



# IE UNIVERSIDAD

TESIS DOCTORAL/ DOCTORAL DISSERTATION

Toma de Decisiones bajo Interacciones Sociales: Procesos y  
Resultados / Decision Making under Social Interactions: Processes  
and Outcomes

Sreyaa Guha

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# Abstract

In my dissertation I study two different types of decision making processes in the presence of social interactions. The first decision making process is investigated under uncertainty where I examine pricing decisions under an impending regime shift. Impending regime shifts represent an uncertainty in the underlying state of the world that is susceptible to change. In such situations, decision makers must make probabilistic judgments of the change to arrive at the pricing decisions (i.e., willingness to pay/accept) for insurance and assets. I examine whether there is a gap between willingness to pay (WTP) and willingness to accept (WTA) and if the gap can be mitigated using social learning. To this end, a model is built integrating prospect theory with the system neglect hypothesis in chapter 1. Model predictions regarding WTA and WTP are validated using data collected through four controlled experiments. Based on this model, in chapter 2, two additional studies are conducted to examine the gap between WTP and WTA. To observe the effect of social learning on this gap, buyers-seller dyads are allowed to reveal their pricing decisions to each other over a multi period trading game. While a significant gap between WTA and WTP is observed, the effect of social learning on this gap is found to be insignificant.

The second decision making process, outlined in chapter 3, is investigated under certainty (i.e., no risks involved) where I examine social interaction based choice formation for commodities. I analytically derive the average choice equilibrium of a socially interacting group using an expectation based choice model that incorporates group influences on individual decisions. Furthermore, I study if the equilibrium changes when firm actions (to influence individual choices) are introduced. Findings show that with firm actions, scenarios emerge where the choice equilibrium is self-defeating for the firm, specifically when decision makers are either privately indifferent between buying and not buying or they privately prefer not buy and only non-reference groups are present.

# Resumen

En mi tesis estudio dos tipos diferentes de procesos de toma de decisiones en presencia de interacciones sociales. El primer proceso de toma de decisiones se investiga bajo la incertidumbre, donde examino las decisiones de fijación de precios ante un cambio de régimen inminente. Los cambios de régimen inminentes representan una incertidumbre en el estado subyacente del mundo que es susceptible de cambiar. En tales situaciones, los responsables de la toma de decisiones deben hacer juicios probabilísticos del cambio para alcanzar decisiones de precios (es decir, la disposición a pagar/aceptar) para los seguros y los activos. Examino si existe una brecha entre la disposición a pagar (WTP, siglas en inglés) y la disposición a aceptar (WTA, siglas en inglés) y si la brecha puede mitigarse utilizando el aprendizaje social. Para ello, se construye un modelo que integra la teoría prospectiva con la hipótesis de abandono del sistema del capítulo 1. Las predicciones del modelo en relación con la WTA y la WTP se validan con los datos recogidos en cuatro experimentos controlados. Sobre la base de este modelo, en el capítulo 2, se realizan dos estudios adicionales para examinar la brecha entre la WTP y la WTA. A fin de observar el efecto del aprendizaje social en esta diferencia, se permite que las diadas de compradores y vendedores se revelen mutuamente sus decisiones de precios en un juego comercial de varios períodos. Aunque se observa una brecha significativa entre la WTA y la WTP, el efecto del aprendizaje social sobre esta diferencia que se detecta es insignificante.

El segundo proceso de toma de decisiones, esbozado en el capítulo 3, se investiga en condiciones de certidumbre (es decir, sin riesgos), donde se examina la formación de la elección basada en la interacción social para los productos. Derivo analíticamente el equilibrio de elección medio de un grupo que interactúa socialmente, para lo que utilizo un modelo de elección basado en expectativas que incorpora las influencias del grupo en las decisiones individuales. Además, estudio si el equilibrio cambia cuando se introducen acciones empresariales (para influir en las elecciones individuales). Los resultados muestran que, con acciones empresariales, surgen escenarios en los que el equilibrio de elección es contraproducente para la empresa, concretamente cuando los responsables de la toma de decisiones son indiferentes en privado entre comprar y no comprar o prefieren en privado no comprar y sólo están presentes los grupos de no referencia.

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# Introduction

Decisions are hardly made in isolation. In real life, decisions can be influenced by one or more decision makers. The social aspect of decision making is at the heart of my dissertation thesis. The influence of others' decisions can vary based on whether the decisions are revealed or only the intentions are conveyed. Additionally, the influence can be different based on whether or not an element of risk is involved in the decision.

Therefore, in my dissertation I study two different types of decision making processes and their outcomes in the presence of social interactions. The first decision making process is regarding pricing decisions for insurances and assets under uncertainty (in chapters 1 and 2). The second decision making process is regarding purchase decisions for commodities under certainty (in chapter 3). To that end, my dissertation is organized into three chapters as follows:

In chapter 1, pricing decisions are studied under an impending regime shift. Impending regime shifts represent an uncertainty in the underlying state of the world that is susceptible to change. Risk attitudes as well as probability judgments regarding the occurrence of a regime shift affect decision making. A model is developed integrating prospect theory (Kahneman and Tversky 1979) with the system neglect hypothesis (Massey and Wu 2005) and changes in empirical pricing decisions are compared to those of a Bayesian risk-neutral agent. The model predicts underreaction in pricing decisions if the environment is unstable and signals are precise and overreaction if the environment is stable and signals are noisy only if the prior probability of regime shift is low. However, if prior probability of regime shift is high, no significant difference is found between such environments. The rationale is that when the prior probability of regime shift is low, changes in risk attitude in reaction to signals of indicative of regime shift amplify system neglect in probability judgments. When the prior probability of regime shift is high,

on the other hand, changes in risk attitude blunt the effect of system neglect resulting in no significant under- and overreaction between the two environments.

In chapter 2, I extend my investigation on pricing decisions under impending regime shifts in the presence of social learning. I examine whether a significant gap exists between the pricing decisions of buyers and sellers, i.e., the gap between willingness to pay and willingness to accept when such pricing decisions are made under impending regime shifts. There is an on going debate regarding the existence of a significant gap between willingness to pay and willingness to accept. While some researchers posit that such a gap exists (Coursey, Hovis & Schulze 1987; Hanemann 1991; Knetsch & Sinden 1984; Randall & Stoll 1980), others purport that the gap exists purely as a function of the design aspects of the experiment itself (Harless 1989; Plott & Zeiler 2005; Singh 1991). In the setting that I study, pricing decisions are explained as a combined effect of system neglect bias in probability judgments and risk attitudes and it is not straightforward to predict the existence of a gap in willingness to pay and willingness to accept under impending regime shifts. The second objective of the study is to investigate whether the gap, if it exists, can be mitigated through social learning. The effect of social learning has not been explored for pricing decisions under regime shifts. Findings from Singh (1991) suggest in the context of risky lotteries, this effect is not significant . I expect that if buyers and sellers of insurance contracts are allowed to reveal their pricing decisions to each other, over time their pricing decisions will converge even in the context of impending regime shifts.

In chapter 3, I study purchase decisions for commodities in the presence of social interactions under certainty. By certainty I mean that the purchase decisions (“buy” or “not buy”) do not involve any risk. Typically, on social forums, the final purchase decisions of the decision makers are not observable to other decision makers or the firm. Only the purchase intentions are conveyed. I analytically model purchase decisions for such settings based on the model suggested by Brock and Durlauf (2001), where a decision maker must form an expectation of others’ choices and incorporate that in her decision making process. In my model, reference group influences are also included. Additionally, firm actions are introduced and the final choice equilibrium of an interacting group of decision makers is derived. The choice equilibria with and without firm actions are compared to evaluate whether firm actions are self defeating.

# Introducción

Las decisiones rara vez se toman de forma aislada. En la vida real, las decisiones pueden estar influidas por uno o varios decisores. El aspecto social de la toma de decisiones es el núcleo de mi tesis doctoral. La influencia de las decisiones de otros puede variar en función de si las decisiones se revelan o sólo se transmiten las intenciones. Además, la influencia puede ser diferente en función de si hay o no un elemento de riesgo en la decisión.

En mi tesis, pues, estudio dos tipos diferentes de procesos de toma de decisiones y sus resultados en presencia de interacciones sociales. El primer proceso de toma de decisiones se centra en las decisiones de fijación de precios de los seguros y los activos en condiciones de incertidumbre (en los capítulos 1 y 2). El segundo proceso de toma de decisiones se centra en las decisiones de compra de productos en condiciones de certidumbre (en el capítulo 3). A tal fin, mi tesis está organizada en tres capítulos, como se indica a continuación: En el capítulo 1, se estudian las decisiones de precios ante un cambio de régimen inminente. Los cambios de régimen inminentes representan una incertidumbre en el estado subyacente del mundo que es susceptible de cambiar. Las actitudes hacia el riesgo y los juicios de probabilidad sobre la eventualidad de un cambio de régimen afectan a la toma de decisiones. Se desarrolla un modelo que integra la teoría prospectiva (Kahneman y Tversky, 1979) con la hipótesis del abandono del sistema (Massey y Wu, 2005) y se comparan los cambios en las decisiones empíricas de fijación de precios con los de un agente bayesiano de riesgo neutral. El modelo predice una reacción insuficiente en las decisiones de fijación de precios si el entorno es inestable y las señales son precisas y una reacción excesiva si el entorno es estable y las señales son ruidosas sólo si la probabilidad previa de cambio de régimen es baja. Sin embargo, si la probabilidad previa de cambio de régimen es alta, no se encuentra ninguna diferencia significativa entre dichos entornos. La razón es que, cuando la probabilidad previa de cambio de régimen es baja, los cambios en la actitud hacia el

riesgo como reacción a las señales indicativas de cambio de régimen amplifican el abandono del sistema en los juicios de probabilidad. En cambio, cuando la probabilidad previa de cambio de régimen es alta, los cambios en la actitud hacia el riesgo atenúan el efecto del abandono del sistema, lo que da lugar a que no haya una reacción excesiva o insuficiente entre los dos entornos.

En el capítulo 2, amplí mi investigación sobre las decisiones de fijación de precios en caso de cambios de régimen inminentes en presencia del aprendizaje social. Examiné si existe una brecha significativa entre las decisiones de precios de los compradores y los vendedores, es decir, la brecha entre la disposición a pagar y la disposición a aceptar cuando dichas decisiones de precios se toman ante cambios de régimen inminentes. El debate sobre la existencia de una brecha significativa entre la disposición a pagar y la disposición a aceptar sigue abierto en la actualidad. Mientras que algunos investigadores afirman que dicha brecha existe (Coursey, Hovis y Schulze 1987; Hanemann 1991; Knetsch y Sinden 1984; Randall y Stoll 1980), otros afirman que la brecha existe puramente en función de los aspectos de diseño del propio experimento (Harless 1989; Plott y Zeiler 2005; Singh 1991). En el escenario que estudié, las decisiones de precios se explican como un efecto combinado del sesgo de abandono del sistema en los juicios de probabilidad y en las actitudes hacia el riesgo, y no es sencillo predecir la existencia de una brecha en la disposición a pagar y en la disposición a aceptar ante cambios de régimen inminentes. El segundo objetivo del estudio es investigar si la brecha, en caso de existir, puede mitigarse mediante el aprendizaje social. El efecto del aprendizaje social no se ha explorado en las decisiones de precios ante los cambios de régimen. Los resultados de Singh (1991) sugieren que, en el contexto de las loterías de riesgo, este efecto no es significativo. Considero que, si se permite a los compradores y vendedores de contratos de seguros revelar sus decisiones de precios a los demás, con el paso del tiempo sus decisiones de precios convergerán incluso en el contexto de cambios de régimen inminentes.

En el capítulo 3, estudié las decisiones de compra de productos en presencia de interacciones sociales en condiciones de certidumbre. Por certidumbre entiendo que las decisiones de compra (“comprar” o “no comprar”) no implican riesgo alguno. Normalmente, en los foros sociales, las decisiones finales de compra de los responsables no son observables para otros responsables o para la empresa. Sólo se transmiten las intenciones de compra. Mi modelo analítico de las

decisiones de compra en estos entornos se basa en el modelo sugerido por Brock y Durlauf (2001), en el que un responsable de la toma de decisiones debe formarse una expectativa de las elecciones de los demás e incorporarla a su proceso de toma de decisiones. En mi modelo también se incluyen las influencias del grupo de referencia. Además, se introducen las acciones empresariales y se deriva el equilibrio de elección final de un grupo de decisores que interactúan. Los equilibrios de elección con y sin acciones empresariales se comparan para evaluar si las acciones empresariales son contraproducentes.



# Chapter 1

## Decision Making under Impending Regime Shifts

### 1.1 Introduction

Chapter 1 is dedicated to understanding the pricing behavior of decision makers (DMs) under uncertainty. Specifically, we develop a model that predicts the pricing behavior under impending regime shifts. Impending regime shifts pose a fundamental challenge to consumers and businesses alike; they require DMs to accurately assess the timing of the regime shift when only partial information is available as well as to effectively act upon such information.

Previous studies have suggested that DMs tend to exhibit a systematic bias when estimating the probability of a regime shift (Massey and Wu 2005; Kremer, Moritz and Siemsen 2011). Particularly, Massey and Wu (2005) (MW from this point onwards) reported experimental evidence in support of the *system neglect hypothesis* in regime shift detection tasks: DMs appear to primarily react to signals they observe rather than the underlying environmental system that generated the signal. In consequence, DMs tend to overreact in stable environments with low probability of regime shift in which they observe noisy signals, and underreact in unstable environments with high probability of regime shift in which they observe precise signals. Kremer, Moritz and Siemsen (2011), on the other hand, study reactions to demand forecasting errors and argue that forecasters overreact to forecast errors in relatively stable

environments, but underreact to errors in relatively unstable environments.

The system neglect hypothesis lays out a comprehensive account of biases in probability judgments that individuals are likely to exhibit when processing signals indicative of a regime shift. However, DMs not only need to accurately predict the likelihood of potential shifts in the environment, but they also need to act upon them by employing appropriate risk mitigation strategies. Taking this into account, it is not immediately obvious how system neglect in probability judgments affects *decision making* under uncertainty.

To understand the effect of impending regime shifts on decision making, we offer a model-based, detailed analysis of the complex relationship between system neglect and risk attitudes. The system neglect hypothesis may be sufficient to characterize how risk-neutral DMs react to signals indicative of regime shifts. However, if risk-neutrality does not represent a realistic description of DMs' preferences, it is necessary to understand the circumstances in which individual risk attitudes are likely to dampen or amplify the influence of system neglect on decision behavior under impending regime shifts. To that end, we first construct a measure that captures how DMs respond to signals in environments with shifting regimes. Specifically, we focus on under- and overreaction in willingness to pay or accept in that we compare the *change* in elicited willingness to pay (accept), as a reaction to signals indicative of regime shift, to the change one would observe from a Bayesian risk-neutral agent. We then develop a model that incorporates prospect theory (Kahneman and Tversky 1979) and system neglect to make predictions about decisions in different environments; we test these predictions in a series of experiments.

Our experimental setup is consistent with the regime shift paradigm in MW: regimes are represented by urns that are filled with different proportions of red and green balls. Over the course of several rounds, balls are sampled with replacement and observed from the starting urn which, over time, may switch to a second urn. We study environments that differ with respect to the transition probability (measuring the stability of the environment) and signal diagnosticity (indicating the noise level of the observed signals) which are also manipulated in MW. Given this setup, we first test our model predictions in a main study where we explore insurance buying decisions under a dreaded regime shift where losses are incurred only after the shift has taken place. We then check the robustness of our findings in a series of experiments where we study different DM roles (buyer and sellers), desirability of regime shift (dreaded and

desirable) and decision domains (insurance and assets).

Our main contribution lies at the intersection of prescriptive and behavioral decision theories. In short, we demonstrate analytically and empirically why system neglect is not sufficient to explain decisions in environments where there is an impending regime shift. Instead, we propose a non-trivial pattern of systematic under- and overreaction in willingness to pay (accept) depending on the type of environment in which the DM operates: We find underreaction in willingness to pay (accept) if the environment is unstable and signals are precise and overreaction if the environment is stable and signals are noisy only if the prior probability of regime shift is low. If the prior probability of regime shift is high, we do not find significant differences between such environments. This is a subtle but important difference from the system neglect hypothesis. When the DM has a low prior probability that a regime shift has occurred, we use the four-fold risk aversion pattern of prospect theory to argue that changes in risk attitude amplify the under-/overreaction pattern of system neglect. When the prior probability of regime shift is high, on the other hand, changes in risk attitude dampen the effect of system neglect resulting in no significant under- and overreaction between the two environments. This pattern of under- and overreaction in willingness to pay implies that we are likely to see “sticky” decisions over time in environments where we predict underreaction and “hypersensitive” decisions in environments where we predict overreaction. Our empirical findings support these predictions.

In addition, we also demonstrate the robustness of the system neglect bias in probability judgments in our experiments, which prevails regardless of the role of the DM, the desirability of the regime shift and the decision domain.

In the subsequent sections, we first provide an overview of the present literature on the system neglect bias as well as decision making in dynamic environments. In §1.2, we present our model. In §1.3 we summarize the research design and empirical findings. Finally, we discuss implications of our research for the existing decision making literature and outline a number of managerial implications. Details of our model for different environments and the stimuli in our experiments are presented in the appendix.

### 1.1.1 System neglect in dynamic environments

System neglect is theoretically grounded in the distinction between the strength and weight of evidence (Griffin and Tversky 1992). Specifically, in an attempt to explain commonly observed behavioral patterns of overconfidence and underconfidence in static environments, Griffin and Tversky (1992) highlighted that DMs differ in their responses to the strength, or magnitude of an observed effect, and to the weight of evidence, which describes the predictive validity or reliability of the information source. For example, in the context of coin-flipping experiments, it has been shown that subjects systematically overweight the proportion of heads observed in a sequence of tosses (i.e. the strength of evidence), whereas they tend to underweight the length of the coin flip sequence (i.e. the weight of evidence). In consequence, a sequence of five heads out of six tosses would have high strength but low weight of evidence and a sequence of 40 heads out of 70 flips would be associated with low strength but high weight of evidence.

Massey and Wu (2005) study how individuals respond to the strength and weight of evidence in dynamic environments where there is an impending regime shift. In unstable environments with precise signals, the weight of evidence that is indicative of regime shift is high. In contrast, in stable environments with noisy signals, the weight of evidence that is indicative of regime shift is low. In consequence, given the same initial prior beliefs and a signal indicative of regime shift, the updated belief that the regime shift has occurred should be higher in unstable environments with precise signals compared to the updated belief in stable environments with noisy signals. However, individuals behave similarly across these systems, not paying attention to the weight of the signal; this results in system neglect. When the weight of evidence is strong (as in unstable environments with precise signals), system neglect predicts underreaction in probability judgments when they are compared against Bayesian probabilities. However, when the weight of evidence is weak (as in stable environments with precise signals), system neglect predicts overreaction in probability judgments.

More recently, other studies have explored implications of systematic under- and overreaction for forecasting approaches and applications (Ketter, Collins, Gini, Gupta and Schrater 2009; Glaser, Langer and Weber 2007; Grushka-Cockayne, Jose and Lichtendahl 2016; Watson and Zheng 2008; Kremer, Moritz and Siemsen 2011), Bayesian learning (Li, Massey and Wu

2014; Moreno and Rosokha 2016), change detection in nonstationary systems with unknown parameters (Brown and Steyvers 2009), random support theory (Brenner, Griffin and Koehler 2005), strategic interactions in games (Kareev, Avrahami and Fiedler 2014), demand censoring in newsvendor decision making (Rudi and Drake 2014), and narrow bracketing of qualitative judgments (Simonsohn and Gino 2013). The behavioral pattern of under- and overreaction in probability judgments has been found to be robust across a wide range of laboratory studies and generally appears to be difficult to overcome through learning (see, for example, Li, Massey and Wu (2014)). However, only few studies have investigated the consequences of system neglect for subsequent decision making under risk. Among the existing studies, Ambuehl and Li (2018) examine how DMs value information that could increase signal diagnosticity and they find that individuals undervalue almost all sources of information and do so to a greater extent the more informative an information source is. Moreover, respondents seemed to disproportionately prefer information that may yield certainty. Both findings were suggested to result from deficiencies in the updating of probability judgments as additional evidence is gathered rather than risk attitude. While Ambuehl and Li (2018) contribute to a better understanding of how individuals value information under uncertainty, the focus of the present paper is different: In environments where signal quality cannot be improved by acquiring additional information and the economic consequences of experiencing regime shifts are well-defined, we examine how DMs price insurance contracts or assets in their attempt to mitigate the risk associated with an impending regime shift.

### **1.1.2 Prospect theory and pricing decisions**

Because we investigate how pricing decisions are affected by impending regime shifts, our predictions are motivated by both system neglect (Massey and Wu 2005) and prospect theory (Kahneman and Tversky 1979). In the literature, there are a number of studies that model how biases in probability judgments affect decisions under uncertainty, particularly, pricing decisions. Notably, these papers (Brenner, Griffin and Koehler 2012; Camerer 1992; Kirchler and Maciejovsky 2002; Fox and Tversky 1998) focus on studying experimental markets, in which DMs are required to price assets under uncertainty in static, stationary environments. For example, Brenner, Griffin and Koehler (2012) adopt a dual-systems framework to argue that

sensitivity to the strength of evidence can be attributed to system 1 thinking, whereas sensitivity to the weight of evidence may result from more deliberate thinking processes associated with system 2. The authors subsequently report findings from a series of laboratory studies involving simulated stock markets, in which pricing decisions and probability judgments appear to be primarily driven by system 1 cognition and are sensitive to the strength of evidence. Moreover, differences in sensitivity to strength-based factors between probability and pricing decisions could at least partially be explained through the properties of value and probability weighting functions underlying prospect theory.

Similar to Brenner, Griffin and Koehler (2012), the present study sets out to investigate linkages between probability miscalibration and judgments concerning the economic valuation of prospects under uncertainty. We use the belief-based account of modelling decisions under uncertainty (Fox and Tversky 1998), in that we simultaneously elicit probability judgments as well as willingness to pay or accept under impending regime shifts. However, our study differs from existing work in a number of important ways: First, we focus explicitly on how the dynamic nature of the environment, characterized by the probability of regime shift in each period and signal diagnosticity, affects decisions under uncertainty. Our setup allows for a detailed analysis of how individuals form beliefs and how their risk preferences affect decisions when there is an impending regime shift and we can draw parallels between the under- and overreaction observed in probability judgments and pricing decisions. Second, using a model, we are able to delineate how system neglect and changes in risk premium as a reaction to signals indicative of regime shift contribute to under- and overreaction in willingness to pay or accept. Third, we study the robustness of our predictions by extending our decision context to encompass several alternative environmental configurations.

## **1.2 A model for pricing decisions under an impending regime shift**

When DMs face uncertainty about the prevailing state of the world (e.g. “Good” versus “Bad”), any decision they make depends on their probability judgments as well as their risk attitude. In this section, we focus on insurance decisions, specifically, we study changes in willingness to

pay for insurance under a dreaded regime shift. Consider DMs living in coastal communities: how does their willingness to pay for flood insurance change if they observe sea levels rising which might be indicative of climate change? Similarly, how do DMs change their willingness to pay for homeowner insurance if hurricanes become more frequent? If the DMs indeed observe that sea levels are rising or hurricanes are becoming more frequent, one would expect their willingness to pay for insurance to increase. If we compare that change in willingness to pay upon receipt of new information to the change one would observe from a Bayesian risk-neutral agent, do DMs under- or overreact?

To study the effect of impending regime shifts on decisions under uncertainty, we first develop a measure for under- and overreaction in willingness to pay and show that it can be written as the sum of the change in risk premium and the effect of system neglect in probability judgments. We then develop our model integrating prospect theory and system neglect hypothesis to study changes in willingness to pay for insurance contracts; (*pricing decisions* from this point forward). We present modifications to our model to study under- and overreaction in pricing decisions in other settings in the appendix.

Because our model utilizes properties of our experimental setup, we first provide a detailed explanation of our experiments. We use the statistical process outlined in MW to construct an environment where there is an impending regime shift. The regimes are represented by two urns containing different combinations of red and green balls. The “Good” regime is represented by a bin predominantly containing green balls whereas the “Bad” regime is represented by a bin predominantly containing red balls. These regimes can switch from “Good” to “Bad”, and the DMs try to infer whether a regime shift has occurred in a given period by observing signals. However, they are left uncertain about the actual state of the world at all times. The process is illustrated in Figure 1.1. Over several rounds, DMs observe signals generated by one of the two regimes. Note that in this section and in our main study we focus on dreaded regime shifts: The system starts in the “Good” regime and can switch to the “Bad” regime with transition probability  $q$ , where the “Bad” regime represents an absorbing state and the system remains in that regime until the end. We introduce additional dimensions to this environment such as different roles for the DM (buyers versus sellers), the desirability of the regime shift, and outcomes in losses versus gains domains in §1.3.2 which are important in studying decisions

under regime shift.

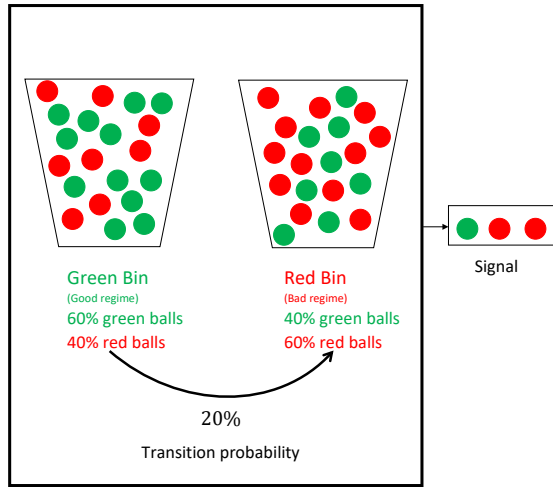


Figure 1.1: Statistical process for the regime shift task

In each time period, a DM contemplating whether to buy a single-period insurance contract, that covers any potential losses if the underlying regime is “Bad”, faces the decision in Figure 1.2. If the state of the world is “Good”, there is no loss, however if it is “Bad”, the loss incurred is equal to 1. Thus, the DM faces a lottery in the losses domain. The process starts in the “Good” regime and can switch to the “Bad” regime at any point in time; the probability judgment that the regime has switched ( $p_t$  in Figure 1.2) is equal to the probability that the “Bad” regime prevails. Payment  $B_t$  in Figure 1.2 denotes the price the DM is willing to pay in period  $t$  for the insurance contract. In each period, a ball is sampled with replacement from one

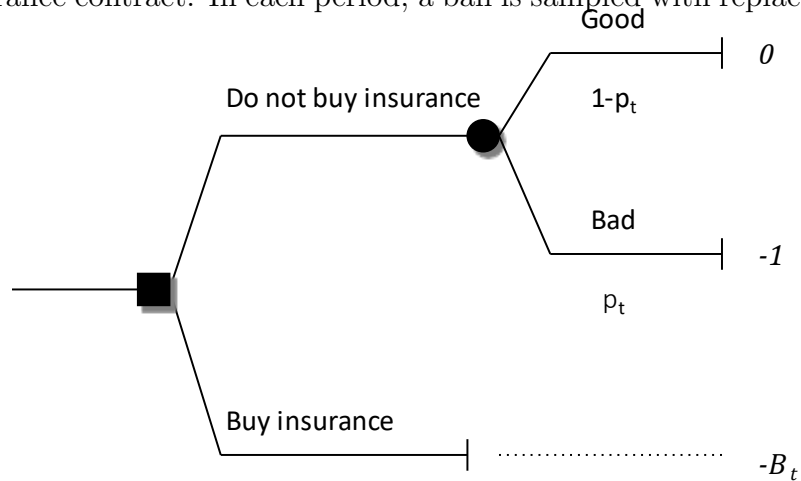


Figure 1.2: Insurance buying decision

of the two regimes; the “Bad” regime produces red balls more often (with probability  $p_B > 0.5$ ) than the “Good” regime (with probability  $p_G < 0.5$ ). As in MW, we assume that  $p_B = 1 - p_G$ .

