1. Substituting $\widehat{s} = \widehat{x} + \frac{1}{\sqrt{\beta}}\Phi^{-1}(\widehat{x})$ (3.2) into (3.4), we have

$$
\begin{aligned}
& 1 - \Phi\left(\sqrt{\alpha+\beta} \cdot \frac{\sqrt{\beta}\Phi^{-1}(\widehat{x}) + \alpha(z - \widehat{x})}{\alpha+\beta}\right) = c \\
\iff & \Phi^{-1}(1-c) = \frac{\sqrt{\beta}\Phi^{-1}(\widehat{x}) + \alpha(z-\widehat{x})}{\sqrt{\alpha+\beta}} \\
\iff & \sqrt{1+\frac{\alpha}{\beta}} \cdot \Phi^{-1}(1-c) + \frac{\alpha(\widehat{x} - z)}{\sqrt{\beta}} = \Phi^{-1}(\widehat{x}). \qquad \text{(A.1)}
\end{aligned}
$$

Since $\min\limits_{x\in(0,1)} \frac{d}{dx}\Phi^{-1}(x) = \min\limits_{x\in(0,1)} \frac{1}{\phi(\Phi^{-1}(x))} = \sqrt{2\pi}$, the equilibrium is in monotone strategies and is unique if and only if

$$
\frac{\alpha}{\sqrt{\beta}} \leq \sqrt{2\pi} \iff \alpha \leq \sqrt{2\pi\beta}.
$$

It only remains to show that the unique monotone equilibrium is the only equilibrium that survives iterated deletion of strictly dominated strategies. Let $h(s)$ denote the threshold that an agent finds it optimal to follow when all other agents use a threshold s. Note that there is a 1-to-1 mapping between the thresholds $\widehat{x}$ that solve (3.2) and the fixed points of h. The monotone equilibria are defined by the fixed points of h. Construct two sequences $\{\underline{s}_j\}_{j=0}^{\infty}$ and $\{\overline{s}_j\}_{j=0}^{\infty}$ by $\underline{s}_0 = -\infty, \underline{s}_j = h(\underline{s}_{j-1})$ and $\overline{s}_0 = \infty, \overline{s}_j = h(\overline{s}_{j-1})$. Each sequence is increasing or decreasing with upper or lower bound. Thus, they both converge to some $\underline{s}$ and $\overline{x}$. By continuity of h, these points must be a fixed point of h, which is $\widehat{s}$. Since the only strategies that survives after j rounds of iterated deletion of dominated strategies are functions k such that $k(s) = 1$ for all $s \leq \underline{s}_j$ and $k(s) = 0$ for all $s > \overline{s}_j$, the only strategy that survives in the limit is the unique monotone equilibrium. □

Proof of Proposition 2. Before jumping into the details of the proposition, we first prove the posterior updating result (3.5). The definition indicates

$$
f^{\theta}(x|s) \propto \left[\frac{f(x|s)}{f(x)}\right]^{\theta} = \left(\frac{\alpha}{\alpha+\beta}\right)^{\frac{\theta}{2}} \qquad \text{(A.2)}
$$

$$
\times \exp\left(-\frac{\theta}{2}\left\{(\alpha+\beta)\left(x - \frac{\alpha z + \beta s}{\alpha+\beta}\right)^2 - \alpha(x-z)^2\right\}\right) \qquad \text{(A.3)}
$$

where $f(\cdot)$ denotes the density function. Since

$$
(A.3) = \exp\left\{-\frac{\alpha+\beta(1+\theta)}{2}\left(x - \frac{\alpha z + \beta(1+\theta)s}{\alpha+\beta(1+\theta)}\right)^2\right\}, \qquad \text{(A.4)}
$$

we obtain the posterior distribution (3.5).