Thus,  $d = \frac{p_B}{p_G}$  can be interpreted as a measure of signal diagnosticity such that environments with higher values for  $d$  generate more precise, and thus more informative, signals.

To define our measure of under-/ overreaction in pricing decisions, we first define the *empirical change* in pricing decisions:  $\Delta B_t^e = B_t^e - B_{t-1}^e$  where  $B_t^e \geq 0$  represents the empirical (reported) willingness to pay for insurance in period  $t$ . This quantity is similar to the empirical change in probability judgments in MW:  $\Delta p_t^e = p_t^e - p_{t-1}^e$  where  $p_t^e$  refers to the empirical probability of a regime shift in period  $t$ .

To formalize the Bayesian risk-neutral response to a signal, we first note that the expected loss from the lottery in Figure 1.2 in any given period  $t$  is  $EL_t = p_t$ . For a risk-neutral agent, their willingness to pay for the lottery is equal to the expected loss. Thus, we calculate changes in willingness to pay for a Bayesian risk-neutral agent as  $\Delta B_t^b = EL_t^b - EL_{t-1}^e = p_t^b - p_{t-1}^e$  where  $p_{t-1}^e$  is the participant's probability of regime shift in the previous period, and  $p_t^b$  is the Bayesian response to the signal observed when the prior is  $p_{t-1}^e$ . This formulation allows us to answer the following question: If the DM, whose probability of regime shift in the previous period was  $p_{t-1}^e$ , was Bayesian and risk-neutral, how would their pricing decisions change?

We use the Bayesian risk-neutral response as a benchmark to evaluate how DMs revise their pricing decisions in each period. Note that the Bayesian risk-neutral response,  $\Delta B_t^b$ , is equivalent to the Bayesian change in probability judgments in MW defined as  $\Delta p_t^b = p_t^b - p_{t-1}^e$ .

Our focus lies on revisions in pricing decisions and we define our measure of under- and overreaction as  $\Delta B_t^e - \Delta B_t^b$ . We can rewrite this measure as the sum of two components: the first component reflects how the risk premium changes in reaction to signals indicative of regime shift and the second component reflects how the probability of regime shift changes in reaction to signals which we label as the "effect of system neglect".

$$\Delta B_t^e - \Delta B_t^b = B_t^e - B_{t-1}^e - (EL_t^b - EL_{t-1}^e) = \underbrace{B_t^e - EL_t^e - (B_{t-1}^e - EL_{t-1}^e)}_{\text{change in risk premium}} + \underbrace{EL_t^e - EL_t^b}_{\text{effect of system neglect}} \quad (1.2.1)$$

The first equality follows from the definitions of  $\Delta B_t^e$  and  $\Delta B_t^b$ . We obtain the second equality by adding and subtracting  $EL_t^e$ , which is the expected loss calculated using the empirically

reported probability of regime shift at time  $t$ . As we have discussed above, this expected loss is  $EL_t^e = p_t^e$ .

The first term in the above expression,  $B_t^e - EL_t^e - (B_{t-1}^e - EL_{t-1}^e)$ , denotes how the risk premium of a DM changes in reaction to a signal indicative of regime shift.<sup>1</sup> A positive risk premium implies risk aversion while a negative risk premium implies risk seeking behavior, however it is not clear how risk premia change as probability judgments change in reaction to signals about regime shift.

The second term,  $EL_t^e - EL_t^b$ , denotes the difference between expected losses calculated using empirical and Bayesian probabilities, respectively. Because the possible loss in Figure 1.2 is equal to 1, this difference becomes  $EL_t^e - EL_t^b = p_t^e - p_t^b = (p_t^e - p_{t-1}^e) - (p_t^b - p_{t-1}^b) = \Delta p_t^e - \Delta p_t^b$  and hence is equivalent to the under- and overreaction measure for probability judgments presented in MW. It is because of this equivalence we interpret the second term in (2.3.2) as the effect of system neglect. We analyze the two terms  $EL_t^e - EL_t^b$  (effect of system neglect) and  $B_t^e - EL_t^e - (B_{t-1}^e - EL_{t-1}^e)$  (change in risk premium) in (2.3.2) separately and then make predictions about their cumulative effect.

*Effect of system neglect:* To study the second term,  $EL_t^e - EL_t^b$  in (2.3.2), we first write Bayesian posterior odds as a function of prior odds when the signal observed is indicative of regime change (i.e. a red ball when the regime shift is dreaded):

$$\frac{p_t^b}{1 - p_t^b} = \frac{d}{1 - q} \frac{p_{t-1}^e}{1 - p_{t-1}^e} + d \frac{q}{1 - q}, \quad (1.2.2)$$

where  $d$  represents the diagnosticity of the signal,  $q$  is the transition probability as outlined earlier,  $p_t^b$  represents the Bayesian posterior probability of regime shift (also equal to the Bayesian posterior probability of the “Bad” state in the current setting) and  $p_{t-1}^e$  denotes the prior probability of regime shift which we take to be the reported probability of regime shift from the previous period.

Consistent with MW, we also develop a *quasi-Bayesian* model that results in a similar expression

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<sup>1</sup>Risk premium is defined as the expected value minus the certainty equivalent of a lottery and it is equal to  $-p_t^e - (-B_t^e) = B_t^e - EL_t^e$ .

for the empirical odds ratio:<sup>2</sup>

$$\frac{p_t^e}{1 - p_t^e} = \frac{d^\beta}{1 - \alpha q} \frac{p_{t-1}^e}{1 - p_{t-1}^e} + d^\beta \frac{\alpha q}{1 - \alpha q}. \quad (1.2.3)$$

In this quasi-Bayesian model,  $\alpha$  captures the DM's sensitivity to the transition probability and  $\beta$  captures the sensitivity to signal diagnosticity. For  $\alpha = 1$  and  $\beta = 1$ , this model results in the Bayesian expression in (1.2.2). Furthermore, as  $\alpha$  decreases, the effect of the transition probability diminishes, whereas as  $\beta$  decreases, the effect of diagnosticity becomes smaller. Equations (1.2.2) and (1.2.3) both describe the odds of regime shift as a function of the prior odds and the characteristics of the stochastic process: stability,  $q$  and diagnosticity,  $d$ . These equations use the sensitivity parameters  $\alpha$  and  $\beta$  to model how empirical probabilities of regime shift differ from the Bayesian probabilities.

MW propose that  $\alpha$  and  $\beta$  in (1.2.3) depend on the dynamics of the environment. They empirically estimate values for  $\alpha$  and  $\beta$  in their experiments and obtain  $\alpha = 1.69$  and  $\beta = 1.78$  for stable environment with noisy signals and  $\alpha = 0.5$  and  $\beta = 0.78$  for unstable environments with precise signals indicating that individuals are more sensitive to the transition probability and signal diagnosticity when the environment is stable and signals are noisy. We will use their estimates in our model to derive predictions and we later compare our own estimates for  $\alpha$  and  $\beta$  against these values.

Using (1.2.2) and (1.2.3), we can show that, in the current setting,

$$EL_t^e - EL_t^b = p_t^e - p_t^b = \frac{d^\beta r_{t-1}^e + d^\beta \alpha q}{1 - \alpha q + d^\beta r_{t-1}^e + d^\beta \alpha q} - \frac{dr_{t-1}^e + dq}{1 - q + dr_{t-1}^e + dq} \quad (1.2.4)$$

where  $r_{t-1}^e = \frac{p_{t-1}^e}{1 - p_{t-1}^e}$ .

Figure 1.3 summarizes how the difference  $EL_t^e - EL_t^b$  changes as a function of prior probability of regime shift ( $p_{t-1}^e$ ) in the current setting. In order to generate the plots, we use the same environmental parameters  $d$  and  $q$  as in our experiments and adopted parameter values for  $\alpha$  and  $\beta$  from those estimated in MW. We also display model predictions for plus/minus three standard errors from these estimates (dashed lines). These plots offer a more detailed view of the system

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<sup>2</sup>This specification is simple and provides almost identical predictions as the quasi-Bayesian model in Massey and Wu (2005).

neglect hypothesis and are consistent with MW. For stable environments with noisy signals, the model predicts overreaction in probability judgments ( $EL_t^e - EL_t^b = \Delta p_t^e - \Delta p_t^b \geq 0$ ) and for unstable environment with precise signals, the model predicts underreaction ( $EL_t^e - EL_t^b = \Delta p_t^e - \Delta p_t^b \leq 0$ ) regardless of the prior probability of regime shift.

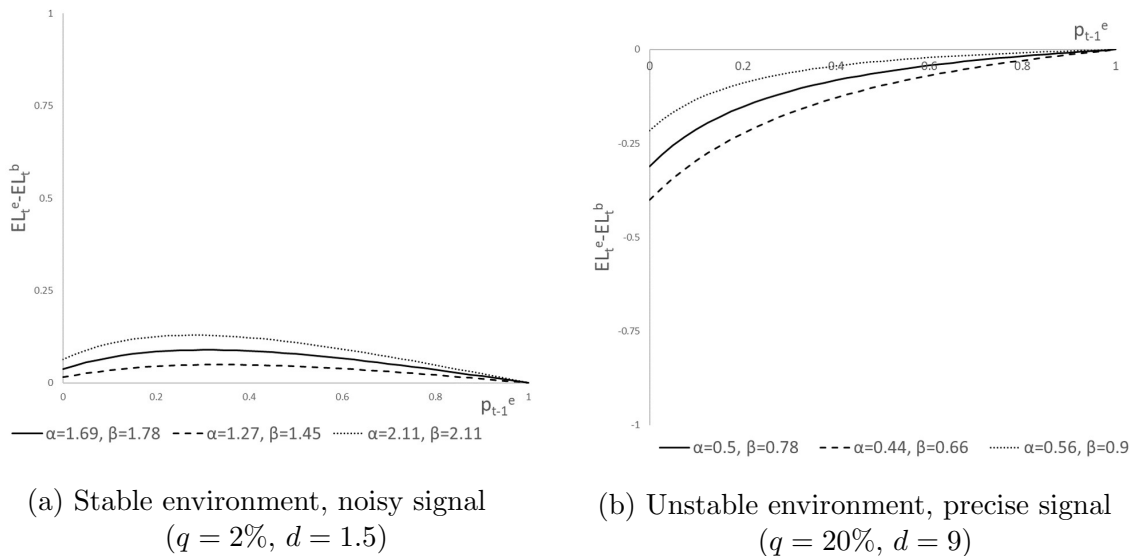


Figure 1.3:  $EL_t^e - EL_t^b$  as a function of prior probability of regime shift ( $p_{t-1}^e$ )

*Change in risk premium:* We will first analyze the risk premium for the lottery in Figure 1.2 using prospect theory and then consider changes in risk premium in reaction to signals about regime shift.

Tversky and Kahneman (1992) propose a fourfold pattern of risk attitudes which governs individual decision behavior: DMs exhibit risk seeking behavior for small probability gains and high probability losses and risk aversion for high probability gains and small probability losses. Because participants face the lottery depicted in Figure 1.2 where outcomes are in the domain of losses, we would expect to observe risk aversion ( $B_t - EL_t^e > 0$ ) when the judged probability of the “Bad” state is low and risk seeking behavior ( $B_t - EL_t^e < 0$ ) when it is high. Because the probability of regime shift is the probability of the “Bad” state when the regime shift is dreaded, we would observe risk aversion when the probability of regime shift is low and risk seeking behavior when the probability of regime shift is high.

We analyze the risk premium,  $B_t^e - EL_t^e$ , in more detail by relying on the following powervalue function (see, for example, Tversky and Kahneman 1992; Brenner, Griffin and Koehler 2012;

Abdellaoui, L'Haridon and Paraschiv 2011):

$$V(x) = \begin{cases} x^\theta & \text{for } x \geq 0, \\ -\lambda(-x)^\theta & \text{for } x < 0. \end{cases} \quad (1.2.5)$$

where  $\theta$  controls the curvature of the value function and  $\lambda$  is the parameter for loss aversion, the extent to which losses loom larger than gains. Tversky and Kahneman (1992) report a median value for  $\theta = 0.88$  and Abdellaoui, L'Haridon and Paraschiv (2011) finds median values for  $\theta$  at the aggregate level ranging between 0.92 and 1.39. Abdellaoui, L'Haridon and Paraschiv (2011) report median values for  $\lambda$  at the aggregate level ranging between 2.24 and 2.62.

Note that, because all outcomes are in the losses domain, we will not need to model loss aversion,  $\lambda$ , in this setting. When we analyze this problem from a seller's point of view in §A.1, the outcomes span both the losses and gains domains and loss aversion,  $\lambda$ , enters into our calculations.

Furthermore, we adopt the following two-parameter probability weighting function from Gonzalez and Wu (1999) (to keep the notation simpler, we will drop the superscript  $e$  in  $B_t^e$  and  $p_t^e$  in what follows):

$$w(p_t) = \frac{\delta p_t^\gamma}{\delta p_t^\gamma + (1 - p_t)^\gamma}, \quad (1.2.6)$$

where  $\delta$  changes the elevation and  $\gamma$  determines the slope of the probability weighting function. Typically, empirical estimates result in  $\gamma < 1$ , producing the well-known inverse-S shaped probability weighting function. Gonzalez and Wu (1999) estimate  $\delta = 0.77$  and  $\gamma = 0.44$ , Abdellaoui (2000) reports  $\delta = 0.65$  and  $\gamma = 0.60$  in the domain of gains and  $\delta = 0.84$  and  $\gamma = 0.65$  in the domain of losses, respectively whereas Abdellaoui, L'Haridon and Paraschiv (2011) report  $\delta = 0.59$  and  $\gamma = 0.66$  in the domain of gains and  $\delta = 0.67$  and  $\gamma = 0.74$  in the domain of losses, respectively.

To calculate the risk premium,  $B_t - EL_t$ , we note that price  $B_t$  that makes a DM indifferent between buying and not buying the insurance contract when their probability of the “Bad”

state is  $p_t$  satisfies the following equation:

$$V(-B_t) = w(p_t)V(-1) + (1 - w(p_t))V(0) = -\lambda w(p_t),$$

where the second equality follows because  $V(-1) = -\lambda$  and  $V(0) = 0$ . Consequently, we obtain  $B_t^\theta = w(p_t)$ . Using this equality we can describe the DM's risk premium as follows:

$$B_t - EL_t = w(p_t)^{\frac{1}{\theta}} - p_t = \left( \frac{\delta p_t^\gamma}{\delta p_t^\gamma + (1 - p_t)^\gamma} \right)^{\frac{1}{\theta}} - p_t \quad (1.2.7)$$

Hence, the risk premium for the lottery in Figure 1.2 depends on both the probability weighting function and  $\theta$  which determines the curvature of the power value function.

To see that the parametric forms we use for the value and probability weighting functions predict the fourfold risk aversion pattern postulated by prospect theory, we focus on period  $t - 1$  without loss of generality, and we plot the risk premium,  $B_{t-1} - EL_{t-1}$ , as a function of the probability of regime shift in that period,  $p_{t-1}^e$ , in Figure 1.4. We take  $\gamma = 0.7$  consistent with estimates in the literature and use a range of values for  $\theta$  and  $\delta$  that are also consistent with previous estimates. We have conducted extensive sensitivity analyses on all parameters and the plots remain qualitatively the same.

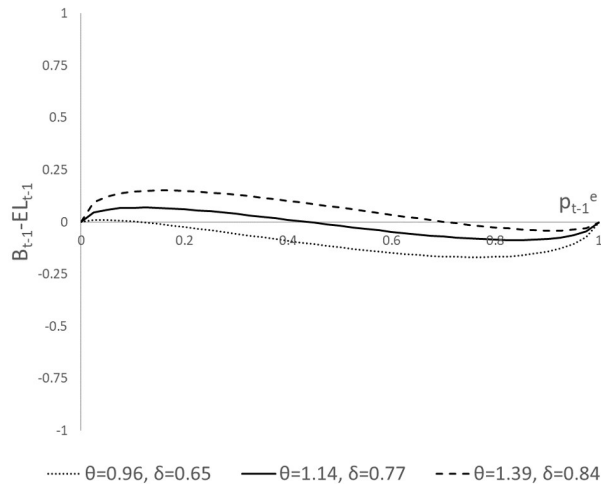


Figure 1.4: Risk premium as a function of probability of regime shift,  $p_{t-1}^e$ .

We can see from Figure 1.4 that for a wide range of probability weighting function and value function parameters, the risk premium for the lotteries in Figure 1.2 exhibit similar properties:

risk aversion (positive risk premium) for small probabilities of losses and risk seeking (negative risk premium) for large probabilities of losses consistent with the fourfold pattern of risk attitudes in Tversky and Kahneman (1992).

Now that we have a detailed model on how risk premia behave, we can focus on the changes in risk premia in reaction to signals about regime shift. Because we are going to focus our analysis on signals indicative of regime shift, we will be looking at what happens to risk premia as the underlying probability of regime shift increases (going from left to right in Figure 1.4).

We write the change in risk premium as

$$B_t - EL_t - (B_{t-1} - EL_{t-1}) = w(p_t)^{\frac{1}{\theta}} - p_t^e - \left( w(p_{t-1})^{\frac{1}{\theta}} - p_{t-1}^e \right) \quad (1.2.8)$$

To see how this difference behaves as a function of the prior empirical probability,  $p_{t-1}^e$ , we use (1.2.3) to calculate  $p_t^e$  as a function of  $p_{t-1}^e$  and obtain Figure 1.5. For a Bayesian risk-neutral DM, note that risk premium is always equal to 0 regardless of the probability, hence the difference,  $B_t - EL_t - (B_{t-1} - EL_{t-1})$  would always be equal to 0. However, Figure 1.5 predicts that DMs become more risk seeking ( $B_t - EL_t - (B_{t-1} - EL_{t-1}) < 0$ ) after observing a signal indicative of regime shift if their prior probabilities are low, and they become less risk seeking ( $B_t - EL_t - (B_{t-1} - EL_{t-1}) > 0$ ) if their prior probabilities are already high. One can understand this prediction from thinking about the four-fold pattern of risk aversion and by studying Figure 1.4. If the DM has a low prior probability, because signals indicative of regime shift increase the underlying probability, the DM becomes more risk seeking. If the DM already has a high prior probability, signals indicative of regime shift do not increase the probability judgments of regime shift significantly (because probabilities are bounded above by 1), and the risk premium gets closer to 0 making the DM less risk seeking.

Using the decomposition in (2.3.2) and using the equations for each component in (1.2.4) and (1.2.8), we obtain specific predictions for under- and overreaction in pricing decisions and present them graphically in Figure 1.6 as a function of the prior probability of regime shift  $p_{t-1}^e$ . We obtained the plots in Figure 1.6 by adding up the graphs from Figures 1.3 and 1.5.

If we compare the left and right panels in Figure 1.6, we see that our model has different predictions depending on the prior probability of regime shift. If the prior probability of regime

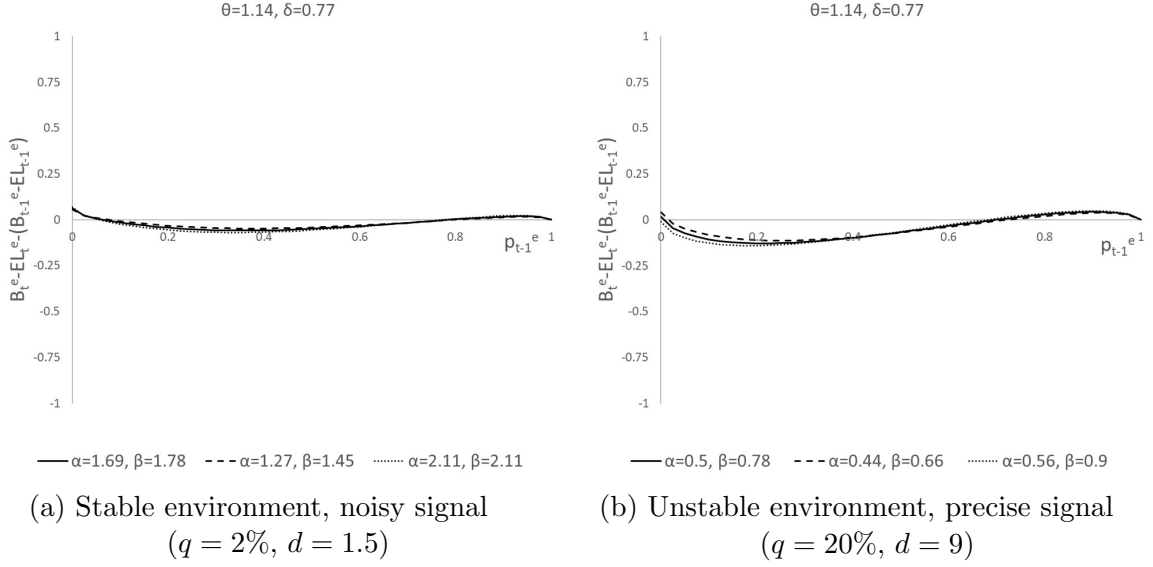


Figure 1.5: Change in the risk premium as a function of prior probability of regime shift,  $p_{t-1}^e$ .

shift is low, the change in pricing decisions displays underreaction for unstable environments with precise signals and overreaction for stable environments with noisy signals. We can see that for unstable environments with precise signals, both the system neglect (Figure 1.3) and the change in risk premium (Figure 1.5b) are negative resulting in underreaction. For stable environments with noisy signals we see that the system neglect effect dominates, resulting in overreaction. Thus, when prior probability of regime shift is low, the change in risk premium is in the same direction as the effect of system neglect in unstable environments with precise signals ( $B_t^e - EL_t^e - (B_{t-1}^e - EL_{t-1}^e) < 0$  and  $EL_t^e - EL_{t-1}^e < 0$ ) and the combined effect is that pricing decisions exhibit relative underreaction similar to probability judgments.

However, if the prior probability of regime shift is already high, the system neglect in probability judgments (Figure 1.3) is not very strong and the change in risk premium ( $B_t^e - EL_t^e - (B_{t-1}^e - EL_{t-1}^e) > 0$ ) given in Figure 1.5 dominates, resulting in no significant under-/overreaction in pricing decisions in Figure 1.6. Thus, prior probability of regime shift helps us to explain when the under-/overreaction pattern in pricing decisions follows the pattern predicted by system neglect in probability judgments.

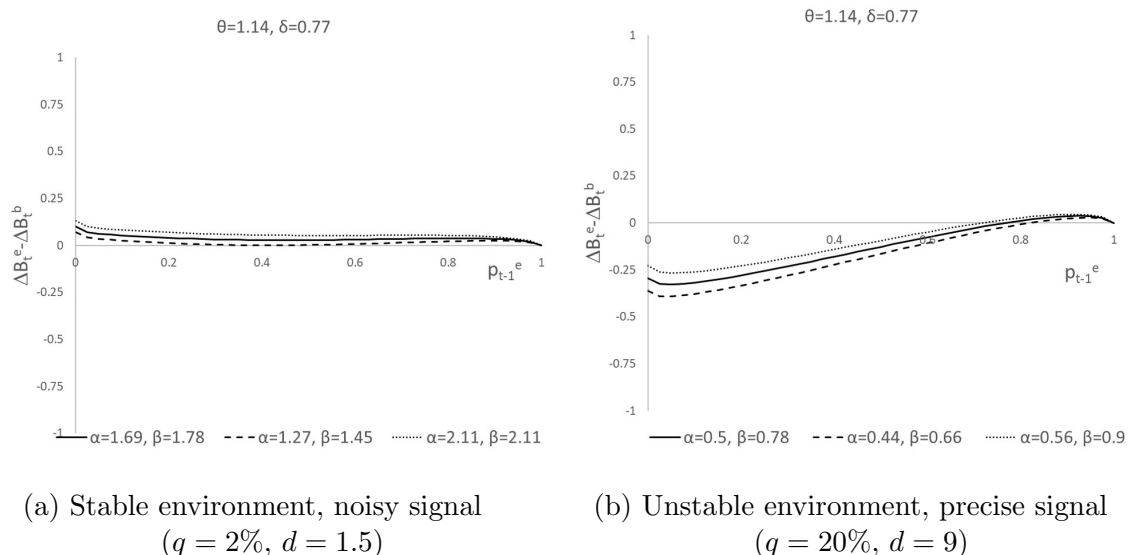


Figure 1.6: Under- and overreaction in pricing decision

### 1.3 Empirical Analyses of Probability Judgments and Pricing Decisions

We examine our model predictions in a series of empirical studies. Consistent with the setting in §1.2, our main study focuses on behavioral responses to dreaded regime shifts in experimental insurance markets. The participants in our main study adopt the role of an insurance buyer or seller who can trade an insurance contract that protects her from incurring losses in a given round. While our model in §1.2 provides predictions for buyers, predictions for sellers are qualitatively the same. We provide a detailed description of our model for sellers in Appendix A.1.

After presenting the results from our main study, we empirically test the robustness of our findings: We study asset pricing decisions in environments with desirable regime shifts, allowing us to examine decision behavior in the domain of gains.

In all our studies, we elicited participants' probability judgments regarding the occurrence of a regime shift as well as pricing decisions for an insurance contract. Each participant provided responses in four within-subject conditions that differed with regards to the underlying transition probability ( $q = 2\%$  and  $q = 20\%$ ) and signal diagnosticity ( $d = \frac{60\%}{40\%}$  and  $d = \frac{90\%}{10\%}$ ). The characteristics of a condition were displayed on the task screen throughout all rounds.

Participants provided responses across 10 rounds in each condition; one signal (a red or a green ball) was sampled and shown to participants in every round. During the experiment, signal and state sequences were randomly generated from the underlying statistical process.

### 1.3.1 Main Study

We recruited 129 participants (male 49.6%, female 50.4%) through the online platform Amazon Mechanical Turk (MTurk).<sup>3</sup> All participants began the task by reading through a series of detailed instruction screens, which informed them about the task itself as well as the pay-off scheme used to determine their final compensation. Subsequently, participants were randomly assigned either to the buyer or the seller role, in which they remained until the end of the experiment.

We endowed buyers with an initial budget of 100 experimental currency units (ECUs) which they could use to purchase insurance contracts across rounds. Sellers, on the other hand, started with an initial budget of 50ECUs and held one insurance contract in each round, which protected them from incurring potential losses if the underlying state was “Bad”.<sup>4</sup>

In the buyer instructions, we emphasized that the insurance would only be worth purchasing if participants believed that the observed signal had originated from the “Bad” regime. In the case of sellers, the instructions highlighted that an insurance contract would only be worth selling, if participants believed that the signal had been sampled from the “Good” regime.

Regardless of the assigned role, in every round participants started out by observing a signal and subsequently provided a judgment regarding their perceived probability (between 0% and 100%) that the regime shift had taken place as well as their willingness to pay/accept for the insurance contract (between 0 and 10 ECUs). Once a decision round had been completed, participants progressed to a result screen on which they received information about whether

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<sup>3</sup>Recent replication studies using MTurk subjects by Lee, Seo and Siemsen (2018) for three classic experiments in behavioral operations have shown nonsignificant differences in results between laboratory and MTurk samples. In fact, their findings suggest MTurk as a more relevant tool for studying individual biases in behavioral operations with the exception that MTurk participants show a slower learning rate compared to a laboratory student sample. In addition, findings from Buhrmester, Kwang and Gosling (2011) indicate that the quality of data collected through MTurk satisfy the psychometric standards reported in published research. Additionally, their findings also suggest that lower compensation rates often employed in MTurk studies are likely to only affect the speed of the data collection but not its underlying quality.

<sup>4</sup>We determined this budget through a pilot study in order to make the average pay-off for both buyers and sellers in our experiment comparable.

or not they had successfully purchased the insurance, but were left uninformed about the underlying state.

We employed a BDM mechanism (Becker, DeGroot & Marshack 1964) to elicit truthful valuations of the insurance contract (for an in depth discussion regarding the truthfulness of responses elicited using this mechanism, see Jaspersen (2016)). In particular, one value between 0 and 10 was randomly drawn, which served as the market price in a given round. For participants in the buyer role, transactions were successfully carried out if their willingness to pay was equal to or higher than the generated market price. For sellers, an insurance contract was successfully sold if their willingness to accept was below the market price.

Participants were informed that the remaining ECUs, after accounting for any costs/profits incurred by trading the insurance contract as well as any uninsured losses incurred during a round, would be used to calculate their pay-off for each condition. We compensated participants using a combination of a fixed participation fee of \$0.50 as well as a performance-based supplement, which was calculated by randomly selecting one condition and converting their remaining ECUs into US dollars. Each ECU was worth \$0.015, which implied that participants could earn up to \$1.50 in addition to the fixed payment. Participants in the buyer role had an average pay-off of \$1.75 and an average completion time of 17.26 minutes. Participants in the seller role had an average payoff of \$1.74 and an average completion time of 21 minutes. We will first present the results for buyers.

### Results for Buyers:

Generally, we find strong evidence of system neglect in probability judgments. Figure 1.7 displays the aggregated pattern of under- and overreaction in probability judgments. Wilcoxon signed-rank tests exhibit significantly more underreaction in unstable environments with precise signals ( $M = -0.24$ ) than in stable environments with noisy signals ( $M = -0.01, V = 3212, p < 0.001$ ).

We next examine under- and overreaction in pricing decisions,  $\Delta B_t^e - \Delta B_t^b$  through a series of local regression analyses as well as non-parametric tests.

**Local regression analysis:** As our model predicts nonlinear patterns of under- and overreaction (Figure 1.6), OLS regression would be unsuitable for accurately capturing the underlying

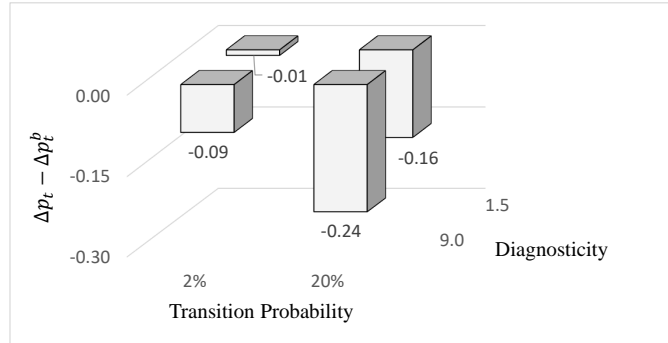


Figure 1.7: Median under- and overreaction in probability judgments of buyers

relationship between our variables of interest. Instead, we fit local regression models (Loader 2006) to elicited pricing decisions using the *Locfit package* in R. Local regressions fit linear or nonlinear (usually polynomial) regression models to a subset of observations around each data point using weighted least squares, where observations close to the one being estimated are assigned a higher weight than those observations that are more distant. To fit a local regression model, it is necessary to determine the degree of local polynomials, the smoothing parameter (which determines the bandwidth, i.e., a subset of observations that is used to fit the regression model around a particular observation) and the weight function to be used in the weighted least square estimation. We generate different local regression models using various combinations of smoothing parameters and degrees of local polynomials and use generalized cross-validation (GCV) scores as a criterion for model selection (see Loader (2006)). GCV scores are estimates of prediction errors.

We compare GCV scores for smoothing parameters ( $\omega$ ) ranging between 0 and 1. For illustrative purposes, Figure 1.8a exhibits the GCV plot in stable environments with noisy signals. The lowest GCV score corresponds to smoothing parameter  $\omega = 0.8$ .<sup>5</sup> We also provide a visual representation of the local regression model plots for different values of  $\omega$  in Figure 1.8b. We can see that the local regression predictions are similar across models with different values for smoothing parameter  $\omega$ . We present the best fitting local regression model in each environment in Figure 1.9. Recall that positive values of  $\Delta B_t^e - \Delta B_t^b$  indicate overreaction whereas negative values indicate underreaction in pricing decisions. Most strikingly, we observe rela-

<sup>5</sup>All plots pertain to quadratic degrees of local polynomials and the default weight function assigns largest weights to the observations close to the fitting point. We performed our analyses with linear local polynomials and the best fit remained the same.

tively more underreaction in pricing decisions for buyers in unstable environments with precise signals when compared with stable environments with noisy signals. This relative difference is most pronounced if the prior probability of regime shift is low and diminishes for higher prior probabilities of regime shift consistent with our model predictions in §1.2.

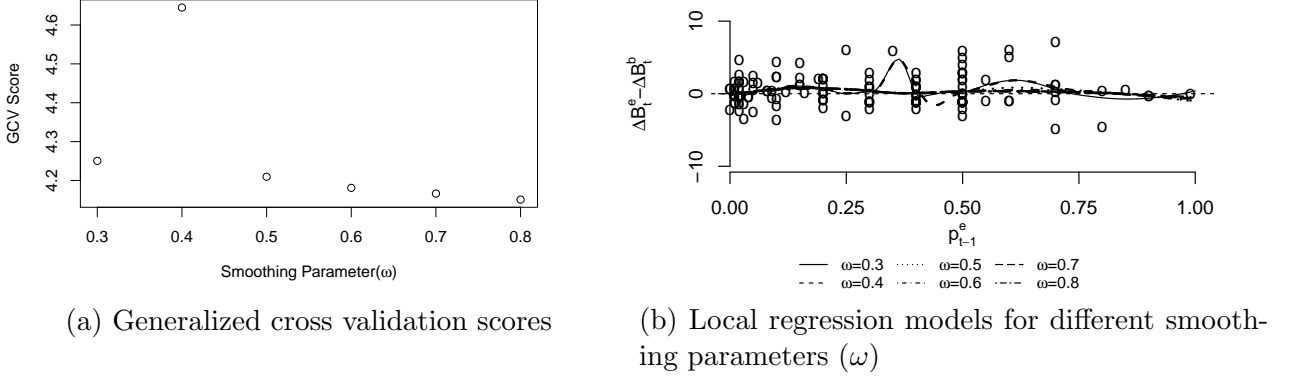


Figure 1.8: Smoothing parameter selection example for Main Study

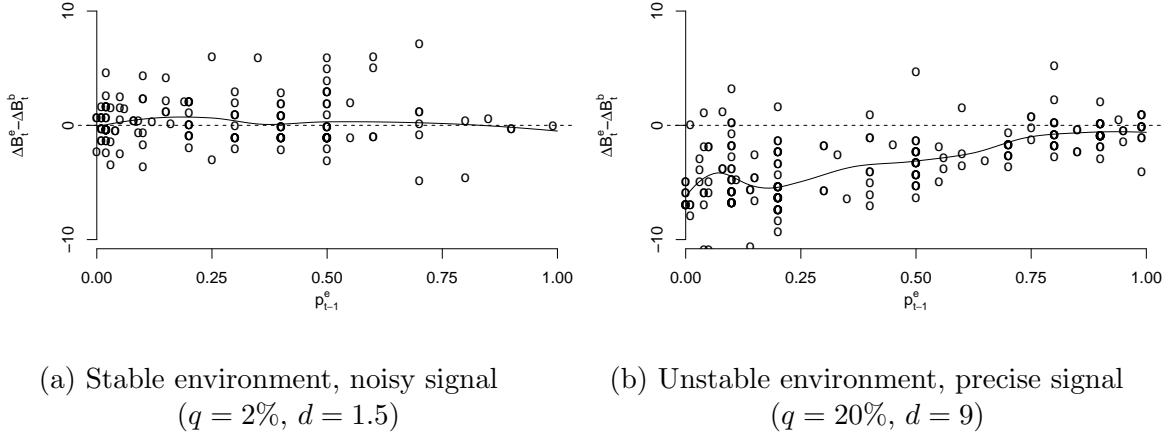


Figure 1.9: Under- and overreaction in pricing decisions of buyers in dreaded regime shift

**Non-parametric Tests:** We next conducted a series of non-parametric tests to support our local regression results. As indicated in Figure 1.9, for unstable environments with precise signals we observed significantly more underreaction in pricing decisions than for stable environments with noisy signals. A Wilcoxon signed-rank test for unpaired samples confirmed this proposition ( $M = -2.79$  and  $M = -0.12$ , respectively,  $W = 30808, p = 0.001$ ). In addition, a more detailed analysis of our under- and overreaction measure reveals that the relative underreaction between the two conditions diminishes as the prior probability of regime shift ( $p_{t-1}^e$ ) increases. Specifically, when comparing median under- and overreaction in both

environments, we find significantly more underreaction in unstable environments with precise signals for all but very high prior probabilities (i.e. for  $p_{t-1}^e > 0.9$  :  $M = -0.68$  and  $M = -0.18, W = 38, p = 0.53$ ).

**Decision Stickiness:** Our model and empirical results demonstrate under- and overreaction in pricing decisions. To study the implications of our findings, we examine DMs’ insurance purchasing decisions across two consecutive time periods and compare their decisions to those of a Bayesian risk-neutral agent. We find that underreaction in pricing judgments leads to sticky decisions: buyers of insurance contracts decide to switch their status from “uninsured” to “insured” less frequently than a Bayesian risk-neutral agent in response to observing a signal indicative of regime shift. Overreaction in pricing decisions, on the other hand, leads to hypersensitive decisions: buyers of insurance contracts switch their status from “uninsured” to “insured” more frequently than a Bayesian risk-neutral agent.

For this analysis, we first compared empirical pricing decisions with the corresponding market prices and counted the number of instances in which buyers successfully traded insurance contracts. We then repeated the procedure for a Bayesian risk-neutral agent using the expected loss  $EL_{t-1}^e$  as a buying price for period  $t - 1$  and the updated expected loss  $EL_t^b$  as a buying price for period  $t$ . Thus, we obtained two insurance decisions for periods  $t - 1$  and  $t$  for each participant and the Bayesian risk-neutral agents. Table 1.1 provides a summary of our analysis. At any period, “buyers’ decision to remain uninsured” is denoted as 0, whereas their preference for being “insured” is denoted as 1. The table shows the proportion of empirical and Bayesian risk-neutral DMs who switched their insurance decisions versus who did not in period  $t$ , separately for when they were uninsured (rows 1 and 2) and insured in period  $t - 1$  (rows 3 and 4).

decision		stable environment, noisy signals ( $q = 2\%, d = 1.5$ )		unstable environment, precise signals ( $q = 20\%, d = 9$ )	
$t - 1$	$t$	Empirical	Bayesian	Empirical	Bayesian
0	0	83(69%)	96(82%)	74(58%)	26(20%)
0	1	37(31%)	21(18%)	54(42%)	102(80%)
1	0	18(41%)	22(52%)	36(30%)	14(13%)
1	1	26(59%)	20(48%)	84(70%)	90(87%)

Table 1.1: Insurance Decisions (Empirical vs. Bayesian)

If the decision in  $t - 1$  was to not buy the insurance (rows 1 and 2 in Table 1.1), then the prior probability of regime shift is likely to be low. In that case, our model and empirical results indicate overreaction in stable environments with noisy signals which implies that participants in our study switch from being uninsured to being insured more often (31%) than a Bayesian risk-neutral agent (18%,  $\chi^2 = 4.64$ ,  $p = 0.03$ ). In unstable environments with precise signals, on the other hand, underreaction in pricing decisions imply that decisions are sticky: participants in our experiment are more likely to stay uninsured (58%) compared to a Bayesian risk-neutral agent (20%,  $\chi^2 = 36.25$ ,  $p < 0.001$ ).

If the decision in period  $t - 1$  was to buy the insurance (rows 3 and 4 in Table 1.1), the prior probability of regime shift is likely to be high and the under- overreaction in pricing judgments diminishes. In stable environment with noisy signals, the majority of buyers indeed hold on to their insurances (59%), but that behavior is not statistically distinguishable from Bayesian risk-neutral agents (48%,  $\chi^2 = 0.72$ ,  $p = 0.39$ ). In unstable environment with precise signals, on the other hand, buyers are more likely to change their insurance decisions (30%) compared to the Bayesian risk-neutral agents (13%,  $\chi^2 = 7.86$ ,  $p = 0.005$ ).

### **Results for Sellers:**

We first note that system neglect in probability judgments is robust to changes in the DM's role. We find significantly more underreaction ( $M = -0.24$ ) in unstable environments with precise signals than in stable environments with noisy signals ( $M = -0.04$ ,  $V = 6187$ ,  $p < 0.001$ ). Furthermore, we find that the under- and overreaction patterns in pricing decisions are also robust to changes in the DM's role. We let the under- and overreaction measure for sellers to be  $\Delta S_t^e - \Delta S_t^b = S_t^e - S_{t-1}^e - (EL_t^b - EL_{t-1}^e)$  where  $S_t^e$  is the empirical pricing decision (i.e. willingness to accept) for sellers in period  $t$ . In Figure 1.10 we again observe relatively more underreaction in pricing decisions for unstable environments with precise signals when compared to stable environments with noisy signals. Furthermore, this underreaction is most pronounced when the prior probability of regime shift is low and diminishes for higher prior probabilities of regime shift. Finally, the pricing decisions of sellers in stable environments with noisy signals once again resemble the behavior of a Bayesian risk-neutral DM, regardless of the perceived prior probability of regime shift.

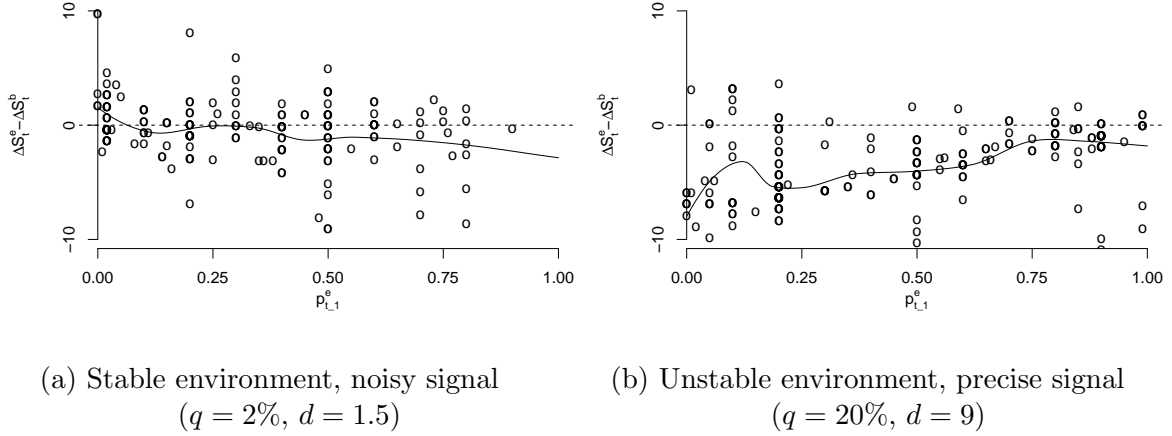


Figure 1.10: Under- and overreaction in pricing decisions of sellers in dreaded regime shift

Non parametric tests indicate that the findings for sellers are largely consistent with the observed behavior of buyers. In particular, again we find significantly more underreaction in unstable environments with precise signals relative to stable environments with noisy signals ( $M = -3.35$  and  $M = -0.22$ , respectively,  $W = 33623$ ,  $p = 0.001$ ). Moreover, we do not find significant differences in pricing decisions for high prior probabilities ( $p_{t-1} > 0.6$  :  $M = -0.7$  and  $M = -0.51$ ,  $W = 1336$ ,  $p = 0.13$ ).

We also analyzed the insurance decisions of sellers and observed a decision stickiness pattern akin to buyers.

### 1.3.2 Extensions and Robustness Checks

In this section we provide several extensions to our main study. Specifically, we examine whether our proposed under- and overreaction pattern in pricing decisions can be generalized across the domains of gains and losses as well as across environments that differ with regards to the desirability of the impending shift. Our follow up experiments employ the same stylized urn problem to simulate decision environments with impending regime shifts. Moreover, we rely on the same pay-off mechanism for calculating participants' individual performance bonus.

**Regime Shift Desirability:** One possible limitation to the generalizability of our findings is related to the fact that decision environments in our main study exclusively shifted from the “Good” to the “Bad” regime. In particular, since we focused on the role of DMs who are dreading an impending regime shift, it can be argued that the observed behavioral pattern may

not necessarily hold in environments where DMs perceive the regime shift as desirable.

Previous studies have suggested that emotional reactions to risky situations may at times differ from cognitive, expectation-based assessments of the same risk, and subsequently emerge as the predominant driver of decision behavior (Loewenstein, Weber, Hsee and Welch 2001). Importantly, since our model in §1.2 does not explicitly account for the role of affect experienced at the time of decision making, our predictions qualitatively hold regardless of whether the shift is dreaded or desirable. Note that the behavioral pattern predicted by our model for desirable regime shift environments looks different from the one in dreaded regime shift settings. When the regime shift is desirable, interpreting our under- overreaction measure requires care. In particular,  $\Delta B_t^e - \Delta B_t^b > 0$  implies underreaction and  $\Delta B_t^e - \Delta B_t^b < 0$  implies overreaction (see Appendix A.2).

For the purpose of empirically testing the effect of regime shift desirability, we created an additional experimental treatment in which DMs began the decision task in the “Bad” regime which over time could switch to the “Good” regime. We recruited a sample of 138 participants on Amazon Mechanical Turk in order to allow for a systematic test of this new treatment. In the following section, we only report the empirical findings for buyers in experimental insurance markets.<sup>6</sup>

Consistent with our main study, we find strong evidence of system neglect in probability judgments in that DMs show more underreaction in unstable environments with precise signals ( $M = -0.23$ ) relative to stable environments with noisy signals ( $M = -0.0124, V = 4706, p < 0.001$ ).

Local regression models as well as nonparametric tests lend further support to our predictions in pricing decisions: In unstable environments with precise signals that indicate a desirable regime shift, pricing decisions suffer to a greater extent from underreaction than in stable environments with noisy signals ( $M = 2.78$  and  $M = 0.38$ , respectively,  $W = 8421, p < 0.001$ ). In addition, underreaction diminishes as DMs increasingly believe that the regime has shifted (i.e. for  $p_{t-1} > 0.9$ :  $M = 0.9$  and  $M = 0.25$ , respectively,  $W = 56, p = 0.18$ ).

**Domain Type:** Since individual risk preferences may change depending on whether DMs are

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<sup>6</sup>Empirical findings for DMs in the role of sellers as well as for experimental asset markets are consistent with the results reported here and are available upon request.

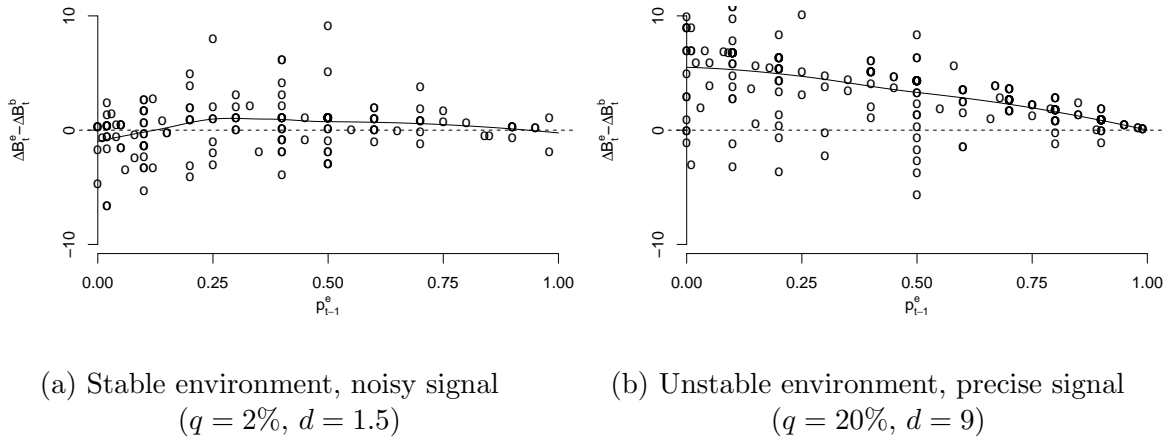


Figure 1.11: Under- and overreaction in pricing decisions of buyers in desirable regime shift

facing losses or gains, one logical extension of our study relates to the question of whether our findings would hold for different regime shift domains. In particular, it is possible that our proposed pattern of under- and overreaction in pricing decisions only applies to insurance settings in which prospects are negative and DMs choose between impending losses of varying magnitudes. In order to address this potential limitation, we studied experimental asset markets as one type of alternative decision environment, in which DMs trade prospects with positive expected pay-offs. We fully develop our model predictions in Appendix A.3 and, for the sake of brevity, focus here on the details of the experimental study involving buyers in dreaded regime shift environments only.

We recruited 255 subjects from Amazon Mechanical Turk, who provided probability and pricing judgments in the role of buyers or sellers in experimental asset markets with dreaded or desirable regime shifts. We endowed buyers and sellers with the same starting budgets as in our main study (i.e. 100 ECUs and 50 ECUs, respectively), which they could use to trade an asset that was associated with a value equal to 10 ECUs if the underlying state was “Good” and 0 ECUs otherwise. Similarly to the insurance domain, assets expired at the end of each round. Upon successfully trading the asset, buyers gained the actual value of the asset (10 or 0 ECUs depending on the underlying state) minus its market price, whereas sellers lost the value of the asset while earning a profit equivalent to the market price. The remaining parts of the experimental design including the procedure for eliciting probability and pricing judgments, the market clearing mechanism as well as the pay-off scheme were identical to our main study.

On average, participants earned a performance supplement equal to \$1.57 in addition to the flat fee of \$0.50. Moreover, participants completed the task on average in 14.8 minutes.

Across all treatments, our results are consistent with the main study in that we find strong empirical support for the presence of system neglect in the probability judgments. In particular, Wilcoxon signed-rank tests show significantly more underreaction in unstable environments with precise signals ( $M = -0.28$ ) than in stable environments with noisy signals ( $M = -0.02$ ,  $V = 78387$ ,  $p < 0.001$ ).

As our analysis of pricing behavior across all treatments reveals similar patterns that are largely consistent with our main study, we only report here our local regression and nonparametric test results for asset buyers in dreaded regime shift settings. In particular, our local regression results are depicted in Figure 1.12) for stable environments with noisy signals on the left panel and unstable environments with precise signals on the right panel. Importantly, we find that asset buyers in unstable environments with precise signals again underreact in their pricing decisions relative to stable environments with noisy signals. Our non-parametric tests show, however, that the relative difference in pricing behavior between the two environments only holds for values of  $p_{t-1}^e \leq 0.6$  after which they become statistically indistinguishable (i.e. for  $p_{t-1} < 0.6$ :  $M = 0.84$  and  $M = 5.78$ , respectively,  $W = 1990$ ,  $p < 0.001$ ). Hence, we conclude that the domain type does not have a systematic influence on under- and overreaction pattern in pricing decisions in environments with shifting regimes.

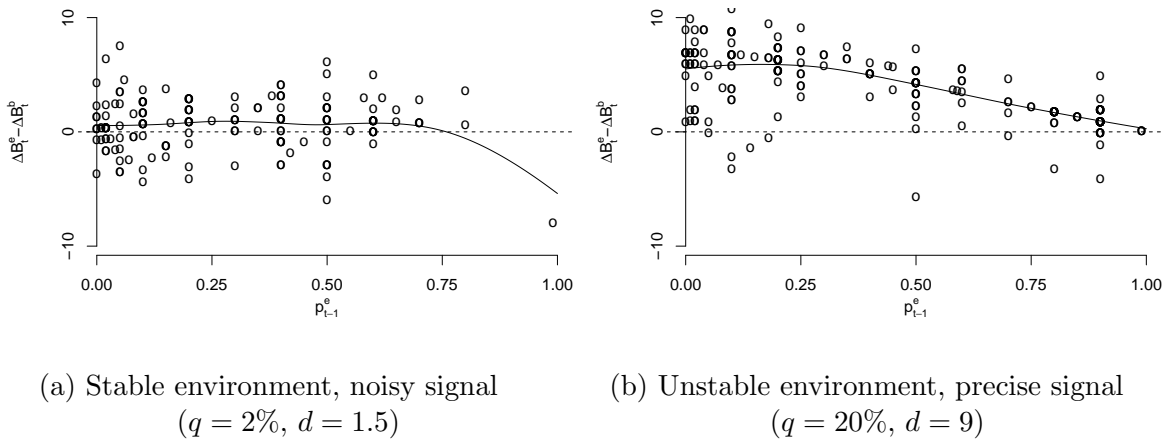


Figure 1.12: Under- and overreaction in pricing decisions of buyers in dreaded regime shift for asset market

***System Neglect Sensitivity Parameters:*** As a final robustness check, we estimated the parameters for the quasi-Bayesian model in (1.2.3) using the empirical data obtained for insurance buyers in dreaded and desirable regime shift environments. In the dreaded regime shift condition, we estimate  $\alpha = 4.1$  and  $\beta = 0.77$  for stable environments with noisy signals and  $\alpha = 0.54$  and  $\beta = 0.12$  for unstable environments with precise signals. In the desirable regime shift condition, we estimate  $\alpha = 4.15$  and  $\beta = 0.97$  for stable environments with noisy signals and  $\alpha = 0.53$  and  $\beta = 0.12$  for unstable environments with precise signals. While these estimates are different from those reported by Massey and Wu (2005), we find that they do not affect the directionality of our model predictions, which remain the same.

## 1.4 General Discussion

We investigated how biases in probability judgments and risk attitudes jointly affect the pricing behavior of DMs under impending regime shifts. We began our journey by proposing a model, which integrates previous research on system neglect with predictions from prospect theory. We then empirically tested the model in a study involving buyers in experimental insurance markets. In a series of follow up studies we found that our model predictions generalize to the behavior of buyers and sellers, to dreaded and desirable regime shifts as well as to the domain of losses and gains. In each analysis, we examined under- and overreaction in probability judgments to study robustness of system neglect, as well as a novel measure of under- and overreaction in pricing decisions, which compares the change in empirically elicited pricing decisions to the change in pricing decisions one would observe from a Bayesian risk-neutral agent.

We observe a distinct pattern of under- and overreaction in pricing decisions across all of our analyses: DMs exhibit relatively more underreaction in unstable environments with precise signals than in stable environments with noisy signals. This behavioral discrepancy is particularly pronounced in situations, in which DMs perceive the probability of regime shift to be small and diminishes as their probability judgment increases. Importantly, our observed pricing pattern can lead to flawed decision making. In unstable environments with precise signals, underreaction may often result in “decision stickiness” in that a previously uninsured DM is likely to remain uninsured upon receipt of a new signal. In stable environments with noisy signals, on

the other hand, DMs are likely to show hypersensitivity in their pricing behavior. Previously uninsured DMs show the tendency to change their insurance status more frequently than they should when observing a new signal. Finally, in the latter environments we also show how DMs' risk attitude dampens the effect of system neglect on pricing decisions, resulting in a behavioral pattern that is akin to the one of a Bayesian, risk neutral agent.