Substituting $\widehat{s} = \widehat{x} + \frac{1}{\sqrt{\beta}}\Phi^{-1}(\widehat{x})$ (3.2) into (3.6), we have

$$\begin{aligned}
& 1-\Phi\left(\sqrt{\alpha+\beta(1+\theta)}\cdot\frac{\sqrt{\beta}(1+\theta)\Phi^{-1}(\widehat{x})+\alpha(z-\widehat{x})}{\alpha+\beta(1+\theta)}\right)=c \\
\iff & \Phi^{-1}(1-c)=\frac{\sqrt{\beta}(1+\theta)\Phi^{-1}(\widehat{x})+\alpha(z-\widehat{x})}{\sqrt{\alpha+\beta(1+\theta)}} \\
\iff & \sqrt{1+\frac{\alpha}{\beta(1+\theta)}}\cdot\frac{\Phi^{-1}(1-c)}{\sqrt{1+\theta}}+\frac{\alpha(\widehat{x}-z)}{\sqrt{\beta}(1+\theta)}=\Phi^{-1}(\widehat{x}) \qquad \text{(A.5)}
\end{aligned}$$

Since $\min_{x\in(0,1)}\frac{d}{dx}\Phi^{-1}(x) = \min_{x\in(0,1)}\frac{1}{\phi(\Phi^{-1}(x))} = \sqrt{2\pi}$, the equilibrium is in monotone strategies and is unique if and only if

$$\begin{aligned}
& \frac{\alpha}{\sqrt{\beta}(1+\theta)} \le \sqrt{2\pi} \\
\iff & \alpha \le (1+\theta)\sqrt{2\pi\beta} \\
\iff & \theta \ge \frac{\alpha}{\sqrt{2\pi\beta}} - 1.
\end{aligned}$$

Finally, the unique monotone equilibrium is the only equilibrium that survives iterated deletion of strictly dominated strategies by exactly the same logic we use in the proof of Proposition 1. $\square$

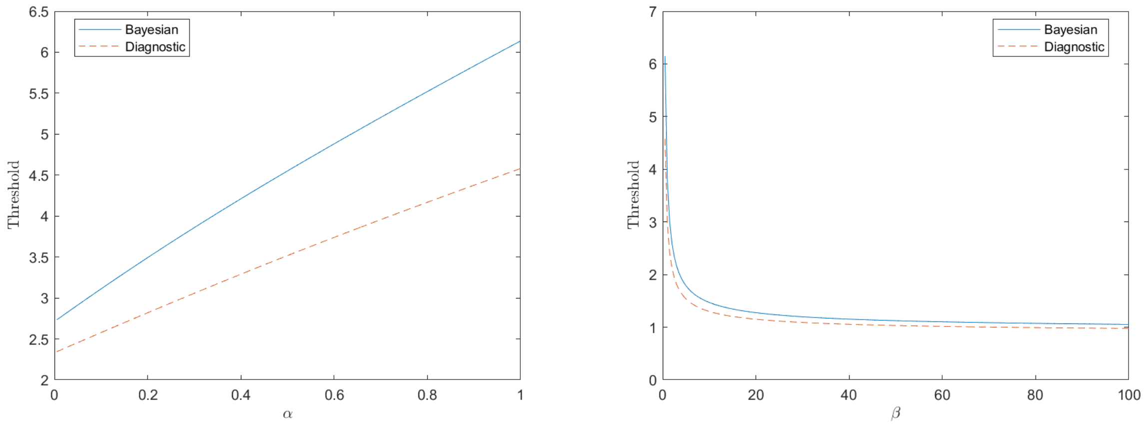
Proof of Proposition 3. As $\beta \to \infty$ with $\alpha < \infty$, (LHS) of (A.1) becomes $\Phi^{-1}(1-c)$ and (RHS) of (A.1) remains the same. Thus, we obtain $x_\infty = 1-c$ since Φ^{-1} is monotone. Similarly, (LHS) of (A.5) becomes $\Phi^{-1}(1-c)/\sqrt{1+\theta}$ and (RHS) of (A.1) remains the same. Thus, we obtain $x_\infty = \Phi\left(\frac{\Phi^{-1}(1-c)}{\sqrt{1+\theta}}\right)$. $\square$