Our findings have a number of important implications for the literature on regime shift detection. First, we demonstrate the robustness of the system neglect bias in probability judgments, which prevailed in our empirical studies across all of our experimental conditions and environments. In particular, the behavioral tendency of DMs to systematically underestimate the likelihood of change in unstable environments with precise signals appeared to emerge independent of the role of the DM (i.e. buyer versus seller), the desirability of regime shift as well as the domain type. This reinforces the notion that system neglect indeed can be primarily attributed to cognitive limitations related to the assessment of probabilities rather than to contextual framing. Second, our research was motivated by the fact that in many organizational environments managers do not only face the challenge of accurately estimating the likelihood of impending regime shifts, but also of efficiently adapting their decision making in response to it. Our findings demonstrate that system neglect alone does not suffice to provide a comprehensive account of managerial decision behavior in dynamic decision environments. Instead, decisions under an impending regime shift are driven by both system neglect and risk attitudes, contingent on the stability of the environmental system as well as the reliability of signals observed.

Our research also contributes to the literature on prospect theory by offering an application of the theory across different dynamic decision environments. Towards this end, our findings highlight the importance of considering system neglect as a critical influencing factor when assessing pricing decisions under risk. We show that its impact may be particularly worrying in unstable environments with precise signals, where DMs' underreaction in probability judgments is likely to turn into the predominant driver of their subsequent decision behavior.

### 1.4.1 Managerial Implications

Our predicted pattern of under- and overreaction in pricing behavior has a number of important implications for the way in which organizations should communicate and utilize information that is indicative of change. In particular, as a consequence of DMs' extremely robust tendency to underestimate the likelihood of regime shifts in unstable environments with precise signals, decision support systems could be used to (1) provide more reliable probability estimates for impending regime shifts and (2) adjust managers' pricing decisions consistently for the purpose of counteracting decision stickiness. Our studies show that adjustments should be particularly considered when DMs perceive the probability of regime shift to be low. Systematically managing indicators of change is therefore expected to result in better decisions both when organizations consider insuring themselves against negative outcomes (i.e. dreaded shift) as well as when they assess whether or not to discontinue the payment for insurance premiums (i.e. desirable shifts). Analogously, when companies associate change with the possibility to earn profits, systematically adjusting managerial judgments may lead to less biased valuations of assets.

Managerial decision making in stable environments with noisy signals, on the other hand, is of lesser concern since our studies show that the probability bias induced by system neglect is often successfully (albeit unintentionally) offset by the DMs risk attitude, resulting in decision behavior that is similar to a Bayesian, risk neutral agent. This appears to hold true regardless of whether the perceived likelihood of regime shift is low or high.

### 1.4.2 Limitations and Paths for Future Research

Our research findings open up the path for a number of follow up studies, which could address some of the limitations associated with our research design. For example, in our empirical studies, we employed a BDM mechanism to elicit pricing judgments for insurance contracts and assets. Using such a mechanism made sense as it allowed us to elicit willingness to pay/accept from our buyers and sellers, which were unaffected by strategic considerations of how other market participants would respond. Future studies, however, could focus on alternative market clearing mechanisms (e.g. open call markets) in order to examine whether our model predictions

hold true in the context of social learning. Importantly, when allowing trading to only occur in situations where buyers' willingness to pay is higher than sellers' willingness to accept, it would be possible to test under which circumstances systematic under- and overreaction in pricing behavior may be amplified or dampened over time.

In addition, since we exclusively rely on empirical data obtained from MTurk, one natural extension of our study would be to test the generalizability of our findings to organization-level field data. Specifically, follow up research could identify settings that typically exhibit the environmental systems studied here. For example, similar to Brenner (2014), one could study the degree to which CEOs under- and overreact when it comes to exercising stock options in response to observing changes in the market.

Finally, future research could focus on studying the implications of our findings for behavioral outcomes that go beyond DMs' preferences for taking risks. In the field of behavioral operations management, one such interesting path could be to test how the under- and overreaction pattern in pricing behavior outlined in this paper influences inventory management decisions. Applying the notion of system neglect to the classic newsvendor problem is extremely relevant, because shifting regimes may be the cause for fundamental changes in the structure of demand uncertainty (Kremer, Moritz and Siemsen 2011) and therefore insights from such a study can complement existing approaches to managing stock outs and excess inventory.

In conclusion, our research shows that understanding how DMs respond to dynamically shifting environments is of critical relevance for both academic scholars as well as for managerial practitioners. While risk taking behavior only represents one possible lens through which the implications of system neglect can be studied, we hope that our findings will continue to motivate researchers to adopt alternative theories, methodological approaches and applied contexts in order to build a comprehensive account of how individuals cope with impending regime shifts.



# Chapter 2

## Role of Social Learning in Decision Making under Regime Shifts

### 2.1 Introduction

In this chapter, first, we examine whether a significant gap exists between the pricing decisions of buyers and sellers, i.e., the gap between willingness to pay and willingness to accept when DMs are making such pricing decisions under impending regime shifts. Second, we study if this gap diminishes over time due to social learning. In addition, we investigate if social learning affects the under- and overreaction in the pricing decisions.

There is an ongoing debate regarding the existence of a significant gap between willingness to pay and willingness to accept. While some researchers posit that such a gap exists (Coursey, Hovis & Schulze 1987; Hanemann 1991; Knetsch & Sinden 1984; Randall & Stoll 1980), others purport that the gap exists purely as a function of the design aspects of the experiment itself (Harless 1989; Plott & Zeiler 2005; Singh 1991). Researchers have also studied the nature of this gap separately under certainty and uncertainty. The studies that have found conclusive evidence towards the existence of the gap under certainty suggest income effect, substitutability of the commodities and the degree of market maturity as the common factors leading to such a gap. The first objective of our study to examine the gap in such pricing decisions under uncertainty. Specifically, we elicit pricing decisions for when the underlying state of the world

is uncertain and DMs need to make pricing decisions based on the probabilistic judgments regarding a shift in the underlying state. Under such regime shifts, probability judgments suffer from system neglect bias and tend to exhibit under- and overreaction. Furthermore, the underlying state of the world determines whether the DMs make losses or gains, the pricing decisions are governed by the psychological theory of loss aversion. Taken together the system neglect bias and the risk attitudes, the pricing decisions in our study constitute a very specific type of decision making under uncertainty and it is not straightforward to predict the existence of a gap in willingness to pay and willingness to accept under impending regime shifts. We consider our work as an exploratory study towards that investigation.

The second objective of our study is to investigate if indeed there exists a gap in pricing decisions of buyers and sellers, whether that can be mitigated through social learning. This effect has not been explored in depth for pricing decisions under uncertainty. Findings from Singh (1991) suggest this effect is not significant. We expect that if buyers and sellers of insurance contracts are allowed to reveal their pricing decisions to each other, over time their pricing decisions will converge even in the context of impending regime shifts.

To this end, in our study we conduct two experiments in which we randomly assign the participants as buyers and sellers of insurance contracts and pair every buyer with a seller. We elicit their pricing decisions for both dreaded and desirable regime shift. Over multiple periods, the buyers and the paired sellers are allowed to reveal their pricing decisions to each other. We find a significant gap between willingness to pay and willingness to accept regardless of the environment (i.e., stable environment with noisy signals vs. unstable environment with precise signals) and the desirability of regime shift. However, we do not find any significant effect of learning in reducing the gap over time. Additionally, we find that learning decreases overreaction and increases underreaction in pricing decisions regardless of the framing (i.e., buyer vs. seller).

The rest of the chapter is arranged as follows. In §2.2, we present a comprehensive account of extant research on the disparity in pricing decisions of buyers and sellers and formulate our hypotheses. We demonstrate the experimental design and the empirical analyses in §2.3. This is followed by §2.4 where we discuss the the implications of our findings. In §2.5 we conclude.

## 2.2 The willingness to pay and willingness to accept disparity

A sizeable mismatch between willingness to pay and willingness to accept (coined by Thaler (1980) as “endowment effect”) is found in many real market transactions (Bishop & Heberlein 1979; Gregory 1982). This phenomenon seems puzzling and therefore this topic has been constantly revisited by researchers from the various perspectives of certainty and uncertainty. Under certainty, some of the common determinants of this gap that have been vastly studied, are income effect, substitutability of product, and market learning (Randall & Stoll 1980; Hanemann 1991; Coursey, Hovis & Schulze 1987). Under uncertainty, the psychological theory of loss aversion explains a discrepancy between willingness to pay and willingness to accept.

Hanemann (1991) theoretically shows that even if the willingness to pay of the DM is her entire income, unless the commodity is highly substitutable, the willingness to accept can be infinite and a gap will exist. Shogren, Shin, Hayes & Kliebenstein (1994) provide further evidence for the degree of substitution as the dominant factor in increasing the gap and at the same time dismiss endowment effect as a possible influence. However, Morrison (1997) presents experimental evidence that shows significant impact of endowment effect after isolating it from the degree of substitution. Many researchers also suggest that studying the gap between willingness to pay and accept under uncertainty adds a potential source of “preference reversal” (Grether & Plott 1979), and therefore recommend studying the same under certainty, which provides a cleaner measurement of the gap (Coursey, Hovis & Schulze 1987). According to Coursey, Hovis & Schulze, when willingness to pay and accepted are elicited under certainty, the factor that dictates the prediction regarding a gap between the two is whether such elicitations are made under mature market settings. Their study suggests that the gap does not exist for mature markets due to market learning effects over time. Using the Vickrey auction setting, the authors show that the opening bids reflect a considerable gap between willingness to pay and accept while the closing bids, obtained after a set of learning trials, do not. Harless (1989) improves upon their experimental design by pairing participants and analyzing within-subject the decisions. The author argues that this allows meaningful interpretation of the observed gap without any disparity in sample properties that usually exist for between-subject designs.

In addition, they introduce risk in the lotteries for their experiments. Under such conditions, their results indicate that there is no significant gap between willingness to pay and accept. On similar lines, in his experimental setting, Singh (1991) pairs participants to trade as buyers and sellers where they reveal their pricing decisions. He finds that the willingness to pay / willingness to accept ratio is significant neither before nor after learning, although the ratio diminishes further with learning.

Both Coursey, Hovis & Schulze (1987) and Harless (1989) are critical of the experimental findings of Knetsch & Sinden (1984) who study the gap under risk. Knetsch & Sinden (1984) evaluate the gap between willingness to pay and accept by comparing the percentage of participants willing to buy or sell raffle tickets worth \$2 for a prize of either \$70 worth of merchandise vouchers or \$50 in cash. Through multiple experiments with different prize manipulations and subjects they find that the percentage of participants in the sellers group who are willing to accept \$2 for the raffle ticket was significantly less than the percentage of participants in the buyers group who are willing to pay \$2 for the raffle ticket. Marshall, Knetsch & Sinden (1986) extend their work to identify factors that would affect the gap between willingness to pay and willingness to accept under uncertain situations. Towards this, the authors find that when DMs act as advisors (deciding for others), the disparity between the measures disappear. The authors use both hypothetical as well as real money transactions and arrive at the same conclusion.

A comprehensive review of the ongoing debate regarding the nature of the willingness to pay and willingness to accept gap is given by Plott & Zeiler (2005). In an attempt to reconcile the extant disagreement, the authors take into account the various dimensions of elicitation (such as using BDM mechanism of elicitation, providing practice rounds, explaining optimal response and commodity type) and analysis of the measures (such as accounting for “house money effect”) that have been addressed in isolation and criticized by turns in various studies. The authors find no conclusive evidence for the gap.

Researchers have also investigated the nature of the willingness to pay and accept gap under situations involving ambiguous lotteries. For example, Einhorn & Hogarth (1985) develop a model and subsequently empirically establish that the gap between willingness to pay and willingness to accept is particularly affected by how people make probability judgments and

choices under varying amounts of ambiguity. Their findings are of specific importance since they delineate the nature of the gap under non-ambiguous and ambiguous situations. Specifically they find that for non-ambiguous situations, this gap does not exist. It is only for ambiguous situations that the gap appears; the willingness to accept being higher than the willingness to pay. However, if there is a situation when the seller has no ambiguity but the buyer does, then the willingness to pay is higher than that of the willingness to accept. This last finding is further qualified by the relationship between the anchoring probability and how sensitive DMs are to ambiguity. When DMs are sensitive to ambiguity in such a way that they overweight higher probabilities, the willingness to pay exceed the willingness to accept.

Hogarth & Kunreuther (1989) experiment with economically sophisticated participants and find that while buying and selling insurances, sellers are more ambiguity averse than buyers. They also find that for both buyers and sellers, the ambiguity aversion is diminished for high probability losses. Eisenberger & Weber (1995) also hypothesize that the willingness to pay/willingness to accept ratio should be inflated under ambiguity. The authors argue that if buyers and sellers hold distinct lower and upper subjective probabilities within a probability distribution of an uncertain event, in an attempt to maintain the status quo, under ambiguity the buyers will reduce their willingness to pay and sellers will increase their willingness to accept thereby increasing the ratio of the two. However, the authors find that although participants distinguish between uncertain and ambiguous lotteries, the willingness to pay / willingness to accept ratio did not differ; the positive/ negative framing of lotteries did not have any effect either.

There have been extensions of studies on willingness to pay and accept gap in dynamic contexts as well. One such study by Kling, List & Zhao (2013) informs us about the dynamic predictions regarding the willingness to pay and willingness to accept gap. The authors provide neoclassical explanations that suggest that the gap appears and widens depending upon the asymmetry in buyer's and seller's perceived cost of delaying transaction, time preference, and lost value of consumption.

Our study is in the context of uncertainty. DMs are uncertain about the underlying state of the world and they have to probabilistic judgments about a change in that state as well as provide pricing judgments for insurance contracts that could protect them against losses or aid in making gains. Under such impending regime shifts we first investigate if a gap between

willingness to pay and willingness to accept for insurances exists. We study this gap for both dreaded and desirable regime shifts. Our model predictions in Chapter 1 are qualitatively identical for dreaded and desirable regime shifts. Therefore, we do not expect to find any difference in our predictions regarding the gap across dreaded and desirable regime shifts. Within a given regime shift type, we also examine the gap separately for stable environment with noisy signals and unstable environments with precise signals. Since the buyer-seller pairs trade within the same environment, we do not expect to find any moderating effect of environment on the gap. In light of that and on the lines of the theory of loss aversion we hypothesize:

**H1:** There exists a significant gap between willingness to pay and willingness to accept regardless of the environment and desirability of regime shift.

We adopt the experimental approach commonly used in the stream of uncertainty and employ a research design that can capture within subject learning effects across different types of environments. The participants are randomly assigned the buyers or the sellers role and every buyer was paired with a seller who reported their pricing decisions over multiple rounds. This design allows the participants to reveal their pricing decisions after every round. We expect learning to occur through the revealed pricing decisions and the gap between willingness to pay and willingness to accept to diminish over time. Accordingly we hypothesize:

**H2:** Learning has a negative effect on the gap between willingness to pay and willingness to accept regardless of the environment and desirability of regime shift.

## 2.3 Empirical Analyses

The participants in our study adopt the role of an insurance buyer or seller who are endowed with an insurance contract that protects them from incurring losses in a given round similar to the all the studies in our previous chapter. As before, we elicited participants' probability judgments regarding the occurrence of a regime shift as well as pricing decisions for an insurance contract that could protect them from incurring losses in a given round. Participants provided responses in four within-subject conditions that differed with regards to their underlying transition probability ( $q = 2\%$  and  $q = 20\%$ ) and signal diagnosticity ( $d = \frac{60\%}{40\%}$  and  $d = \frac{90\%}{10\%}$ ). The characteristics of a condition were displayed on the task screen throughout all

rounds. Participants provided responses across 10 rounds in each condition; one signal (a red or a green ball) was sampled and shown to participants in every round. During the experiment, signal and state sequences were randomly generated from the underlying statistical process.

### **2.3.1 The Social Learning Study**

A total of 236 participants (male 58%, female 42%) were recruited through the online platform Amazon Mechanical Turk (MTurk). All participants began the task by reading through a series of detailed instruction screens, which informed them about the task itself as well as the pay-off scheme used to determine their final compensation. Subsequently, participants were randomly assigned either to the buyer or the seller role, in which they remained until the end of the experiment.

However, to facilitate learning, every buyer was paired with a seller. In every round both the buyer and the seller would provide a judgment regarding their perceived probability (between 0% and 100%) that the regime shift had taken place as well as their willingness to pay/accept for the insurance contract (between 0 and 10 ECUs). We again used the BDM mechanism (Becker, DeGroot & Marshack 1964) to elicit truthful valuations of the insurance contract, i.e., one value between 0 and 10 was randomly drawn, which served as the market price in a given round. For participants in the buyer role, transactions were successfully carried out if the pricing decision was equal to or higher than the generated market price. For sellers, an insurance contract was successfully sold if the willingness to accept was below the market price. In the buyer instructions, we emphasized that the insurance would only be worth purchasing if participants believed that the observed signal had originated from the “Bad” regime. In the case of sellers, the instructions highlighted that an insurance contract would only be worth selling, if participants believed that the signal had been sampled from the “Good” regime.

After every round, for every buyer-seller dyad, the pricing decisions of the buyers and sellers from the previous round was revealed to the each other. This was in particular the learning manipulation that was introduced in this study to induce social learning.

Similar to our study in chapter 1, we endowed buyers with an initial budget of 100 experimental currency units (ECUs) which they could use to purchase insurance contracts across the 10

rounds. Sellers, on the other hand, were endowed with one insurance contract in each round, which protected them from potential losses that would be incurred if the underlying state was the “Bad” regime as well as with an initial budget of 50 ECUs. Participants were informed that the remaining ECUs, after accounting for any costs/profits incurred by trading the insurance contract as well as any uninsured losses incurred during a round, would be used to calculate their pay-off for each condition. We compensated participants using a combination of a fixed participation fee of \$0.50 as well as a performance-based supplement, which was calculated by randomly selecting one condition and converting their remaining ECUs into US dollars. Each ECU was worth \$0.015, which implied that participants could earn up to \$1.50 in addition to the fixed payment. Participants in the buyer role had an average pay-off of \$1.41 and an average completion time of 15.23 minutes. The sellers an average pay-off of \$1.43 and an average completion time of 19.54 minutes.

### 2.3.2 Method

#### Willingness to Pay and Willingness to Accept

In this section we analyze the change in willingness to pay of the buyers and willingness to accept of the sellers over multiple rounds. Since the buyer-seller pairs were exposed to each other’s pricing decisions in every round, we would expect the gap between willingness to pay and accept to reduce over the rounds. Towards this, we analyze only the learning sample. We calculate the difference between willingness to pay and accept to create a variable  $WTA - WTP$ . First, for dreaded regime shift, Wilcoxon signed rank tests reveals that there is an overall (i.e, considering all rounds), the  $WTA - WTP$  is significantly different from zero ( $M = 1.5, V = 26974, p < 0.001$ ) when the environment is stable and signals are noisy. For unstable environment with precise signals we find a significant  $WTA - WTP$  gap as well ( $M = 1, V = 20310, p < 0.001$ ). The  $WTA - WTP$  is significantly larger for stable environment with precise signals ( $W = 33361, p = 0.005$ ). Under desirable regime shift as well, we observe that the  $WTA - WTP$  gap is significant both for stable environment with noisy signals ( $M = 1, V = 23425, p < 0.001$ ) and unstable environment with precise signals ( $M = 1, V = 21189, p < 0.001$ ). However, the gaps are not different across the environments ( $W = 41299, p = 0.3$ ). Together these results provide full support for H1.

For the analyses regarding hypothesis 2, we aggregated the variable  $WTA - WTP$  by round and computed the median for each round. We run an OLS regression with the median  $WTA - WTP$  as the dependent variable. Since we are interested to observe the effect of time on the  $WTA - WTP$  gap across the two environments, our independent variables are *Round* and *Environment* (2.3.1).

$$WTA - WTP = \beta_0 + \beta_1 * Round + \beta_2 * Environment + \beta_3 * Round * Environment \quad (2.3.1)$$

Table 2.1 and 2.2 exhibit the results for the dreaded and the desirable regime shift, respectively. In both tables, Model 1 includes the two independent variables *Round* and *Environment*. Additionally, model 2 includes the interaction term of the two independent variables. For dreaded regime shift, we observe that while *Round* has a negative effect on  $WTA - WTP$  suggesting that with increasing rounds the gap reduces, this effect is not significant (5.9%,  $p > 0.01$ ). However, the coefficient of *Environment* suggests that for unstable environment with precise signals,  $WTA - WTP$  is 104.1% ( $p < 0.05\%$ ) lower. We do not find any significant interaction between *Round* and *Environment*. The predicted values of  $WTA - WTP$  are shown in Figure 2.1.

Table 2.1: Median WTA-WTP-Dreaded Regime Shift

	<i>Dependent variable:</i>	
	Median WTA-WTP	
	(1)	(2)
Intercept	2.230*** (0.497)	2.537*** (0.606)
Round	-0.059 (0.072)	-0.112 (0.094)
Environment	-1.041** (0.396)	-1.860* (0.996)
Round * Environment		0.133 (0.149)
Observations	17	17
Adjusted R <sup>2</sup>	0.278	0.268
F Statistic	4.080** (df = 2; 14)	2.951* (df = 3; 13)

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

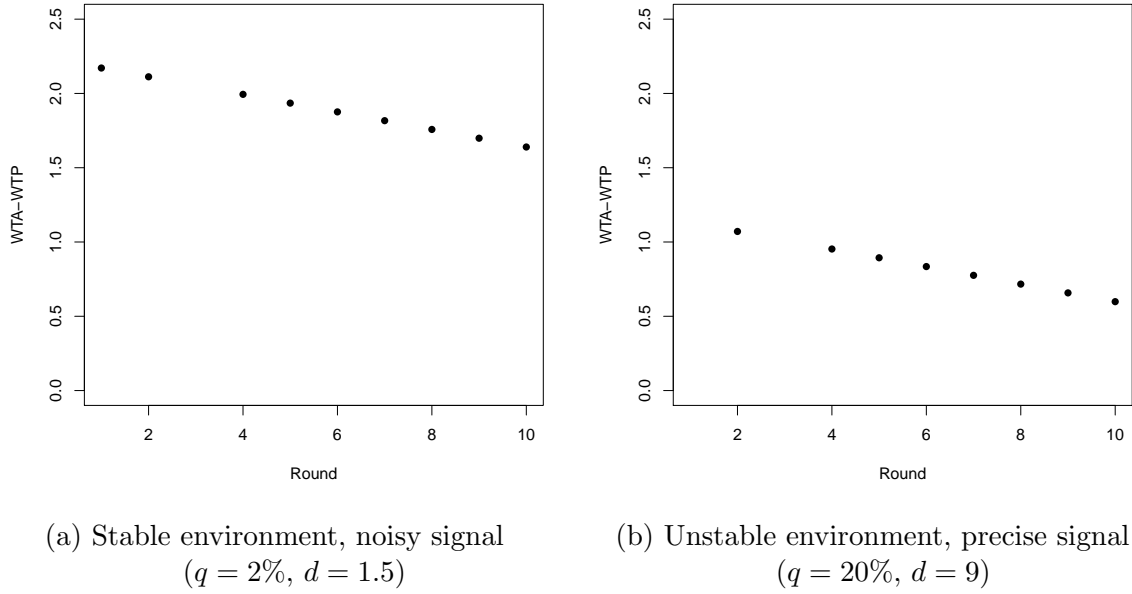


Figure 2.1: Predicted  $WTA - WTP$  for dreaded regime shifts

For desirable regime shift, we observe that *Round* has a positive effect on  $WTA - WTP$  suggesting that with increasing rounds the gap increases although that effect is not significant ( $p > 0.01$ ). *Environment* also does not have any significant impact on the gap ( $p > 0.01$ ). The predicted values of  $WTA - WTP$  are shown in Figure 2.2. Overall, our empirical analyses for both dreaded and desirable regime shifts suggests that there is no significant effect of learning on the willingness to pay and accept gap and therefore, we do not find evidence in support of H2.

Table 2.2: Median WTA-WTP- Desirable Regime shift

	<i>Dependent variable:</i>	
	Median WTA-WTP	
	(1)	(2)
Constant	0.719 (0.519)	0.503 (0.644)
Round	0.049 (0.075)	0.086 (0.100)
Environment	-0.060 (0.413)	0.518 (1.058)
Round * Environment		-0.094 (0.158)
Observations	17	17
Adjusted R <sup>2</sup>	-0.110	-0.163
F Statistic	0.210 (df = 2; 14)	0.252 (df = 3; 13)

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

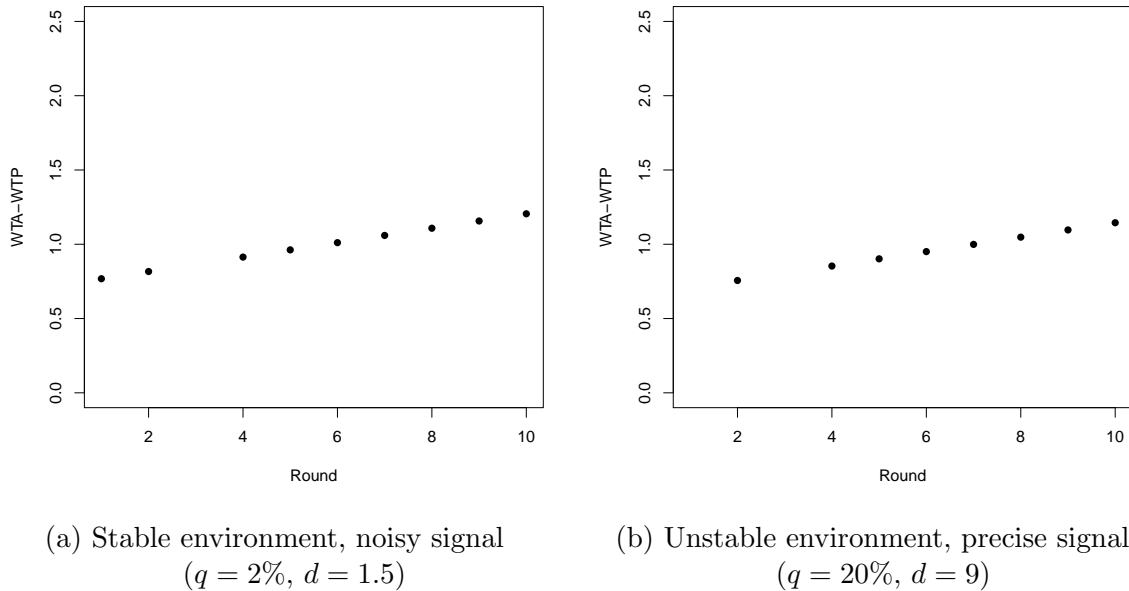


Figure 2.2: Predicted  $WTA - WTP$  for desirable regime shifts

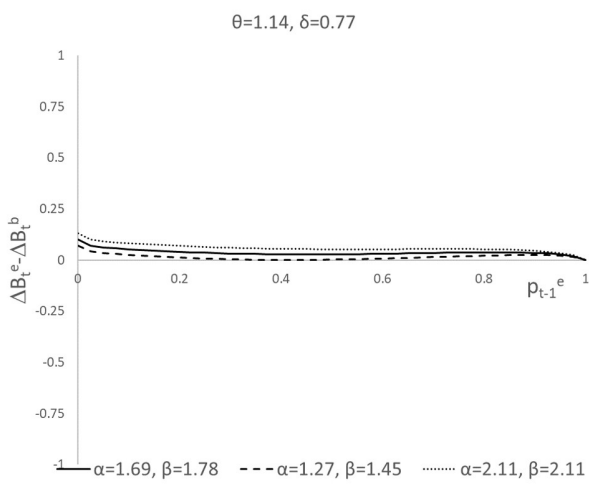
### Pricing Decisions for Dreaded Regime Shift

Recall that in our model in Chapter 1 we developed our under- overreaction measure for pricing decisions (2.3.2) for buyers in the dreaded regime shift conditions. For sellers we used the

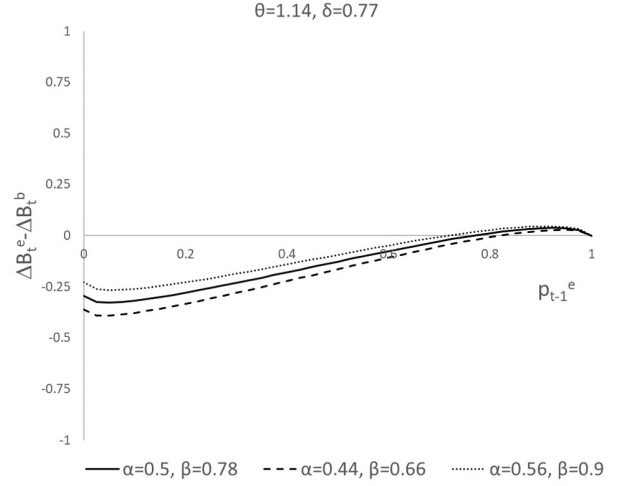
measure shown in A.1.1 in appendix A.1 of chapter 1.

$$\Delta B_t^e - \Delta B_t^b = \underbrace{B_t^e - EL_t^e - (B_{t-1}^e - EL_{t-1}^e)}_{\text{change in risk premium}} + \underbrace{EL_t^e - EL_t^b}_{\text{effect of system neglect}} \quad (2.3.2)$$

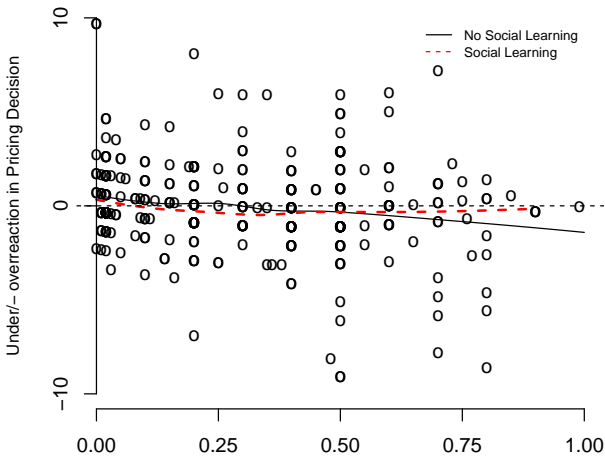
Based on this model, we a predicted distinct under- overreaction pattern in pricing decisions for unstable environments with precise signals and stable environments with noisy signals (Figure 2.3a and 2.3b).