Proof of Corollary 1. Since $\Phi(\cdot)$ is an monotone increasing function and $\Phi^{-1}(\cdot)$ undergoes a sign change at $c = \frac{1}{2}$, the order of the two equilibrium thresholds flips at $c = \frac{1}{2}$. $\square$

B Additional Simulation Results

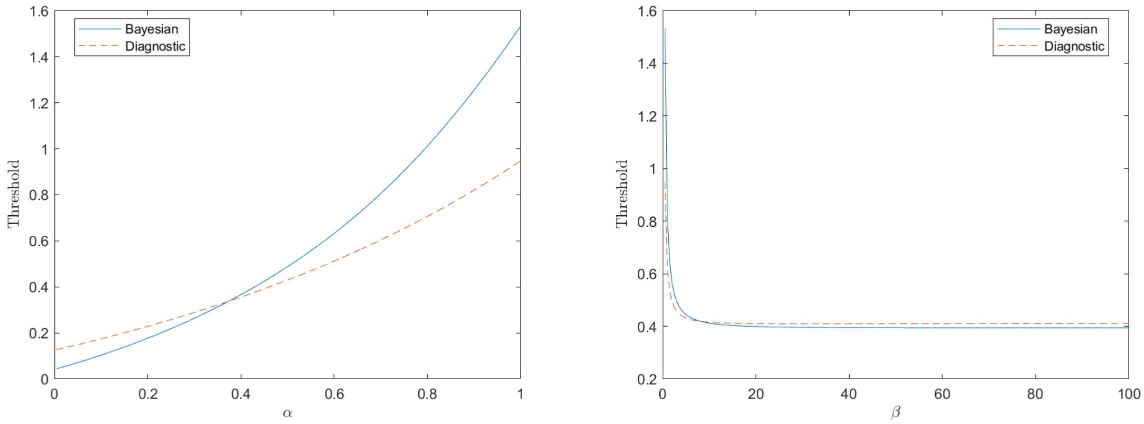
We report here sensitivity analysis with respect to α and β when $c = 0.1, 0.6, 0.9$.

Figure 8: Sensitivity analysis when $c = 0.1$



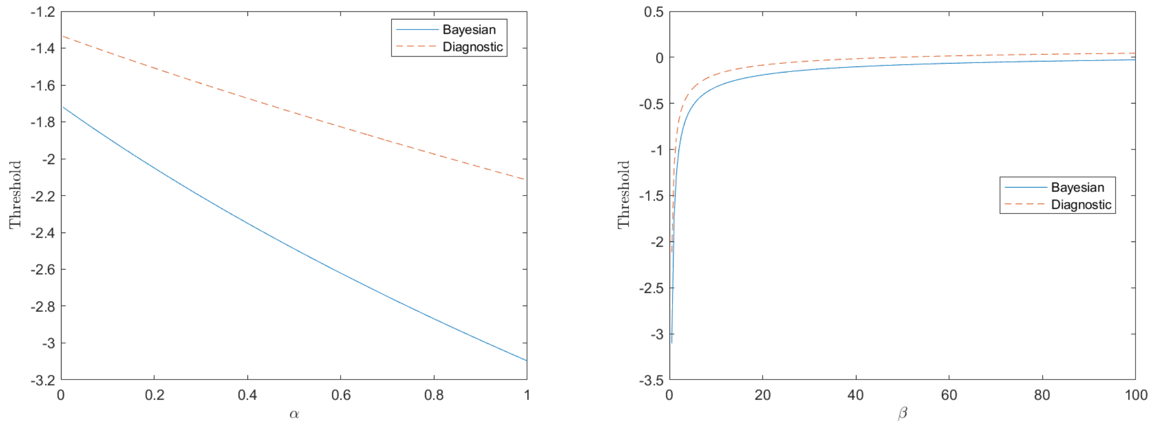
(a) α (b) β

Figure 9: Sensitivity analysis when $c = 0.6$



(a) α (b) β

Figure 10: Sensitivity analysis when $c = 0.9$



(a) α (b) β

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