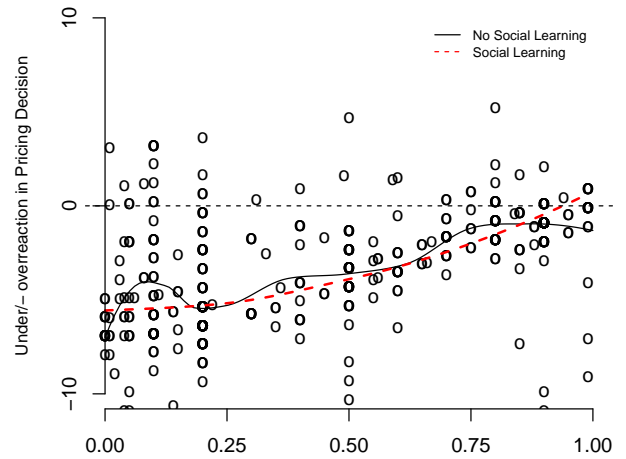
(a) Stable environment, noisy signal  
( $q = 2\%$ ,  $d = 1.5$ )  
Model Prediction



(b) Unstable environment, precise signal  
( $q = 20\%$ ,  $d = 9$ )  
Model Prediction



(c) Stable environment, noisy signal  
( $q = 2\%$ ,  $d = 1.5$ )  
Empirical Result



(d) Unstable environment, precise signal  
( $q = 20\%$ ,  $d = 9$ )  
Empirical Result

Figure 2.3: Under- overreaction in pricing decisions

As the first step of our analysis we ran local regressions separately on the sample with learning

and on the sample without learning (data collected in chapter I). Figures 2.3c and 2.3d show the model plots. Overall, for both samples we observe that the empirical data follows the predicted pattern. Furthermore, to understand if there are differences in magnitudes exist in the median under- overreaction in pricing decisions across the two samples we also conducted non-parametric tests. Wilcoxon signed rank tests for unpaired samples suggest that for unstable environments with precise signals, that overall that there is significantly more underreaction for the learning sample ( $M = -4.81$ ) compared to the sample without learning ( $M = -3.31, W = 81662, p < 0.001$ ). A detailed analysis shows that this difference does not exist for higher priors (i.e. for  $p_{t-1} > 0.5$  :  $M = -1.79$  and  $M = -0.99, W = 8585.5, p = 0.12$ ). For stable environment with noisy signals we do not observe any overall significant difference in under-overreaction between the samples with and without learning ( $M = -.42$  and  $M = -0.12, W = 58330, p = 0.14$ ).

Combined findings from the visual plots using local regressions and the non-parametric tests suggest that there is a significant effect of learning on the under- overreaction in pricing decisions based on the environment, i.e., stable environment with noisy signals vs. unstable environment with precise signals. To examine if there exists an interaction effect of learning and environment we combined the two samples and ran an OLS regression with round fixed effects as per the econometric model shown in 2.3.3.

$$\begin{aligned}
\textit{Under - overreaction in pricing decisions} = & \beta_0 + \beta_1 * \textit{Learning} + \beta_2 * \textit{Environment} \\
& + \beta_3 * \textit{Learning} * \textit{Environment} + \beta_4 * \textit{Role} \\
& + \beta_5 * \textit{Cumulative Insurance}
\end{aligned}
\tag{2.3.3}$$

**Dependent variable:** Our first dependent variable was the measure capturing under- overreaction in pricing decisions (*Under - overreaction in pricing decisions*).

**Independent variables:** Since our primary objective is to observe the effect of learning on the under- overreaction in pricing decisions, our first independent variable of interest is *Learning*. It is a dummy variable which takes a value of 1 if the participant is exposed to learning treatment. Second, as per our model predictions, our dependent variable under- overreaction in pricing decisions is moderated by the environment, i.e., pricing decisions exhibit more underreaction

when the environment is unstable and signal are precise compared to when environments are stable and signals are noisy. Therefore, we include the variable *Environment*. This is a dummy variable which takes a value of 1 if the pricing decision is for unstable environments with precise signals. Furthermore, we also look at the interaction of *Learning* and *Environment* to detect any moderation effect of environment.

**Control variables:** We include two control variables. To control for any effect of the role that the participants assumed during the experiment we include the control variable of *Role*. Additionally, adjustments in pricing decisions over rounds can also be affected by the number of times the participants are successful in getting insured prior to the any round. Therefore, to control for this effect we include the variable *Cumulative Insurance* that calculates the cumulative incidences of being insured prior to a round under consideration.

**Fixed Effect:** Since our aim is to observe if under- overreaction in pricing decisions are affected due to learning between paired participants, we need to control for any effect of learning that can occur due to playing multi period games. The round effects were included in order to control for this effect. The standard errors were clustered at the participant level.

The model results are shown in Table 2.3. Model 1 includes the control variable. Model 2 also includes the independent variables *Learning* and *Environment*. Additionally, model 3 includes the interaction term. All models include round fixed effects.

We observe that none of the controls in Model 1 are significant. Model 2 reveals a negative effect of *Learning* and *Environment* variables on under- overreaction in pricing decisions. Particularly, the coefficient of *Learning* suggests that overreaction (underreaction) in pricing decision for a given environment is decreased (increased) by 51.4% ( $p < 0.05$ ) on being exposed to the decisions of a paired participant. The coefficient of *Environment* suggests that for a given learning condition, there is 375% ( $p < 0.01$ ) more underreaction for unstable environment with precise signals compared to stable environment with noisy signals. In model 3, we observe that there is a significant interaction between *Learning* and *Environment* suggesting that the decrease (increase) in overreaction(underreaction) in pricing decisions due to learning is 81.3% ( $p < 0.05$ ) more when the environment is unstable and signals are precise (see Figure 2.4). Furthermore, a conditional effect of *Environment* suggests that regardless of whether

Table 2.3: OLS with Round-Fixed Effects

	<i>Dependent variable:</i>		
	Under - overreaction in pricing decisions		
	(1)	(2)	(3)
Intercept	-1.387*** (0.279)	-0.068 (0.265)	-0.260 (0.271)
Learning		-0.514** (0.221)	-0.082 (0.193)
Environment		-3.750*** (0.185)	-3.396*** (0.234)
Learning * Environment			-0.813** (0.358)
Cumulative Insurance	-0.105 (0.073)	-0.042 (0.065)	-0.057 (0.064)
Role	0.024 (0.228)	0.237 (0.215)	0.240 (0.215)
Round Fixed Effects	Included	Included	Included
Observations	1,422	1,422	1,422
Adjusted R <sup>2</sup>	0.032	0.302	0.304
F Statistic	5.646*** (df = 10; 1411)	52.125*** (df = 12; 1409)	48.795*** (df = 13; 1408)

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

the participants are exposed to learning or not, there is 339% ( $p < 0.01$ ) more underreaction for unstable environments with precise signals. This finding is in line with our main model predictions of Chapter 1.

### Effect of System Neglect & Change in Risk Premium

Since the measure of under- overreaction in pricing decision is composed of two subcomponents, one reflecting the change in risk premium and the other reflecting the effect of system neglect, we are interested to understand if the effect of learning is pronounced in both the components. Therefore, we further examine whether the model predictions for the subcomponents also hold in our empirical data and whether there are any significant difference between the samples with and without learning. Figure 2.5 exhibits the model predictions and the empirical findings for the effect of system neglect. As we can see, data from both the samples follow the predictions.

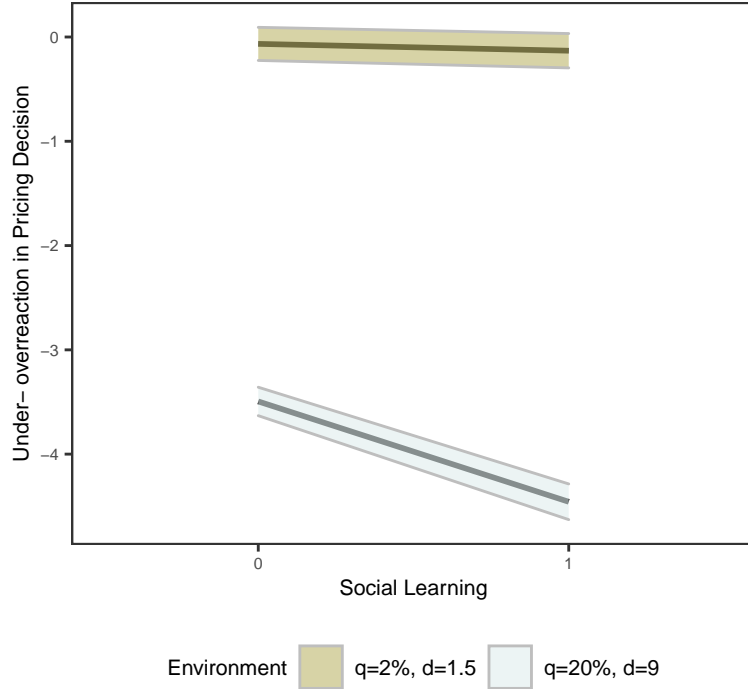
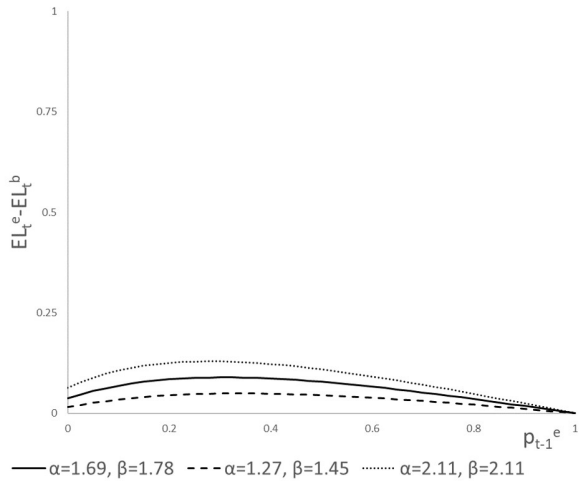
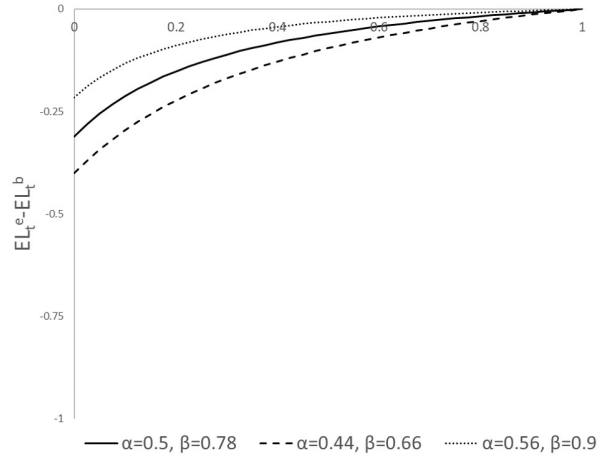


Figure 2.4: Interaction effect of learning and environment on under- overreaction in pricing decisions.

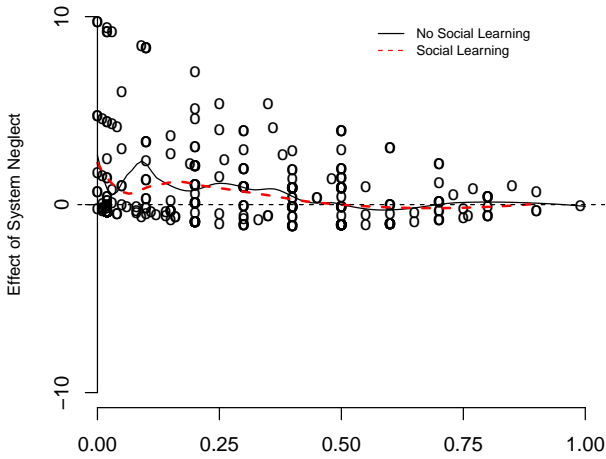
Wilcoxon signed ranked tests reveal that there does not exist any significant overall difference in overreaction in probability judgements between the sample with learning ( $M = -0.12$ ) and the one without learning samples ( $M = -0.12, W = 53840, p = 0.72$ ) for stable environment with noisy signals. A detailed analysis with different probability ranges exhibit the same result. For unstable environments with precise signals, Wilcoxon tests reveal no overall significant difference between the two samples ( $M = -2.50$  and  $M = -1.92, W = 67320, p = 0.67$ ). However, we find that the learning sample exhibits less underreaction in probability judgments for lower priors (i.e. for  $p_{t-1} < 0.5$  :  $M = -3.57$  and  $M = -4.78, W = 23839, p = 0.001$ ).



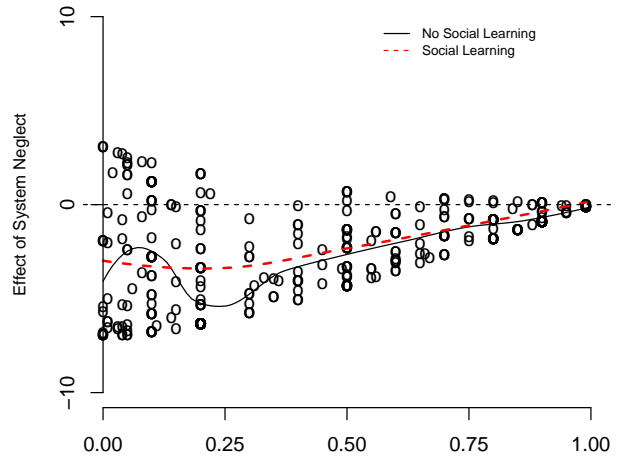
(a) Stable environment, noisy signal  
 $(q = 2\%, d = 1.5)$   
 Model Prediction



(b) Unstable environment, precise signal  
 $(q = 20\%, d = 9)$   
 Model Prediction



(c) Stable environment, noisy signal  
 $(q = 2\%, d = 1.5)$   
 Empirical Result



(d) Unstable environment, precise signal  
 $(q = 20\%, d = 9)$   
 Empirical Result

Figure 2.5: Effect of system neglect

Next we look at the predictions regarding the change in risk premium for the learning and no-learning samples across the two environments. The empirical data visually broadly follows the model predictions (see Figure 2.6). For both environments the data for the learning sample follows the model predictions more closely. In addition, the local regressions visually suggest that there are differences in change in risk premium between the two samples for unstable environments with precise signals. In fact, Wilcoxon tests do reveal that for lower priors there is significantly more change in risk premium in the learning group compared to the no-learning group (i.e. for  $p_{t-1} < 0.5$  :  $M = -1.5$  and  $M = 0, W = 34882, p = 0.001$ ) for unstable

environments with precise signals. However, there exists no difference between the samples for stable environments with noisy signals.

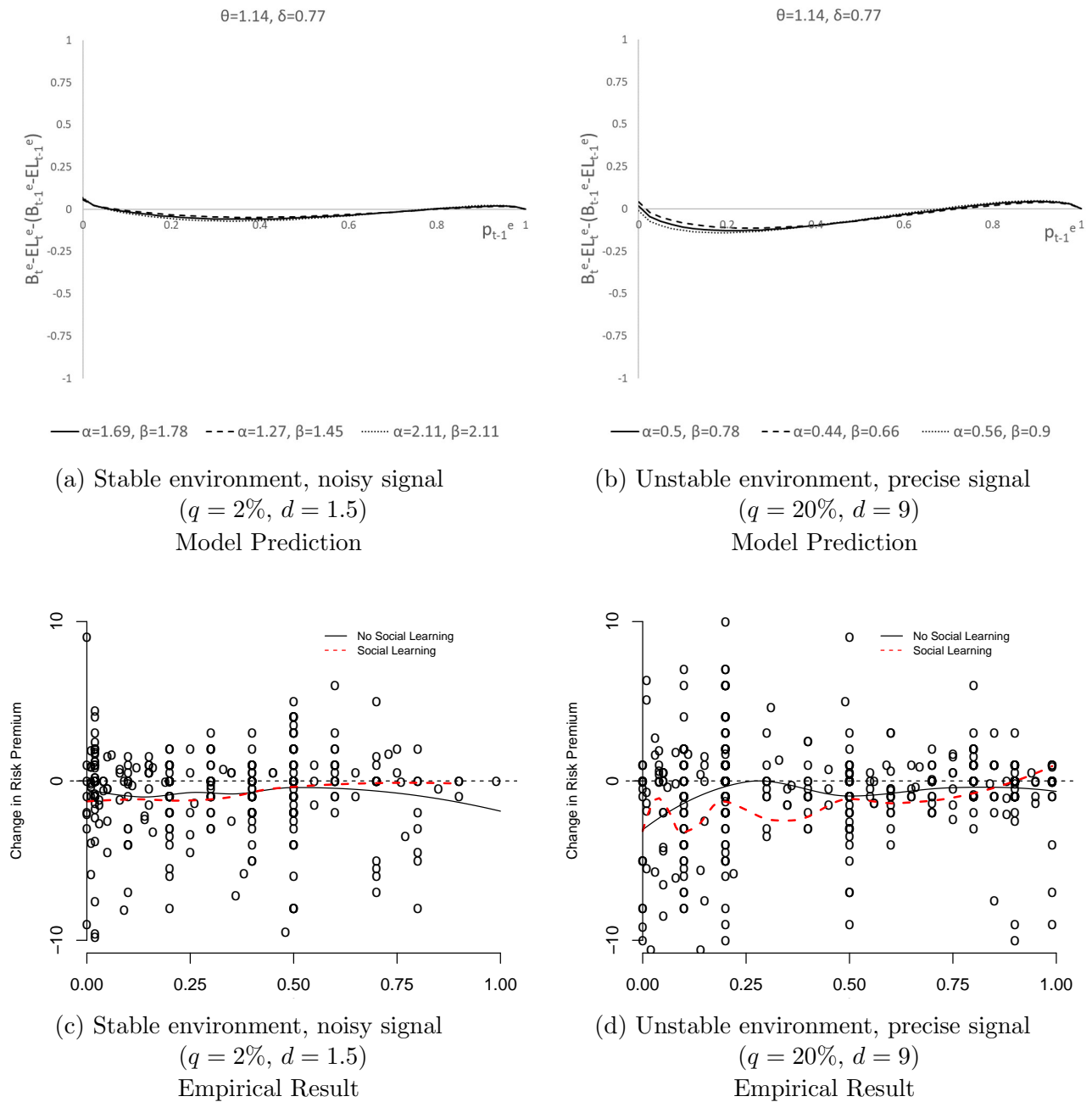


Figure 2.6: Change in risk premium

The findings from the local regression analysis and non-parametric tests indicate that while the under- overreaction in probability judgments is not affected by the learning treatment regardless of priors. However, the change in risk premium is affected by the learning treatment for an unstable environment with precise signals specifically for lower priors. To consolidate these findings, we run two OLS regressions. For the first regression (2.3.4), the dependent variable, *Effect of system neglect*, denotes the under- overreaction in probability judgments. For the

second regression (2.3.5), the dependent variable is *Change in risk premium*. For both the regressions, same independent variables and control variables as in (2.3.3) were used.

$$\begin{aligned} \text{Effect of system neglect} = & \beta_0 + \beta_1 * \text{Learning} + \beta_2 * \text{Environment} + \beta_3 * \text{Learning} * \text{Environment} \\ & + \beta_4 * \text{Role} + \beta_5 * \text{Cumulative Insurance} \end{aligned} \quad (2.3.4)$$

$$\begin{aligned} \text{Change in risk premium} = & \beta_0 + \beta_1 * \text{Learning} + \beta_2 * \text{Environment} + \beta_3 * \text{Learning} * \text{Environment} \\ & + \beta_4 * \text{Role} + \beta_5 * \text{Cumulative Insurance} \end{aligned} \quad (2.3.5)$$

Table 2.4 exhibits the results of the regressions. As before, model 1 includes the control variables. Model 2 also includes the independent variables *Learning* and *Environment* and model 3 includes the additional interaction term. All models include round fixed effects. We observe that *Learning* is not significant on *Effect of system neglect*, i.e., there exists no significant impact of being exposed to others' pricing decisions on the under- overreaction in probability judgments of shifts ( $p > 0.1$ ). The effect of system neglect is only affected by *Environment* ( $p < 0.01$ ), which is in line with the finding of Massey and Wu (2005). Furthermore, there is no significant interaction effect of *Learning* and *Environment* on the under- overreaction in probability judgments.

For the three models with *Change in risk premium* as the dependent variable, we observe that both *Learning* and *Environment* have significant effects. Particularly, we find that the change in risk premium is 67.5% ( $p < 0.01$ ) more negative for the learning sample and the change in risk premium is 32.2% ( $p < 0.01$ ) more negative for unstable environment with precise signals. We also observe a marginally significant interaction effect of *Learning* and *Environment* on the change in risk premium. The interaction effect suggests that the decrease in risk premium due to learning is 62.5% ( $p < 0.01$ ) more when the environment is unstable and signals are precise (see Figure 2.7).

Table 2.4: OLS with Round-Fixed Effects

	<i>Dependent variable:</i>					
	Effect of System Neglect			Change in Risk Premium		
	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-0.481*	0.414	0.369	-0.906***	-0.482	-0.629*
	(0.277)	(0.262)	(0.265)	(0.305)	(0.319)	(0.328)
Learning		0.160	0.261		-0.675***	-0.343
		(0.193)	(0.218)		(0.223)	(0.270)
Environment		-3.428***	-3.346***		-0.322*	-0.050
		(0.186)	(0.258)		(0.169)	(0.179)
Learning * Environment			-0.189			-0.625*
			(0.361)			(0.334)
Cumulative Insurance	-0.032	0.021	0.018	-0.074	-0.063	-0.074
	(0.071)	(0.066)	(0.067)	(0.062)	(0.063)	(0.063)
Role	-0.077	0.136	0.137	0.101	0.101	0.104
	(0.223)	(0.203)	(0.203)	(0.212)	(0.209)	(0.209)
Round Fixed Effects	Included	Included	Included	Included	Included	Included
Observations	1,422	1,422	1,422	1,422	1,422	1,422
Adjusted R <sup>2</sup>	0.005	0.321	0.320	0.019	0.028	0.030
F Statistic	1.680*	56.870***	52.513***	3.721***	4.470***	4.368***
	(df = 10;	(df = 12;	(df = 13;	(df = 10;	(df = 12;	(df = 13;
	1411)	1409)	1408)	1411)	1409)	1408)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

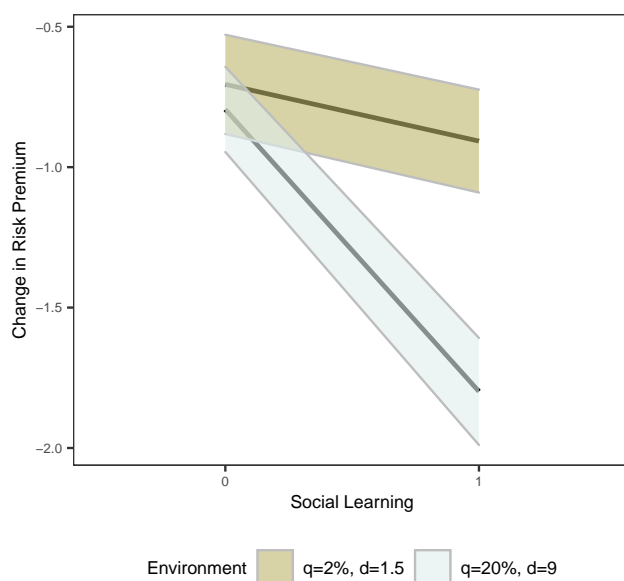


Figure 2.7: Interaction effect of learning and environment on change in risk premium.

### 2.3.3 Pricing Decisions for Desirable Regime Shift

We performed identical analyses for desirable regime shift. Table 2.5 shows the results of regressions on the three dependent variables viz. Under- overreaction in pricing decisions, effect of system neglect and change in risk premium. The figures with the empirical results for the samples with and without learning are provided in Appendices §B.1, §B.2, §B.3. The results are consistent with those for the dreaded regime shift. We find that learning decreases (increases) the overreaction (underreaction) in pricing decisions by 43.1% ( $p < 0.05$ ) for a given environment.<sup>1</sup> Also, for a given learning condition there is 357% ( $p < 0.01$ ) more underreaction for unstable environment with precise signals compared to stable environment with noisy signals. There is a significant interaction between *Learning* and *Environment* suggesting that the decrease (increase) in overreaction (underreaction) in pricing decisions due to learning is 130.9% ( $p < 0.01$ ) more when the environment is unstable and signals are precise (see Figure 2.8a). We also find significant conditional effects of the environment (300%,  $p < 0.01$ ). There is significant interaction effects of *Learning* and *Environment* on change in risk premium suggesting that the decrease in risk premium due to learning is 106.5% ( $p < 0.01$ ) more when the environment in unstable and signals are precise (Figure 2.8b).

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<sup>1</sup>For desirable regime shifts, since positive measures of our dependent variables denote underreaction and negative variables denote overreaction, a positive coefficient suggests increase in underreaction or decrease in overreaction.

Table 2.5: OLS with Round-Fixed Effects

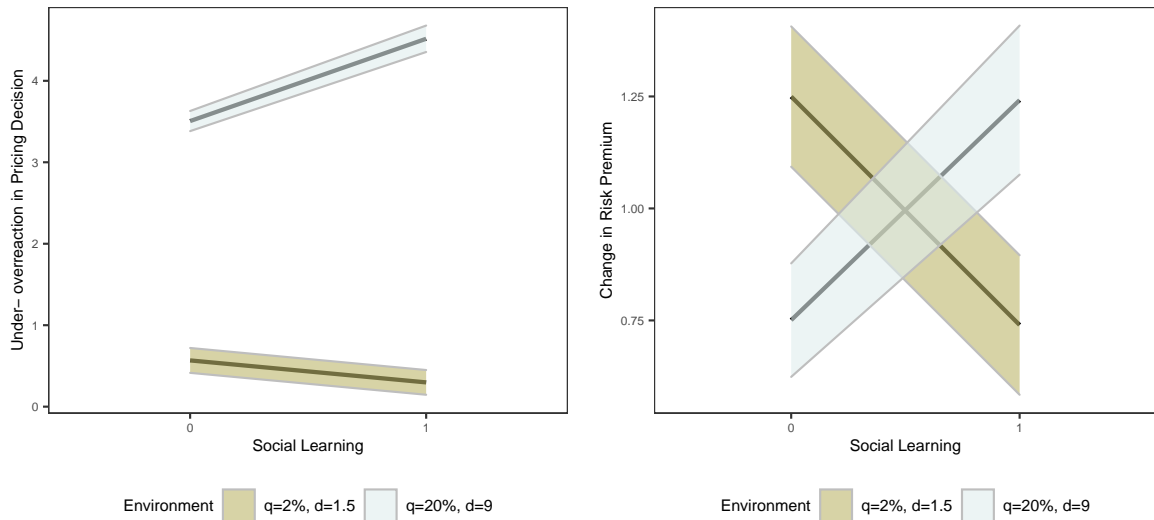
	<i>Dependent variable:</i>					
	Under-overreaction in pricing decision		Effect of system neglect		Change in risk premium	
	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	1.033*** (0.260)	1.395*** (0.260)	-0.511* (0.263)	-0.443* (0.255)	1.543*** (0.321)	1.838*** (0.330)
Learning	0.431** (0.202)	-0.270 (0.194)	0.399** (0.201)	0.268 (0.172)	0.033 (0.188)	-0.538** (0.220)
Environment	3.571*** (0.173)	3.007*** (0.220)	3.546*** (0.159)	3.441*** (0.207)	0.025 (0.151)	-0.433*** (0.161)
Learning * Environment		1.309*** (0.353)		0.244 (0.327)		1.065*** (0.305)
Cumulative Insurance	-0.035 (0.058)	-0.030 (0.056)	0.027 (0.055)	0.028 (0.055)	-0.062 (0.043)	-0.058 (0.043)
Role	-0.316 (0.205)	-0.298 (0.203)	-0.385** (0.194)	-0.381* (0.195)	0.069 (0.186)	0.083 (0.185)
Round Fixed Effects	Included	Included	Included	Included	Included	Included
Observations	1,619	1,619	1,619	1,619	1,619	1,619
Adjusted R <sup>2</sup>	0.261	0.269	0.351	0.351	0.001	0.008
F Statistic	48.541*** (df = 12; 1606)	46.788*** (df = 13; 1605)	74.001*** (df = 12; 1606)	68.384*** (df = 13; 1605)	1.111 (df = 12; 1606)	1.956** (df = 13; 1605)

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

## 2.4 General Discussion

The current study focuses on the effect of learning on the willingness to pay and willingness to accept gap. Many studies before us have shown that this gap exists under uncertainty. In our setting, DMs reported their willingness to pay and willingness to accept for insurance contracts under an impending regime shift. Under impending regime shifts the underlying state of the world is uncertain and therefore DMs' probability judgments can suffer from under- and overreaction. If there are differences in this under- and overreaction between buyers and sellers, or in other words if buyers and sellers perceive the probability of the regime differentially, that



(a) Under-overreaction in pricing decisions

(b) Change in risk premium

Figure 2.8: Interaction effects of learning and environment

would most likely reflect in their pricing decisions. The first finding of our study confirms the existence of a gap in the pricing decisions of the buyers and the sellers. This gap between willingness to pay and willingness to accept persists regardless of the desirability of the regime shift.

Second, we expected to find the gap between willingness to pay and willingness to accept to diminish over time as the DMs in the buyer's and seller's role learned from each others' revealed pricing decisions. We did not find evidence of a significant effect of learning over time on the gap, although the gap reduces over time when the regime shift is dreaded. For the desirable regime shift, however, we observe a non significant *increase* in the gap over time with learning. Although willingness to accept has usually been found to be higher than willingness to pay in line with the theory of loss aversion, Einhorn & Hogarth (1985) also theoretically show that if the sellers have no ambiguity regarding an event but the buyers do, the relationship can reverse. Our intuition is that for both dreaded and desirable regime shifts, the sellers' probability judgments of regime shift are closer to the normative judgments compared to those of the buyers'. As a result we observe the following: For dreaded regime shift, on observing signals indicative of regime shift, over time the priors of the buyers diverge from the sellers in way such the priors of the buyers are below those of the sellers. As a result, the willingness to pay is less than the willingness to accept. For desirable regime shift, priors of the buyers

diverge from the sellers in way such the priors of the buyers are above those of the sellers. As a result, the willingness to pay is higher than the willingness to accept.

Finally, we show that the overall behavioral pattern regarding under- and overreaction in willingness to pay and willingness to accept is similar with learning. However, we do find that with learning there is diminished overreaction when the environment is stable and signals are noisy. When the environment is unstable and signals are precise there is increased underreaction with learning. Additionally, we find the effect of learning is higher in case of the latter. Since the learning manipulation was intended to affect the willingness to pay and accept elicitation, we expected the change in risk premium to be affected by this manipulation as well. Our results indicate that learning affects the change in risk premium and that this effect is higher when the environment is unstable and the signals are precise. Our learning manipulation did not allow participants to reveal their probability judgments of regime shift. Therefore, as expected, for both dreaded and desirable regime shifts we find no effect of learning on the measure that captures the effect of system neglect. For all our analyses, we examined if the behavior was different for buyers and sellers. No significant difference was observed.

## **2.5 Concluding Remarks**

We set out to explore the role of learning on the nature of the willingness to pay and willingness to accept gap under impending regime shifts. The primary objective of our study was to determine if such a gap exists and if the gap can be mitigated over time with learning. Although we find confirmatory evidence of the existence of this gap, we did not find any significant effect of learning on this gap over time. Our results hold regardless of the desirability of regime shift. However we find significant influence of learning on under- and overreaction in pricing decisions. In our studies we the buyers and sellers to reveal only the pricing decisions and not the probability judgments of regime shift. Since the subjective probability judgments of regime shift combined with the risk attitude determines the under- and overreaction in pricing decisions, further work is warranted to examine if by allowing the probability judgments to be revealed, whether the effect of learning still holds or whether it is amplified or attenuated.

# Chapter 3

## Social interaction based in choice formation in presence of firm action

### 3.1 Introduction

In the last chapter of this dissertation, we look at purchase decisions of consumers in a social setting where the purchase decisions do not have any risks involved. Specifically, the purchase decisions that we study are binary choices to “buy” or “not buy” a commodity. What forms an integral part of consumer choices is others choose. This knowledge becomes available during social interactions. Social interaction, as defined by Godes et al. (2005) is “an action or actions that (a) is taken by an individual not actively engaged in selling the product or service and that (b) impacts others’ expected utility for that product or service”. This is why firms foster word-of-mouth in online forums (Godes and Mayzlin 2009; Chevalier and Mayzlin 2006) to convince more consumers to make favorable choices. Social interaction is a useful tool to propagate information and research by Godes and Mayzlin (2009) provides evidence that firms use the network ties to their benefit to create product awareness. Some firms even go to the extent of inflating the actual user ratings or manufacture biased reviews (Dellarocas 2006; Mayzlin, Dover and Chevalier 2014). Consumers feel safe to buy a product when they have information that other consumers have bought the product or are willing to buy it. Sometimes this information can outweigh any marketing action undertaken by the firm. Both online and offline consumer choices often exhibit herding (Huang and Chen 2006) and bandwagon effect (Myers, Wojcicki

and Aardema 2009).

However, not always, choices are communicated during social interactions. Sometimes only intentions are conveyed. Because consumers only express their inclination to buy the product during social interactions, either offline or on online discussion forums. Whether they finally purchase the product or not is not typically observable to other consumers and the firm (unless the consumers revisit the forums after purchase and disclose that explicitly). If the consumers express their choices explicitly, then the firm can undertake appropriate actions such as promotional chats (Mayzlin 2006). In other cases, for example, during pre-launch periods of products, consumer evaluations are not available simply because the product is not available in the market yet. During such interactions consumers can only exchange their thoughts or intentions to purchase the product. Therefore, each consumer must form an *expectation* of others' choices and incorporate that into her own choice formation. Since intentions are only indicative of choices and not the final choices, per say, any choice formed based only on expectations is not straightforward to assess. And if all consumers form choices based on expectations it becomes particularly difficult for the firm to understand what would be the *average* or *majority* choice of a group of such interacting consumers. Once the product is launched, the average choices, before consumers start interacting socially, could be either to buy or to not buy. Initial consumer evaluations are critical for the firm. For example, if the firm could observe the individual choices, the firm could invest in incentivizing word-of-mouth or consumer reviews when more consumers had positive evaluations. Past research provides evidence of firm actions being generally beneficial for firm (see for example, Godes and Mayzlin (2009) and Basuroy, Chatterjee and Ravid (2003) for positive effects of word of mouth). On the other hand if evaluations were not positive, the firm could engage in private chats or direct promotions and discounts to convince some consumers privately first. However, since the choices of consumers are unobservable when choices are made based on expectations it would be hard for them to choose the right strategies. In such a stage can firm actions be self-defeating?

To address our research question we build a utility discrete choice model. As a first step we assume that consumers choose to buy or not buy a product. A utility structure is defined to capture the utility derived from this choice which the consumer wants to maximize. This utility structure captures the private and social utility from the choice (as derived in Brock

and Durlauf (2001)). Private utility is intended to capture the effect of the consumer's private choice independent of the effect of social interactions, while social utility, derived from social interactions determines the effect of expected choices of other consumers. To derive the nature of social utility we incorporate the concept of reference group to capture the effect of reference group association on a choice. Reference groups can influence the way individuals evaluate and act because these individuals try to align their behavior with that of these groups (Merton 1968). Within a reference group, the consumer is incentivized to conform to the group choice whereas within a non reference group she is incentivized to not conform to the group choice.<sup>1</sup> Finally, we incorporate the effect of firm's actions on both private and social utilities. The average choice level for a community of interacting consumers is then derived using Curie-Weiss model of Mean Field Theory (Ellis 1985).

The rest of the paper is organized as follows: In §3.2 we review the related research on firm's manipulation strategies followed by §3.3 where we develop the model and derive the propositions based on model properties. §3.4 includes a brief discussion on the econometric implementation of the model. In that process, we also point out the limitations of our model. In §3.5 we conclude.

## 3.2 Firm Action

The effect of firm actions on consumer choice formation have been investigated from different perspectives. However, most of these prior investigations are not in the context of social interactions. For example, Mayzlin (2006) examines the positive and negative effects of promotional chats by firms on the internet as a game between the firm and the consumers. The uninformed consumer updates her belief about the product after receiving the promotional chat and her utility is maximized if she develops accurate perceptions of the superior product. The firm's pay-off depends on the consumer beliefs about the product after receiving the promotional chat. An interesting addition to the discourse on promotional chat has been made by Sussan, Gould and Weisfeld-Spolter (2006). They find that word-of-mouth adds value to advertisements only when they are posted at 3rd-party sponsored websites. However, unlike these studies where

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<sup>1</sup>The influence of reference group association has been studied widely in consumer research, specifically in the contexts of brand choice and brand purchase decisions (Bearden and Etzel 1982), in addition to sociological contexts like alcohol behavior and religiosity (Cochran, Beeghley and Bock 1988).

consumers already know about the choices of other consumers, our study investigates choice formation when choices of others are not known and only expectations of the choices can be formed based on social interactions.

Dellarocas (2006) investigates the effect of inflating the firm's true ratings on firm profits. Mayzlin, Dover and Chevalier (2014) perform an econometric analysis of online review manipulation in the context of promotional reviews for hotels for two types of forums - TripAdvisor, which allows reviews from unverified customers; and Expedia, that only allows verified customer reviews. The objective of these studies are mainly to understand the extent to which firms can try to conceal the negative effects of consumer opinions. Godes et al. (2005) propose that a firm can adopt one of the four mutually exclusive strategies to manage the social interactions within a community, namely – Observer, Moderator, Mediator and Participant. Firms as Observer can choose to just observe the social interactions and learn about consumer preferences from them, or Moderate these social interactions by fostering their own discussion forums, or Mediate by deciding how the consumer generated information is spread or become a Participant and engage directly in conversations with consumers. The firm's role becomes increasingly prominent as it evolves from an Observer role to a Participant role. In our study we attempt to model this continuum and examine its effects on choices formation.

Two studies that are closest to investigating firm actions in the presence social dependencies are by Godes and Mayzlin (2009) and Miller, Fabian and Lin (2009). A field test and experiment by Godes and Mayzlin (2009) uses firm created word of mouth to understand the consumer characteristics and relational ties which help in driving sales. They find that for products for which the awareness levels are comparatively low, promoting word of mouth through loyal customers is not the best strategy. The less loyal customers' networks lack awareness about the product and therefore creating word of mouth through the less loyal customers brings in incremental sales. Although opinion leadership does not add to this effect, the effect is bigger when word of mouth is exchanged between acquaintances rather than friends or relatives. These findings are suggestive of social dependencies that drive certain interactions to be more powerful in preference formation than others. Miller, Fabian and Lin (2009) operationalize firm action through deployment of advocates into communities to shape demand. In their model, consumers are spread across communities and they can switch from one community to the other based on

random or affinity switching or not switch at all. Every community has consumers possessing favorable, unfavorable and neutral views of the firm's product and they post these views in the community forum. The firm advocates are allocated based on proportion of the postings. The objective of such an allocation is to increase the adoption rate for the product. Preference diffusion occurs as the probability of changing preference increases with the proportion of majority postings crossing a certain threshold. The authors posit that the mechanism is through learning or, in more general, socializing. We further advance their research forward by modelling the this mechanism by specifying a social utility structure attached to the preference emerging from social interactions. We not only accommodate for unequal strength of social interactions but also account for self-selection. The intuition behind such a parametrization is that in Miller, Fabian and Lin (2009), every posting can equally increase probability of preference switching but in our model the effect is not uniform, which is more realistic.

### 3.3 Model

We develop a discrete choice model where the choices are made under social interactions. Let  $I$  be the total number of interacting individuals each with a binary choice  $\{-1,1\}$ . These individuals develop choices in a non-cooperative manner. The set of all possible preferences is denoted by  $\omega=(\omega_1,\omega_2,\dots,\omega_I)$ . Therefore,  $\omega_i$ , denotes the preference for individual  $i$ . The set of preferences of all individuals, other than  $i$ , is denoted by  $\omega_{-i}$ . In the absence of social interactions, an individual  $i$  makes a choices that maximizes her private utility (3.3.1) from that choice. This private utility depends on her personal characteristics ( $Z_i$ ) and random shocks ( $\varepsilon_i(\omega_i)$ ), i.e.,

$$\max_{\omega_i \in \{-1,1\}} V(\omega_i, Z_i, \varepsilon_i(\omega_i)) \quad (3.3.1)$$

However, in the presence of social interactions, the pay-off attached to a choice also includes the influence of the *expected* behavior of others on individual  $i$ 's choice. Let that expectation or belief concerning the choices of others be denoted by  $\mu_i^e(\omega_{-i})$  which is conditioned by the average characteristics  $Z_{-i}$ . Accordingly the pay-off is now given by,

$$\max_{\omega_i \in \{-1, 1\}} V(\omega_i, Z_i, \mu_i^e(\omega_{-i}), \varepsilon_i(\omega_i)) \quad (3.3.2)$$

Assuming that the pay-off can be additively decomposed into three terms, we can write,

$$V(\omega_i) = \underbrace{u(\omega_i, Z_i)}_{\text{deterministic private utility}} + \underbrace{S(\omega_i, Z_i, \mu_i^e(\omega_{-i}))}_{\text{deterministic social utility}} + \underbrace{\varepsilon_i(\omega_i)}_{\text{random private utility}} \quad (3.3.3)$$

The deterministic private utility can be written as a linear function such that  $u(\omega_i, Z_i) = h_i \omega_i + k_i$ . This implies  $u(1, Z_i) = h_i + k_i$  and  $u(-1, Z_i) = -h_i + k_i$ . Therefore, the difference between the deterministic private utilities from the two choices  $\{-1, 1\}$  is given by  $h_i = \frac{u(1, Z_i) - u(-1, Z_i)}{2}$ . That is,  $h_i$  is proportional to the deterministic private utility difference between the two choices  $\{-1, 1\}$ .

As is common in discrete choice models under social interactions, we assume that the social utility term embodies a generalised quadratic conformity effect and we can represent it as follows,

$$S(\omega_i, Z_i, \mu_i^e(\omega_{-i})) = -E_i \sum_{j \neq i} \frac{J_{i,j}}{2} (\omega_i - \omega_j)^2 \quad (3.3.4)$$

Eq.3.3.4 is the most basic form of social utility attached to the choice of individual  $i$  based on the expectation of individual  $j$ 's choice.  $E_i$  is the expectation function.  $(\omega_i - \omega_j)^2$  denotes the choice distance between individual  $i$  and  $j$  and  $J_{i,j}$  is a measure of the disutility of non-conformance. Therefore, a higher  $J_{i,j}$  denotes a higher incentive to conform. In order to check this, we first simplify eq.3.3.4 as follows,

$$\begin{aligned}
-E_i \sum_{j \neq i} \frac{J_{i,j}}{2} (\omega_i - \omega_j)^2 &= -E_i \sum_{j \neq i} \frac{J_{i,j}}{2} (\omega_i^2 + \omega_j^2 - 2\omega_i \omega_j) \\
&= -E_i \sum_{j \neq i} \frac{J_{i,j}}{2} (2 - 2\omega_i \omega_j), \quad (\because \omega_i^2 = \omega_j^2 = 1) \\
&= \sum_{j \neq i} J_{i,j} (\omega_i E_i(\omega_j) - 1) \\
&= \sum_{j \neq i} J_{i,j} \omega_i E_i(\omega_j), \quad (\text{assuming multiplicative form})
\end{aligned} \tag{3.3.5}$$

From eq.3.3.5, we can see if  $J_{i,j} \geq 0$

1. for  $\omega_i = 1$  and  $E_i(\omega_j) = 1$ , social utility  $\geq 0$
2. for  $\omega_i = -1$  and  $E_i(\omega_j) = -1$ , social utility  $\geq 0$
3. for  $\omega_i = 1$  and  $E_i(\omega_j) = -1$ , social utility  $< 0$
4. for  $\omega_i = -1$  and  $E_i(\omega_j) = 1$ , social utility  $< 0$

Similarly, from eq.3.3.5, we can see if  $J_{i,j} < 0$

1. for  $\omega_i = 1$  and  $E_i(\omega_j) = 1$ , social utility  $< 0$
2. for  $\omega_i = -1$  and  $E_i(\omega_j) = -1$ , social utility  $< 0$
3. for  $\omega_i = 1$  and  $E_i(\omega_j) = -1$ , social utility  $> 0$
4. for  $\omega_i = -1$  and  $E_i(\omega_j) = 1$ , social utility  $> 0$

This check clearly establishes that when  $J_{i,j} \geq 0$ , there is an incentive to conform and when  $J_{i,j} < 0$ , there is an incentive to not conform. In a marketing context, this occurs when a product is launched and we interact on social media before deciding to buy the product. Till any user evaluation or review is available, we try to form their choices based on their own characteristics and also on the expectation of others' choices. There are certain consumers that we wish to match our choices with and some that we refrain matching our choices with. As suggested by Merton (1968)(p. 336), individuals tend to orient themselves to even those groups which they have no membership with. Such orientations can shape their behavior as individuals try to align their preferences with those of the reference group. The reason could be compliance,

identification or internalization (Kelman 1961). Of these three, the *internalization* process leads to the formation of *informational* reference group influence. An individual makes inferences by observing the behaviors of members of informational reference groups as it enhances her knowledge of the environment or her “ability to cope with some aspect of this environment, e.g., purchasing a product” (Park and Lessig (1977) p. 103).  $J_{i,j}$  for any  $i$  and  $j$  captures the alignment to reference groups and can be seen as a function of the individual characteristics of the individuals such that  $J_{i,j} = J(Z_i, Z_j)$ . The closer  $Z_i$  is to  $Z_j$ , the higher is the value of the disutility of non conformance and greater is the incentive to conform. In the event of higher similarity between individuals and belongingness to the same reference group,  $Z_i$  is closer to  $Z_j$  and thus the disutility is very high.

We can simply characterize the  $J_{i,j}$ s by creating two separate conditions for reference group and non reference groups respectively, i.e., we assume that the total population of consumers is divided into two subpopulations, one of which serves as the reference group and the other serves as the non reference group for  $i$ .

Reference Group	Non Reference Group
$J_{i,j}^R \geq 0$	$J_{i,j}^{NR} < 0$

Table 3.1: Characteristics of  $J_{i,j}$  based on Reference Group

- (a) **Reference Group (R):** When individual  $j$  belongs to the same reference group of individual  $i$ , the disutility from non conformance is non-negative and very high. For more similar  $i - j$  pairs, higher disutilities will be realised. Therefore, for this condition, we may write  $J_{i,j}^R \geq 0$ . A reference group is strong when the value of  $J_{i,j}^R$  is highly non negative and it is weak when the that value is comparatively less non negative.
- (b) **Non Reference Group (NR):** When individuals  $i$  and  $j$  belong to different reference groups, the disutility from non conformance would be very low, possibly negative. Accordingly, for this condition we may write  $J_{i,j}^{NR} < 0$ . Within a non reference group a more similar  $i - j$  pair would imply comparatively less disutility from non conformance. A non reference group is strong when the value of  $J_{i,j}^R$  is highly negative it is weak when that comparatively less negative.

Table 3.1 shows this characterization of  $J_{i,j}$  across the four conditions. Therefore, the overall

relationship among the four  $J_{i,j}$ s can be written as

$$J_{i,j}^{NR} < 0 \leq J_{i,j}^R \quad (3.3.6)$$

Assuming each of these sub-populations to be homogenous within themselves (i.e., the disutility from non-conformance between  $i$  and any other individual within the same condition is the same) and that these sub-populations are equal in size, we can re-write the social utility term (eq.3.3.5) for the Reference group sub-population as,

$$S(\omega_i, Z_i, \mu_i^e(\omega_{-i})) = J_{i,j}^R \omega_i E_i(\bar{\omega}_j) \quad (3.3.7)$$

$E_i(\bar{\omega}_j)$  denotes the subjective expectation of individual  $i$  of the population average and is equal to  $\left(\frac{I-1}{2}\right)^{-1} \sum_{j \neq i} E_i(\omega_j)$ . Similarly for the non reference groups, the subjective expectation of individual  $i$  of the corresponding population average is  $E_i(\bar{\omega}_k)$ . The social utility for the two groups taken together can be written as,

$$S(\omega_i, Z_i, \mu_i^e(\omega_{-i})) = \omega_i \left( J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k) \right) \quad (3.3.8)$$

The pay-off in eq.3.3.3, can therefore be written as,

$$V(\omega_i) = h_i + \omega_i \left( J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k) \right) + \varepsilon_i(\omega_i) \quad (3.3.9)$$

### Incorporation of Firm Action

Now that we have established the setting of consumer choice formation under the expectation of the choices of others, we will incorporate the effect of firm action in the pay-off.

**(a) In deterministic private utility:** Since any marketing action undertaken by the firm is aimed at convincing the consumer to buy the product, these actions should increase

the deterministic private utility from buying. Since  $h_i$  captures the deterministic private utility difference between buying and not buying, firm action increases  $h_i$  by some factor such that this difference is much higher or  $u(1, Z_i) \gg u(-1, Z_i)$ . We let this factor be  $\alpha_i$ .  $\alpha_i$  captures the combined effect of all marketing actions undertaken by the firm and increases the deterministic private utility by  $1 + \alpha_i$ . Accordingly,  $h_i(1 + \alpha_i)$  is proportional to the deterministic private utility difference between buying and not buying.

**(a) In social utility:** When individual  $i$  is interacting within a reference group, she has self consistent expectations from the members of that group. She believes that if the action of the firm increases her utility from choosing to buy the product, it affects the members of a reference group in a similar way and to the same extent. This is because of the inherent nature of reference groups that encourage shared views and opinions. Since both  $i$  and any  $j$  within a reference group are affected to the same extent, the disutility from conformance with any  $j$ ,  $J^R$  remains unaffected in the social utility term. using similar logical argument, we can say that within a non reference group, according to  $i$ 's expectation, firm actions affect the group members in a reverse way, i.e., if the firm action increases  $i$ 's utility from choosing to buy then it decreases the utility from choosing to buy for the non reference group members. As a result, the disutility from non conformance increases from before. Therefore,  $J^{NR}$  is incorporated as  $J^{NR}(1 - \alpha_i)$  in the social utility term.

### Equilibrium Formation

Assuming the errors  $\varepsilon_i(1)$  and  $\varepsilon_i(-1)$  are independent and extreme value distributed, the difference between the errors are logistically distributed, i.e.,

$$Prob(\varepsilon_i(-1) - \varepsilon_i(1) \leq x) = \frac{1}{1 + e^{-\beta x}}, \quad (\beta \geq 0) \quad (3.3.10)$$

The probability of individual  $i$ 's choice is given as

$$P(\omega_i) = \frac{\exp(\beta(u(\omega_i, Z_i) + \omega_i(J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)))}{\sum_{v_i \in \{-1,1\}} \exp(\beta(u(v_i, Z_i) + \omega_i(J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)))}$$

And the joint probability measure over all preferences is given by

$$P(\omega_i) = \frac{\exp(\sum_{i=1}^I (\beta u(\omega_i, Z_i) + \beta \omega_i (J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)))}{\sum_{v_i \in \{-1,1\}} \cdots \sum_{v_i \in \{-1,1\}} \exp(\beta u(v_i) + \beta v_i (J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)))}$$

Using the linearization of the deterministic private utility and the incorporation of firm action, the expected value of an individual's preference, conditional on her expectation of others' preferences is given as

$$\begin{aligned} E_i(\omega_i) &= 1 \cdot \frac{\exp(\beta h_i(1 + \alpha_i) + \beta(J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)(1 - \alpha_i)))}{\exp(\beta h_i(1 + \alpha_i) + \beta(J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)(1 - \alpha_i))) + \exp(-\beta h_i(1 + \alpha_i) - \beta(J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)(1 - \alpha_i)))} \\ &\quad - 1 \cdot \frac{\exp(-\beta h_i(1 + \alpha_i) - \beta(J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)(1 - \alpha_i)))}{\exp(\beta h_i(1 + \alpha_i) + \beta(J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)(1 - \alpha_i))) + \exp(-\beta h_i(1 + \alpha_i) - \beta(J_{i,j}^R E_i(\bar{\omega}_j) + J_{i,k}^{NR} E_i(\bar{\omega}_k)(1 - \alpha_i)))} \\ &= \tanh(\beta h(1 + \alpha) + \beta(J^R E_i(\bar{\omega}_j) + J^{R-NH} E_i(\bar{\omega}_k)(1 - \alpha))) \end{aligned} \quad (3.3.11)$$

By symmetry of expectations equations, at self-consistent equilibrium expectation of  $i$ 's choice is equal to the expectation of the average choice for the subset of the population that represents the reference group and is equal to the negative expectation of the average choice for the other subset that represents the non reference group. Therefore,

$$E_i(\omega_i) = E_i(\omega_j) = -E_i(\omega_k) \quad (3.3.12)$$

Hence a self-consistent, or rational expectations equilibrium will always exist and we conclude Proposition 1.

**Proposition 1** *When individuals choose in a non-cooperative setting and under firm actions according to eq.3.3.8, there exists at least one expected preference level  $m^*$  that emerges for a system of  $I$  interacting individuals such that*

$$m^* = \tanh(\beta h(1 + \alpha) + \beta(J^R - J^{NR}(1 - \alpha))m^*) \quad (3.3.13)$$

The solutions to eq.3.3.13 will denote the equilibrium value. If there exist multiple solutions to eq.3.3.13 that would indicate multiple equilibria. A equilibrium refers to the mean choice level that the largest percentage of individuals choose. In case of multiple equilibria, there are

multiple mean choice levels.

From the properties of  $\tanh(\cdot)$  function, we derive the following propositions where we list the system properties.

**Proposition 2**      *When an individual is privately indifferent between buying and not buying ( $h_i = 0$ ),*

(a) *If the reference group is strong and the non reference group is weak, there are three equilibria of average choices- one positive, one negative and one zero. Increase in firm actions cannot change the equilibria formed.*

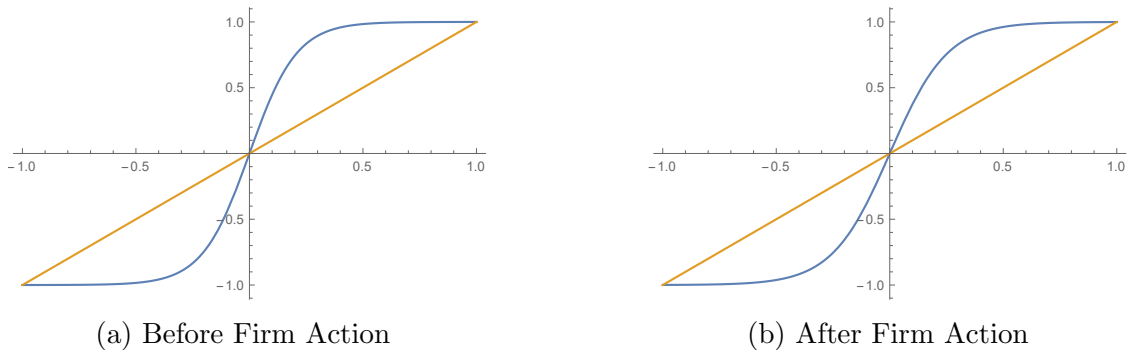


Figure 3.1: Average Choice Formation: Proposition 2a

(b) *If the reference group is weak and the non reference group is weak, there is unique zero equilibrium of average choices. Increase in firm actions cannot change the equilibrium formed.*

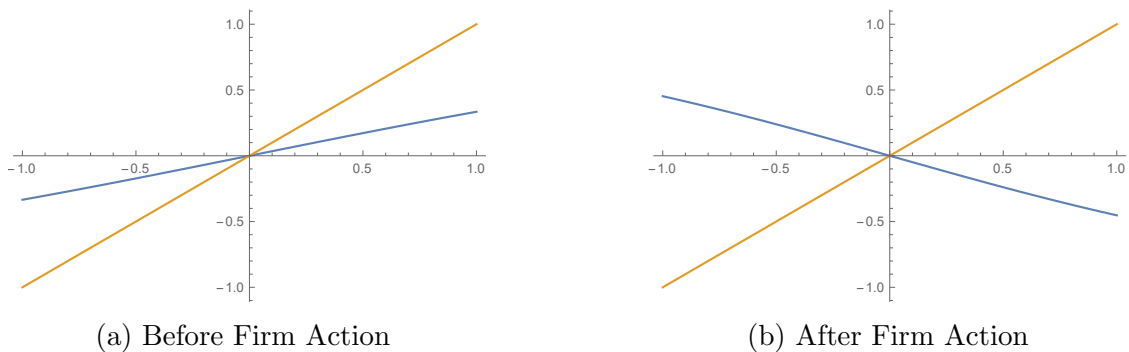


Figure 3.2: Average Choice Formation: Proposition 2b

(c) *If the reference group is strong and the non reference group is strong, there are three equilibria of average choices- one positive, one negative and one zero. Increase in*

*firm actions changes the equilibrium to a unique zero.*

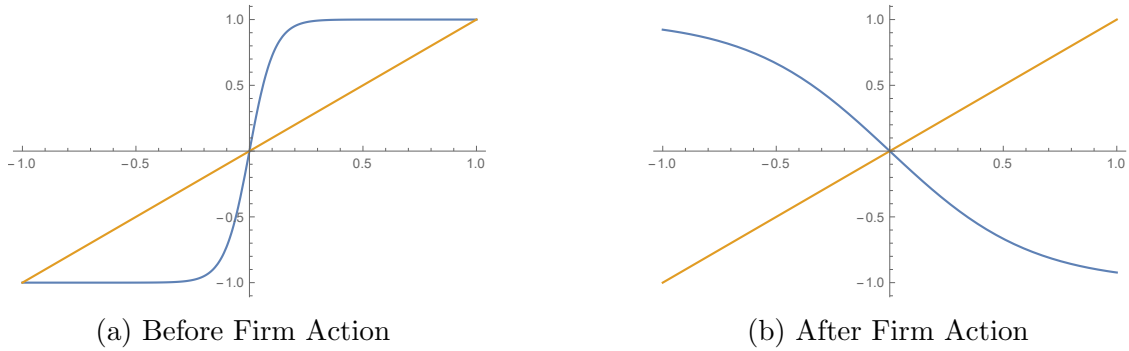


Figure 3.3: Average Choice Formation: Proposition 2c

*(d) If the reference group is weak and the non reference group is strong, there are three equilibria of average choices- one positive, one negative and one zero. Increase in firm actions changes the equilibrium to a unique zero.*

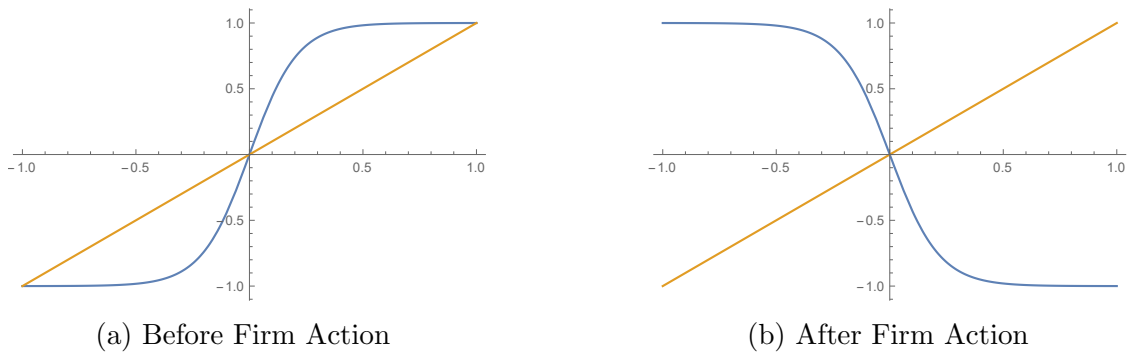
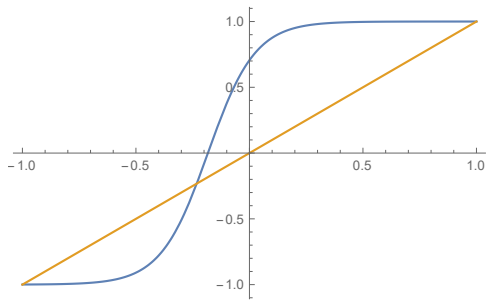


Figure 3.4: Average Choice Formation: Proposition 2d

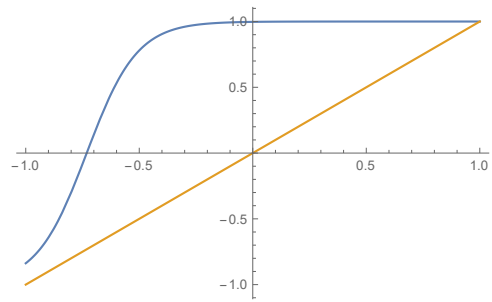
From proposition 2 we can see that firm actions can be detrimental whenever individual  $i$  is privately indifferent between buying and not buying and the non reference group is strong. In these cases, without firm actions there was a possibility of the positive majority choice (pertaining to the positive equilibrium points in Figures 3.3a and 3.4a). But with firm action, there is only one possible equilibrium where all consumers are indifferent (unique zero equilibrium in Figures Figure 3.3b and 3.4b). In such scenarios firm actions are self-defeating.

**Proposition 3**      *When an individual is privately prefers to buy ( $h_i > 0$ ),*

*(a) If the reference group is strong and the non reference group is weak, there are three equilibria of average choices- one positive and two negatives. Increase in firm actions changes the equilibrium to a unique positive.*



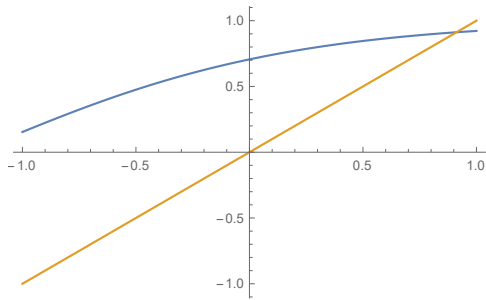
(a) Before Firm Action



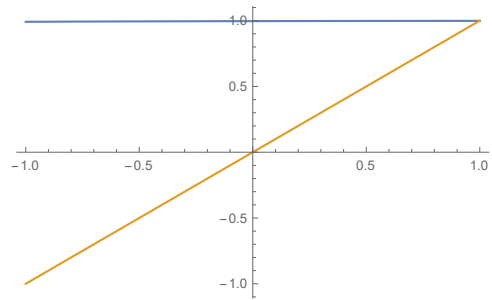
(b) After Firm Action

Figure 3.5: Average Choice Formation: Proposition 3a

(b) *If the reference group is weak and the non reference group is weak, there is unique positive equilibrium of average choices. Increase in firm actions cannot change the equilibrium formed.*



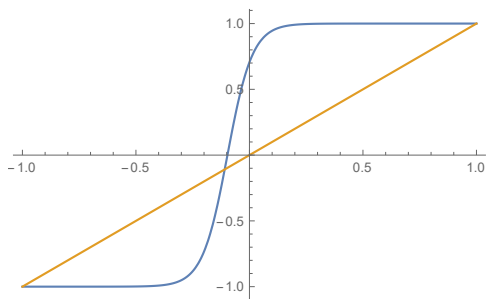
(a) Before Firm Action



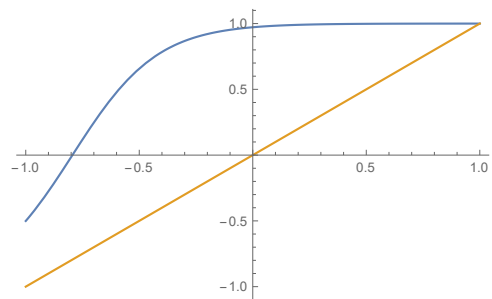
(b) After Firm Action

Figure 3.6: Average Choice Formation: Proposition 3b

(c) *If the reference group is strong and the non reference group is strong, there are three equilibria of average choices- one positive and two negatives. Increase in firm actions changes the equilibrium to a unique positive.*



(a) Before Firm Action



(b) After Firm Action

Figure 3.7: Average Choice Formation: Proposition 3c

(d) *If the reference group is weak and the non reference group is strong, there are three*

*equilibria of average choices- one positive and two negatives. Increase in firm actions changes the equilibrium to a unique positive.*

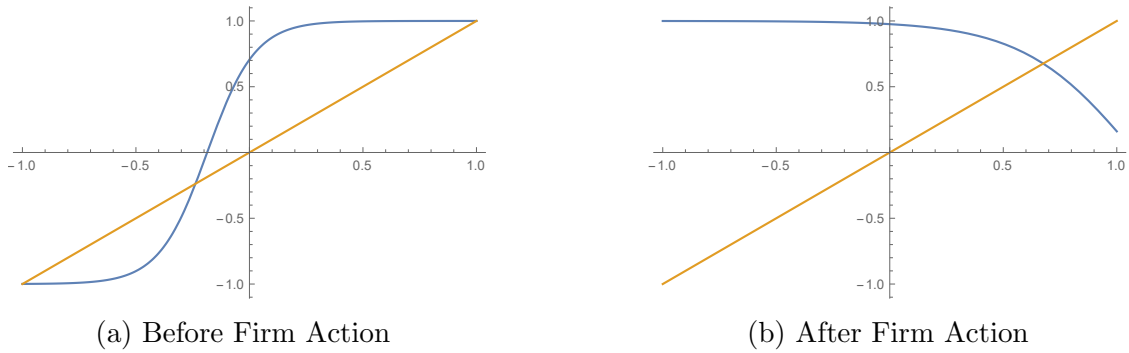


Figure 3.8: Average Choice Formation: Proposition 3d

From proposition 3 we see that firm action is always beneficial to the firm under any condition of reference and non reference groups. Firm action causes majority of the consumers to choose to buy (unique positive equilibria in Figures 3.5b, 3.6b, 3.7b and 3.8b).

**Proposition 4**      *When an individual is privately prefers not to buy ( $h_i < 0$ ),*

*(a) If the reference group is strong and the non reference group is weak, there are three equilibria of average choices- two positives and one negative. Increase in firm actions changes the equilibrium to a unique positive.*

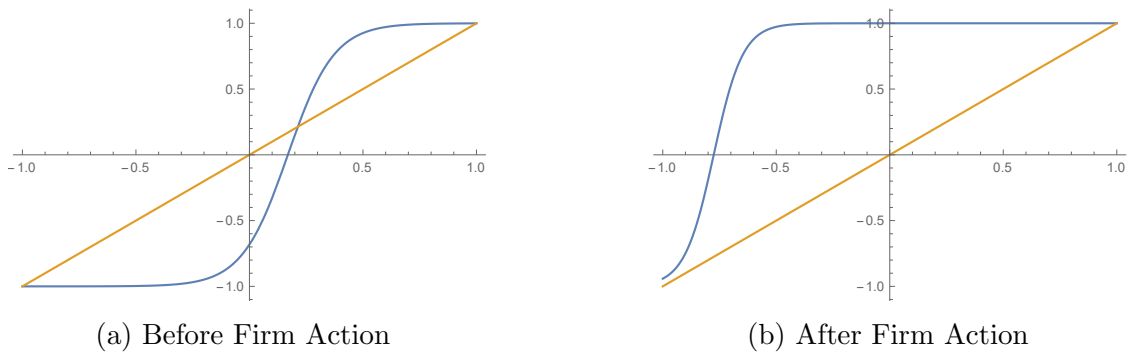


Figure 3.9: Average Choice Formation: Proposition 4a

*(b) If the reference group is weak and the non reference group is weak, there is unique negative equilibrium of average choices. Increase in firm actions changes the equilibrium to a unique positive.*

*(c) If the reference group is strong and the non reference group is strong, there are three equilibria of average choices- two positives and one negative. Increase in firm actions*

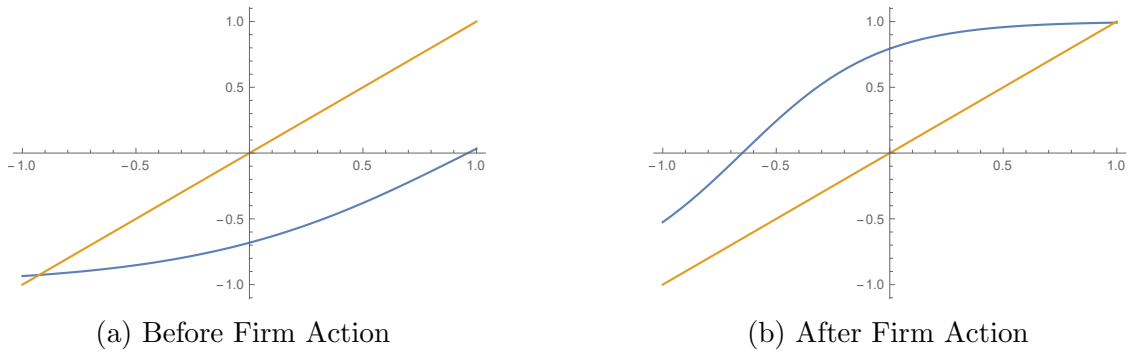


Figure 3.10: Average Choice Formation: Proposition 4b

*changes the equilibria to two negatives and one positive.*

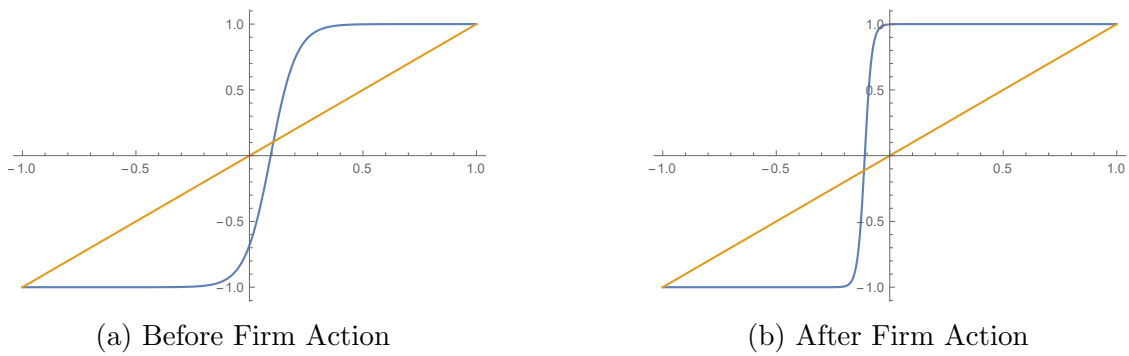


Figure 3.11: Average Choice Formation: Proposition 4c

*(d) If the reference group is weak and the non reference group is strong, there are three equilibria of average choices- two positives and one negative. Increase in firm actions changes the equilibria to two negatives and one positive.*

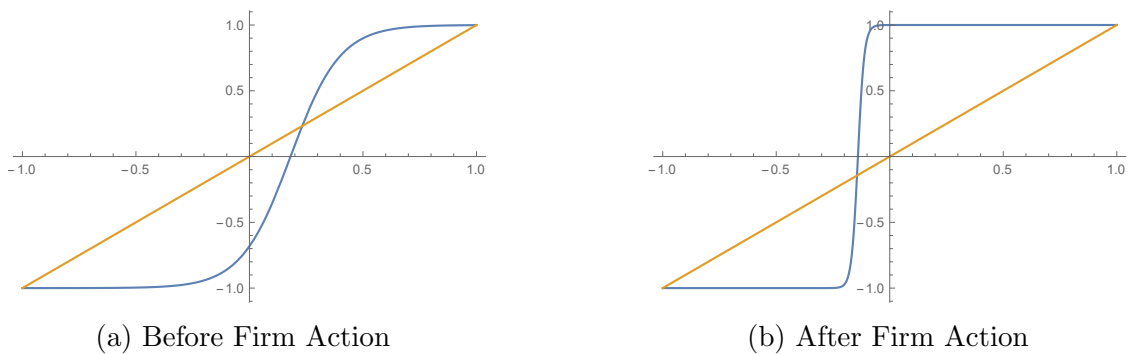


Figure 3.12: Average Choice Formation: Proposition 4d

Finally from proposition 4, it emerges that firm actions can be detrimental whenever individual  $i$  is privately prefers not to buy and the non reference group is strong. In these cases, without firm actions there are two possibilities of positive majority choice (pertaining to the two positive

equilibrium points in Figure 3.11a and 3.12a). But with firm action, that changes to one possibility of positive majority choice (Figure 3.11b and 3.12b). Again in these scenarios firm actions are self-defeating.

### 3.4 Econometrics

To help identify the parameters, we provide a brief explanation of the econometric explanation of our model. We shall parametrize the private utility component, the disutilities from non-conformance within reference groups and firm actions and then derive the likelihood for the binary preferences following the logistic density function. This is empirically feasible because the error terms in our utility specification follows the extreme-valued distribution.  $h_i$  is proportional to the difference in deterministic private utilities between  $u(1, Z_i)$  and  $u(-1, Z_i)$  where  $Z_i$  captures the individual characteristics. We assume that there exists an  $r$ -length vector of individual specific observables  $Z_i$ , such that

$$h_i = c + c'Z_i \quad (3.4.1)$$

The disutility from non conformance within a reference group and from conformance with a non reference group can be captured by a vector which is a difference between  $Z_i$  and  $Z_{-i}$ .  $Z_{-i}$  is the average of individual characteristics of all individuals other than  $i$  in the reference or non reference group. Accordingly we can write,

$$J_{i,j} = d + d'(Z_i - Z_{-i}), \quad \text{for reference group} \quad (3.4.2)$$

$$J_{i,j} = k - k'(Z_i - Z_{-i}), \quad \text{for non reference group} \quad (3.4.3)$$

Finally, as already discussed under §2, firm action can include different strategies undertaken by firms to drive consumer preferences towards a desired direction.  $A_i$  represents a  $t$ -length vector of all such strategies which are distinct and generate utility for the consumer in her preference formation process.

$$\alpha_i = p + p'A_i \quad (3.4.4)$$

Therefore, the likelihood can be written as follows:

$$\begin{aligned}
& L(\omega_I | Z_i, (Z_i - Z_{-i}), A_i, E(\omega_{-i}) \forall i) \\
&= \Pi_i \text{Prob}(\omega_i = 1 | Z_i, (Z_i - Z_{-i}), A_i, E(\omega_{-i}))^{(1+\omega_i)/2} \cdot \text{Prob}(\omega_i = -1 | Z_i, (Z_i - Z_{-i}), A_i, E(\omega_{-i}))^{(1-\omega_i)/2} \\
&\sim \Pi_i (\exp(\beta c + \beta c' Z_i + \beta(d + d'(Z_i - Z_{-i}) + (1 - p + p' A_i)(k - k'(Z_i - Z_{-i}))) E(\omega_{-i}))^{(1+\omega_i)/2} \\
&\quad \times (\exp(-\beta c - \beta c' Z_i - \beta(d + d'(Z_i - Z_{-i}) + (1 - p + p' A_i)(k - k'(Z_i - Z_{-i}))) E(\omega_{-i}))^{(1-\omega_i)/2}
\end{aligned}$$

We normalize  $\beta = 1$ , without loss of generality. Even with the normalizations of  $\beta$ , identification remains an issue in our model due to the presence of the conditional probability measure that one consumer places on the choices of the others  $E(\omega_{-i})$ , which incorporates rational expectations. To address this identification issue, we would proceed as discussed in Brock and Durlauf (2001) by assuming conditional distributions of regressors/vectors. Therefore, we need to assume

$$\begin{aligned}
E(\omega_{-i}) &= \int \tanh(c + c' Z + d + d'(Z - Z_{-i}) + (1 - p + p' A)(k - k'(Z - Z_{-i}))) E(\omega_{-i}) \\
&\quad dF_{(Z_i | (Z_i - Z_{-i}), A_i)} dF_{(Z_i - Z_{-i} | Z_i, A_i)} dF_{(A_i | Z_i, (Z_i - Z_{-i}))}
\end{aligned} \tag{3.4.5}$$

where,  $dF_{(Z_i | (Z_i - Z_{-i}), A_i)}$  denotes the conditional distribution of  $Z_i$  given  $(Z_i - Z_{-i})$ , and  $A_i$  and so forth. The above econometric specification gives us a broad idea about the method for estimating the parameters of our theoretical model, which is relatively straight-forward given the distributional assumptions which we have imposed on the random component of our utility function specification.

Although our model of firm actions identifies both scenarios where firm action bears undesirable consequences for the firm and where it stands as desired strategic action, it does not address a few issues. First, the model that we have developed is static in time. The model posits social-interactions as a single period game. In a dynamic setting, the individuals observe, at any random period, the game played by the other individuals and then adopt a new strategy in response to the game played by others. When all individuals choose to respond in this fashion, an overall dynamic framework emerges. However, for long time horizons, large aberrations will

occur, and the pattern or sample path of average preferences can diverge from the mean field approximation. Second, since our model is not dynamic, it does not incorporate the learning of the individuals based on prior experience with similar products. When individuals have prior experiences with similar products, they have a reference point to judge the likeability of a product which is currently under consideration. In presence of such a reference, the private utility component can be stronger. Also, this reference can be a moving average which is conditioned with each complete preference formation process. Lastly, our model estimates preference formation as between choosing and not choosing (binary choice model). However, consumers can be faced with multiple choices (for e.g. different donation amounts for charity). When consumers are faced with a set of choices, the more the number of consumers whose behavior is determined by the random utility component, the lesser are the chances of social utility affecting the multiplicity of self-consistent equilibria. This is because, as more consumers are guided by the randomness in their decision, to have rational expectations of others' choices, is a difficult assumption to impose on the model. There is also a possibility of accruing negative social utility with the unchosen but available choices. These are worthy avenues of future research.

### **3.5 Concluding Remarks**

We present a model of majority choice outcomes in a community of socially interacting consumers, when firms try to influence consumers to buy. We find that while consumers' private utilities from a choice have a significant impact on the final choice equilibria for the community, the expectation based social utility plays an equally important role in deciding the impact of the firm actions. We find that firm actions are self-defeating in some cases when the consumers are either privately indifferent between buying and not buying or when the consumers privately prefer not to buy. Under these two scenarios the presence of strong non reference groups engenders harmful effects of firm actions for the firms. However, when consumers privately prefer to buy, firm actions are always beneficial for the firm. This is problematic because firms need to undertake marketing actions primarily to convert consumers who are not willing to buy or are undecided about the products. Our predictions can be empirically tested using either experimental data or data collected from online forums, discussion boards or firm hosted threads

as our findings are not constrained by online or offline interaction environment.

# Conclusions

The objective of this dissertation was to understand two different types of decision making processes and their outcomes in the presence of social interactions. One of the processes was investigated under uncertainty and the other was studied under certainty. For the decision making process under uncertainty, I looked at pricing decisions of buyers and sellers under impending regime shift. Impending regime shifts are characterized by a prevailing uncertainty in the underlying state of the world that is susceptible to change. Under such impending regime shifts, I first explain the pricing behavior of decision makers as a combination of system neglect bias in probability judgments regarding the impending shift and risk attitudes of the decision maker. My model predictions and analysis in chapter 1 suggest that pricing decisions under impending regime shifts exhibit significantly more underreaction when the environment is unstable and signals are precise. This finding is robust to framing (i.e., buyers vs. sellers), desirability of regime shift (i.e., dreaded regime shift vs. desirable regime shift) and domain (i.e., domain of losses vs. gains). In chapter 2 I use this model to further study if a gap exists in the pricing decisions of buyers and sellers, i.e., if the gap between willingness to pay and willingness to accept is significant. For this study, I elicit pricing judgments of buyer-seller pairs who also learn each other's pricing decisions over multiple rounds of trading. The findings confirm the existence of a significant gap in willingness to pay and willingness to accept. This gap is present regardless of the environment, i.e., stable environment with noisy signals and unstable environment with precise signals. In addition, this gap exists regardless of the desirability of the regime shift. Furthermore, I examine if the gap between willingness to pay and willingness to accept diminishes with learning. Previous studies have found evidence both in favor and against this result, albeit not in the setting of impending regime shifts. I do not find any confirmatory evidence towards a significant impact of learning on the gap between willingness

to pay and willingness to accept. However, I find that overreaction in pricing judgments is reduced for stable environments with noisy signals and underreaction in pricing judgments is increased for unstable environments with precise signals with learning for both buyers and sellers. This effect is more pronounced for unstable environments with precise signals. Taken together, these findings contribute to the literature on pricing decisions under uncertainty and specifically to the stream of research relating to system neglect hypothesis and prospect theory.

The second process of decision making was studied in the context of purchase decisions for a group of interacting consumers. The purchase decisions are binary (buy or not buy) and the utility attached to the decisions incorporates private and social utility components that account for the effect of personal preference and social preference towards a commodity. The social utility component is informed by the expectation of purchase decisions of other decision makers and includes reference group effects. The objective of this analytical exercise was to derive decision equilibrium that would denote the average or majority decisions of the group of interacting decision makers. Results of this analysis are particularly useful for firms since they attempt to intervene online interaction platforms with marketing actions to elicit favorable decisions from consumers towards their products. Therefore, in my analytical model the effect of firm actions was also parametrized and decision equilibrium for the group was re-evaluated. Contrary to expectations, the findings suggest that firm actions are self defeating under certain scenarios as the altered decision equilibrium is worse ,i.e., average “not buy” decisions or indecisions emerge in the equilibria. This specifically occurs when the decision makers are privately indifferent between buying and not buying. It also occurs when the decision maker’s private preference is to “not buy” and only non-reference groups are present. These findings can encourage the firm to understand the social structure of an interacting group of potential consumers and determine when it is appropriate to intervene with marketing actions. The findings of this study further advance the literature on social interaction based choice formation and also lays out testable propositions regarding the effects of firm actions on purchase decisions of interacting individuals.

# Conclusiones

El objetivo de la presente tesis era comprender dos tipos diferentes de procesos de toma de decisiones y sus resultados en presencia de interacciones sociales. Uno de los procesos se investigó bajo la incertidumbre y el otro se estudió bajo la certidumbre. Para el proceso de toma de decisiones en condiciones de incertidumbre, he estudiado las decisiones de fijación de precios de compradores y vendedores ante la inminencia de un cambio de régimen. Los cambios de régimen inminentes se caracterizan por la incertidumbre reinante en el estado subyacente del mundo que es susceptible de cambiar. En tales cambios de régimen inminentes, explico en primer lugar el comportamiento de los responsables de la fijación de precios como una combinación del sesgo de abandono del sistema en los juicios de probabilidad sobre el cambio inminente y las actitudes hacia el riesgo del responsable de la toma de decisiones. Las predicciones de mi modelo y el análisis realizado en el capítulo 1 sugieren que las decisiones de fijación de precios en caso de cambios de régimen inminentes presentan una reacción significativamente más baja cuando el entorno es inestable y las señales son precisas. Esta conclusión es robusta en cuanto al marco (es decir, compradores frente a vendedores), la conveniencia del cambio de régimen (es decir, cambio de régimen temido frente a cambio de régimen deseable) y el dominio (es decir, dominio de pérdidas frente a ganancias). En el capítulo 2 utilizo este modelo para estudiar más a fondo si existe una brecha en las decisiones de precios de compradores y vendedores; es decir, si la brecha entre la disposición a pagar y la disposición a aceptar es significativa. Para este estudio, obtengo los juicios sobre los precios de las parejas de compradores y vendedores que también van conociendo las decisiones de precios de los demás a lo largo de múltiples rondas de negociación. Los resultados confirman la existencia de una brecha significativa en la disposición a pagar y la disposición a aceptar. Esta brecha está presente independientemente del entorno, es decir, entorno estable con señales ruidosas y entorno inestable con señales precisas. Además, esta

brecha existe independientemente de la conveniencia del cambio de régimen. Además, examino si la brecha entre la disposición a pagar y la disposición a aceptar disminuye con el aprendizaje. Estudios anteriores han encontrado pruebas tanto a favor como en contra de este resultado, aunque no en el contexto de cambios de régimen inminentes. No encuentro ninguna prueba que confirme un impacto significativo del aprendizaje en la diferencia entre la disposición a pagar y la disposición a aceptar. Sin embargo, sí vemos que la reacción exagerada en los juicios sobre los precios se reduce en entornos estables con señales ruidosas y la reacción insuficiente en los juicios sobre los precios se intensifica en entornos inestables con señales precisas con aprendizaje, tanto para los compradores como para los vendedores. Este efecto es más pronunciado en entornos inestables con señales precisas. En conjunto, estos resultados contribuyen a la literatura sobre las decisiones de precios en condiciones de incertidumbre y, en concreto, a la corriente de investigación relacionada con la hipótesis del abandono del sistema y la teoría prospectiva.

El segundo proceso de toma de decisiones se estudió en el contexto de las decisiones de compra de un grupo de consumidores que interactúan. Las decisiones de compra son binarias (comprar o no comprar) y la utilidad asociada a las decisiones incorpora componentes de utilidad privada y social que dan cuenta del efecto de la preferencia personal y la preferencia social hacia un producto. El componente de utilidad social se basa en la expectativa de las decisiones de compra de otros decisores e incluye los efectos del grupo de referencia. El objetivo de este ejercicio analítico era derivar el equilibrio de decisión que denotaría las decisiones medias o mayoritarias del grupo de decisores que interactúan. Los resultados de este análisis son especialmente útiles para las empresas, ya que intentan intervenir en las plataformas de interacción online con acciones de marketing para inducir decisiones favorables de los consumidores hacia sus productos. Por tanto, en mi modelo analítico también se parametrizó el efecto de las acciones empresariales y se reevaluó el equilibrio de decisión para el grupo. Al contrario de lo que se esperaba, los resultados sugieren que las acciones empresariales son contraproducentes en determinados escenarios, ya que el equilibrio de decisión alterado es peor, es decir, surgen decisiones medias de “no comprar” o indecisiones en los equilibrios. Esto ocurre específicamente cuando los responsables de la toma de decisiones son indiferentes en privado entre comprar y no comprar. También ocurre cuando la preferencia privada de los responsables de la toma de decisiones es

“no comprar” y sólo hay grupos de no referencia. Estos resultados pueden animar a la empresa a comprender la estructura social de un grupo de consumidores potenciales que interactúa y determinar cuándo es conveniente intervenir con acciones de marketing. Los resultados de este estudio suponen un avance en la literatura sobre la formación de la elección basada en la interacción social y también establecen propuestas comprobables sobre los efectos de las acciones empresariales en las decisiones de compra de los individuos que interactúan.



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# Appendices



# Appendix A

## A.1 A model for sellers under dreaded regime shift in the insurance market setting

Sellers in the insurance market setting report their pricing decisions (i.e. willingness to accept) for an insurance contract that would cover the losses incurred in the current period if the regime is the “Bad” regime. Similar to the task of buyers, the task requires sellers to detect if and when the underlying regime changes.

In each round, sellers are endowed with an insurance contract that protects them from incurring potential losses in that round; this insurance contract expires at the end of the round. Thus, sellers face the decision depicted in Figure A.1 when they are contemplating their pricing decision,  $S_t$ , for the insurance contract. The probability that the “Bad” regime prevails is equal to the probability of regime shift in the dreaded regime shift condition. There is no loss in the “Good” regime and there is a sure loss of \$1 in the “Bad” regime.

As before, we define first the *empirical change*:  $\Delta S_t^e = S_t^e - S_{t-1}^e$ , where  $S_t^e \geq 0$  is the empirical (reported) pricing decision for insurance in period  $t$ . We also define the *Bayesian risk-neutral change*:  $\Delta S_t^b = EL_t^b - EL_{t-1}^e = p_t^b - p_{t-1}^e$  because the price that a Bayesian risk-neutral DM would accept for the insurance contract is equal to the expected loss without the insurance.

We take  $\Delta S_t^e - \Delta S_t^b$  as our measure of under- and overreaction in pricing judgments for sellers and rewrite it to separate the effects of the change in risk premium and system neglect as

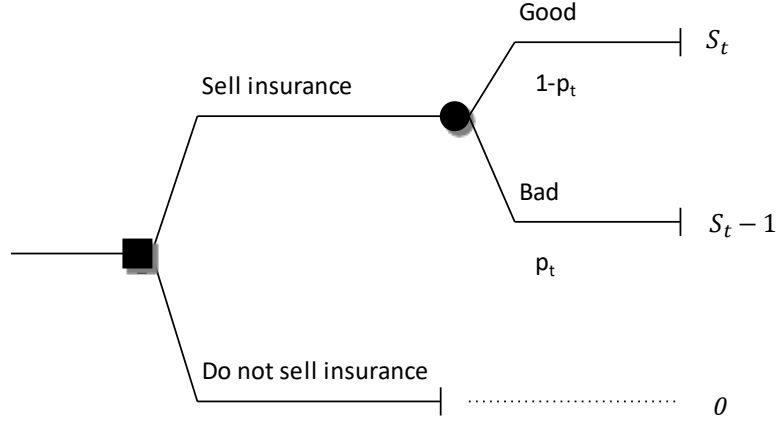


Figure A.1: Lottery insurance sellers face under a dreaded regime shift,  $P(\text{regime shift in period } t) = p_t$ .

follows:

$$\Delta S_t^e - \Delta S_t^b = S_t^e - S_{t-1}^e - (EL_t^b - EL_{t-1}^e) = \underbrace{S_t^e - EL_t^e - (S_{t-1}^e - EL_{t-1}^e)}_{\text{change in risk premium}} + \underbrace{(EL_t^e - EL_t^b)}_{\text{effect of system neglect}} . \quad (\text{A.1.1})$$

We analyze the change in risk premium and the effect of system neglect separately and then make predictions about their cumulative effect.

*Effect of system neglect:* The effect of system neglect,  $EL_t^e - EL_t^b$  was analyzed in §1.2.

*Change in risk premium:* To analyze the change in risk premium, we continue to use the value function in (1.2.5) and the probability weighting function in (1.2.6). First, we note that price  $S_t$  that makes the seller indifferent between selling and not selling the insurance satisfies the following:

$$0 = w(p_t^e)V(S_t - 1) + (1 - w(p_t^e))V(S_t),$$

which implies  $\left(\frac{S_t}{1-S_t}\right)^\theta = \lambda\delta \left(\frac{p_t^e}{1-p_t^e}\right)^\gamma$ . Using this equality we can write

$$S_t - EL_t^e = \frac{y_t}{1 + y_t} - p_t^e,$$

where  $y_t = (\delta\lambda)^{\frac{1}{\theta}} \left(\frac{p_t^e}{1-p_t^e}\right)^{\frac{\gamma}{\theta}}$ . Thus,  $S_t - EL_t^e$  depends on the parameters  $\theta$ ,  $\gamma$  and on the product  $\delta\lambda$ . Taking period  $t - 1$  without loss of generality, we present the risk premium as a function of

the probability of regime shift in period  $t-1$  (which is equal to the probability of “Bad” state if the regime shift is dreaded). We use  $\theta = 1.14$  and  $\gamma = 0.7$  consistent with §1.2 and display the risk premium for different values of  $\delta\lambda$ , which are consistent with estimates from the literature for these parameters, in Figure A.2. We expect the DMs to be generally risk averse except for very high probabilities of regime shift.

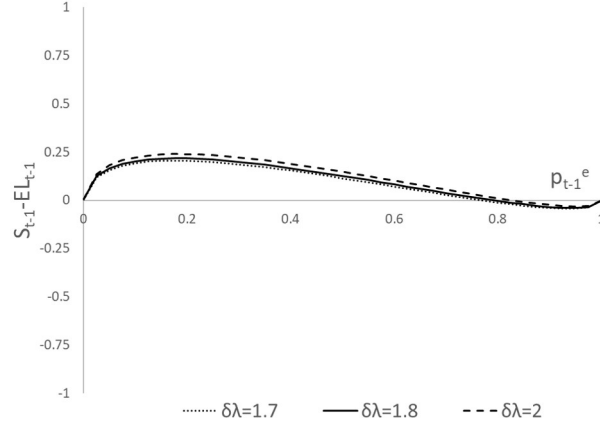


Figure A.2: Risk premium,  $S_{t-1} - EL_{t-1}^e$ , as a function of probability of regime shift  $p_{t-1}$ .

Next, we write the change in risk premium in reaction to a signal indicative of regime shift. Because such a signal increases the probability of regime shift in Figure A.2, we are looking at the differences in risk premia going from left to right. The change in risk premium can be written as follows:

$$S_t - EL_t^e - (S_{t-1} - EL_{t-1}^e) = \frac{y_t}{1 + y_t} - p_t^e - \left( \frac{y_{t-1}}{1 + y_{t-1}} - p_{t-1}^e \right) \quad (\text{A.1.2})$$

where  $y_t = (\delta\lambda)^{\frac{1}{\theta}} \left( \frac{p_t^e}{1-p_t^e} \right)^{\frac{\gamma}{\theta}}$  as above. To see how this difference behaves as a function of the prior empirical probability,  $p_{t-1}^e$ , we use (1.2.3) to calculate  $p_t^e$  as a function of  $p_{t-1}^e$  and obtain Figure A.3. For a Bayesian risk-neutral DM, note that risk premium,  $S_t - EL_t^e$ , for any round  $t$  is always equal to 0 regardless of the probability, hence the difference,  $S_t - EL_t - (S_{t-1} - EL_{t-1})$  would always be equal to 0. However, Figure A.3 predicts that DMs become more risk seeking ( $S_t - EL_t - (S_{t-1} - EL_{t-1}) < 0$ ) after observing a signal indicative of regime shift except when the prior probability is very low. This pattern is qualitatively the same as the pattern we observe for buyers in Figure 1.5.

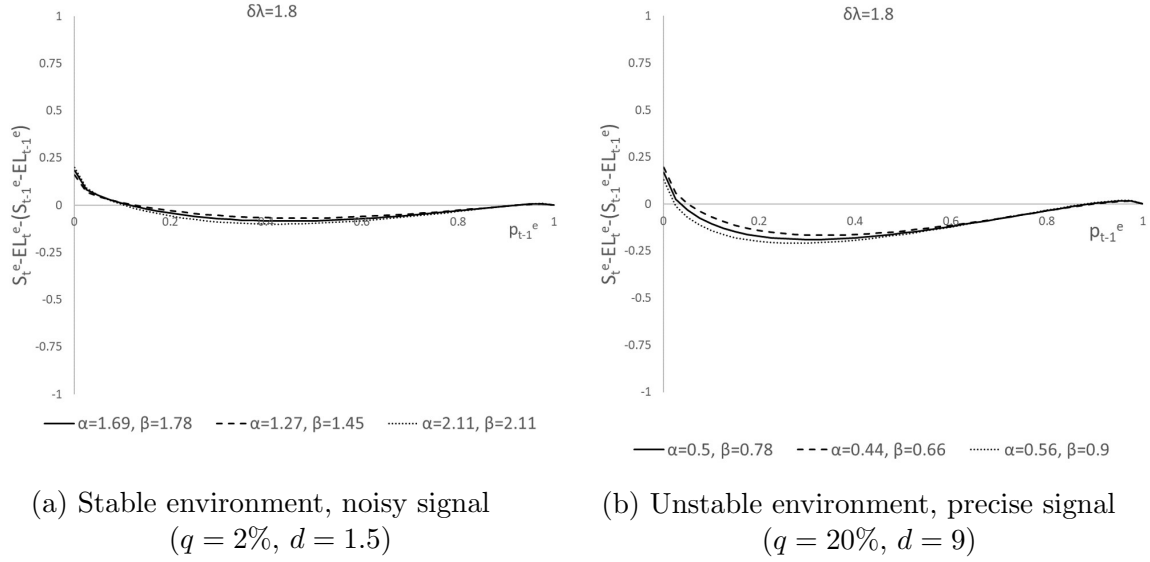


Figure A.3: Change in the risk premium as a function of prior probability of regime shift,  $p_{t-1}^e$ , for sellers

Using the decomposition in (A.1.1) and using the equations for each component in (1.2.4) and (A.3.2), we obtain specific predictions for under- and overreaction in pricing judgments and present them graphically in Figure A.4 as a function of the prior probability of regime shift  $p_{t-1}^e$ . We obtained the plots in Figure A.4 by adding up the graphs from Figures 1.3 and A.3. The predictions for sellers is qualitatively the same as the predictions for buyers in § 1.2.

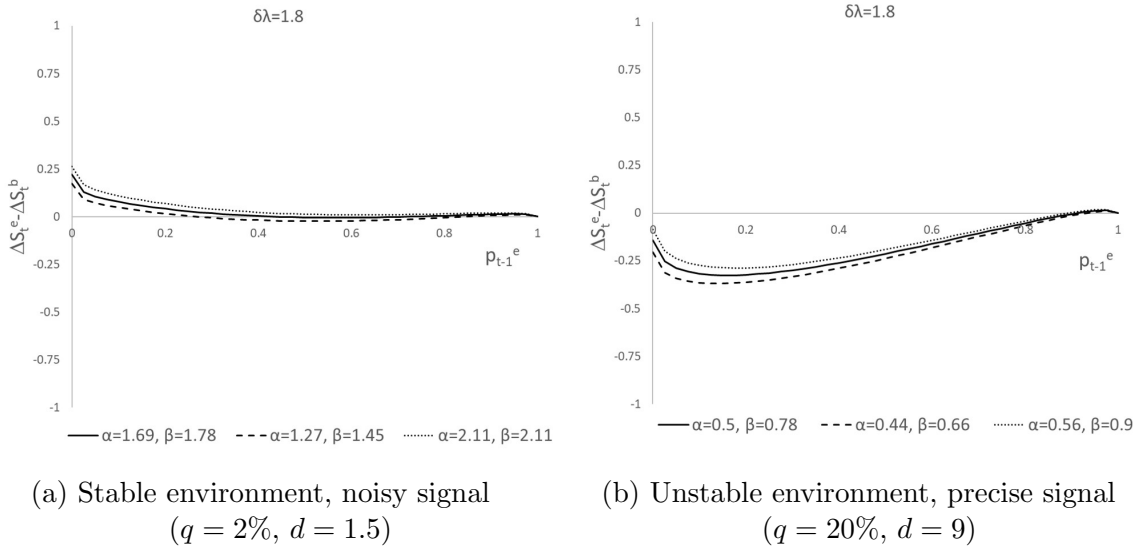


Figure A.4: Under- and overreaction in pricing decisions for sellers

## A.2 A model for buyers under desirable regime shift in the insurance market setting

We present our model for buyers in this section. When the regime shift is desirable, and the DMs contemplate buying an insurance, they face the lottery in Figure A.5. Because the regime shifts from “Bad” to “Good” in this setting, the probability of regime shift,  $p_t$ , is equal to the probability of the “Good” state.

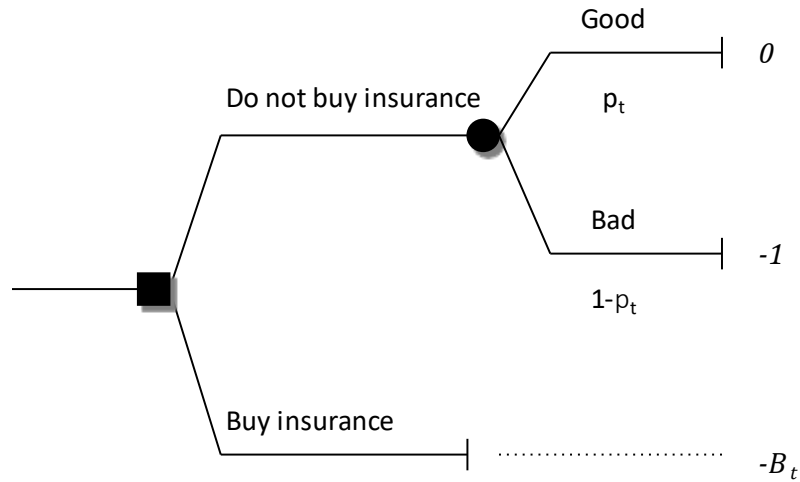


Figure A.5: Insurance buying decision, desirable regime shift

Consider our under-/overreaction measure  $\Delta B_t^e - \Delta B_t^b = B_t^e - B_{t-1}^e - (EL_t^b - EL_{t-1}^e)$ . Interpreting this measure requires care in the desirable regime shift setting. Note that we have  $B_t^e - B_{t-1}^e < 0$  and  $EL_t^b - EL_{t-1}^e < 0$  because both the empirical pricing decision for the insurance contract and the expected loss for a Bayesian risk-neutral agent decrease upon receipt of a signal indicative of a desirable regime shift. Then,  $\Delta B_t^e - \Delta B_t^b > 0$  implies that the decrease in empirical pricing decisions is higher than the decrease in the Bayesian expected loss which indicates overreaction. Using a similar argument, one can see that  $\Delta B_t^e - \Delta B_t^b < 0$  indicates underreaction.

We can again study the effect of impending regime shifts on the two components in (2.3.2) separately and then make predictions about their cumulative effect.

*Effect of system neglect.* Because the expected loss is equal to  $(1 - p_t)$  when the regime shift is

desirable, we have

$$EL_t^e - EL_t^b = (1 - p_t^e) - (1 - p_t^b) = p_t^b - p_t^e = \frac{dr_{t-1}^e + dq}{1 - q + dr_{t-1}^e + dq} - \frac{d^\beta r_{t-1}^e + d^\beta \alpha q}{1 - \alpha q + d^\beta r_{t-1}^e + d^\beta \alpha q} \quad (\text{A.2.1})$$

where  $r_{t-1}^e = \frac{p_{t-1}^e}{1 - p_{t-1}^e}$ . Plotting this difference as a function of the prior probability of regime shift ( $p_{t-1}^e$ ) as before, we obtain the plots in Figure A.6. These plots are the mirror images of plots in Figure 1.3 around the  $x$ -axis because we have  $EL_t^e - EL_t^b = p_t^e - p_t^b$  in the dreaded regime shift condition.

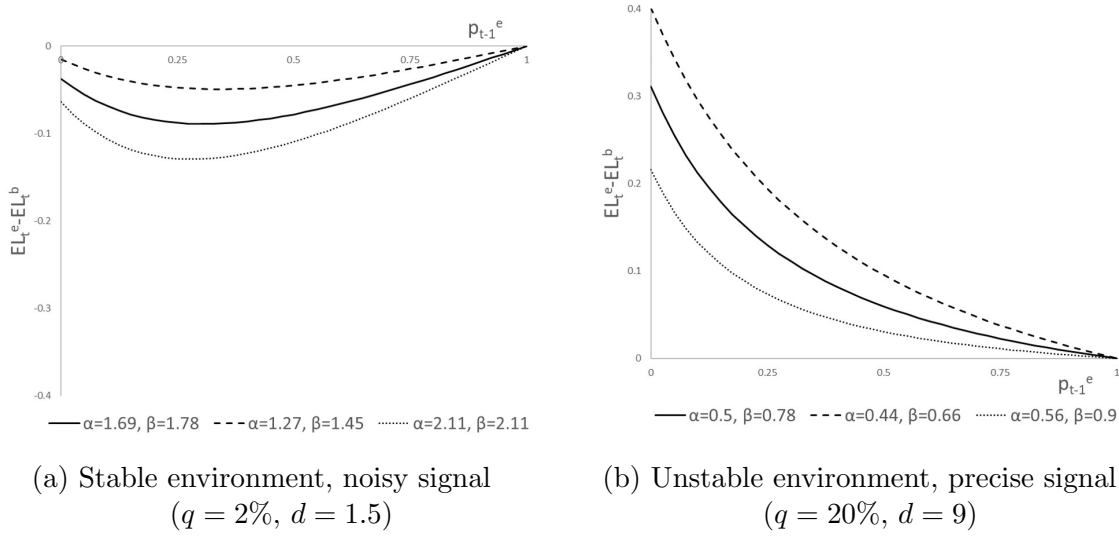


Figure A.6:  $EL_t^e - EL_t^b$  as a function of prior probability of regime shift ( $p_{t-1}^e$ ) for desirable regime shifts

*Change in risk premium:* To calculate the risk premium,  $B_t - EL_t$ , we note that the price  $B_t$  that makes a DM indifferent between buying and not buying the insurance contract when the their probability of the “Bad” state is  $1 - p_t$  satisfies the following equation:

$$V(-B_t) = w(1 - p_t)V(-1) + (1 - w(1 - p_t))V(0) = -\lambda w(1 - p_t),$$

where the second equality follows because  $V(-1) = -\lambda$  and  $V(0) = 0$ . Consequently, we obtain  $B_t^\theta = w(1 - p_t)$ . Using this equality we can describe the DM’s risk premium as follows:

$$B_t - EL_t = w(1 - p_t)^{\frac{1}{\theta}} - (1 - p_t) = \left( \frac{\delta(1 - p_t)^\gamma}{\delta(1 - p_t)^\gamma + p_t^\gamma} \right)^{\frac{1}{\theta}} - (1 - p_t) \quad (\text{A.2.2})$$

We again focus on period  $t-1$  without loss of generality and plot the risk premium as a function of the probability of regime shift. If the probability of regime shift is low, which implies that the probability of the “Bad” state is high, prospect theory predicts risk seeking behaviour. If the probability of regime shift is high, which implies that the probability of “Bad” state is low, prospect theory predicts risk averse behaviour. Thus, Figure A.7 is consistent with the fourfold risk aversion pattern in prospect theory.

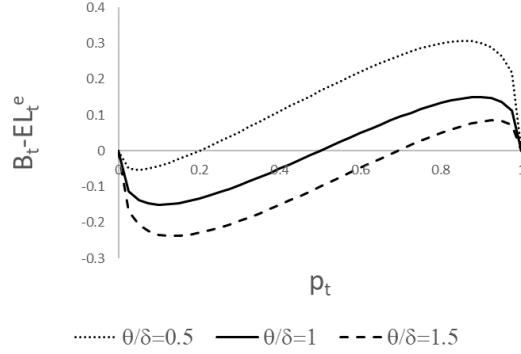


Figure A.7: Risk premium as a function of probability of regime shift,  $p_{t-1}^e$  when the regime shift is desirable.

This figure is the mirror image of Figure 1.4 with respect to  $p_{t-1} = 0.5$  line, recall that we have  $B_t - EL_t = w(p_t)^{\frac{1}{\theta}} - p_t$  in the dreaded shift condition.

As before, we can write the change in risk premium as

$$B_t - EL_t - (B_{t-1} - EL_{t-1}) = w(1 - p_t)^{\frac{1}{\theta}} - (1 - p_t^e) - \left( w(1 - p_{t-1})^{\frac{1}{\theta}} - (1 - p_{t-1}^e) \right) \quad (\text{A.2.3})$$

To see how this difference behaves as a function of the prior empirical probability,  $p_{t-1}^e$ , we use (1.2.3) to calculate  $p_t^e$  as a function of  $p_{t-1}^e$  and obtain Figure A.8. Regardless of the environment stability and signal diagnosticity, we expect the risk premium to increase from period  $t-1$  to  $t$  as DMs receive signal indicative of regime shift especially if the prior probability of regime shift is not too low. Recall that signals indicative of regime shift decrease the probability of “Bad” state in the desirable regime shift condition which makes DMs more risk averse according to prospect theory’s fourfold risk aversion pattern.

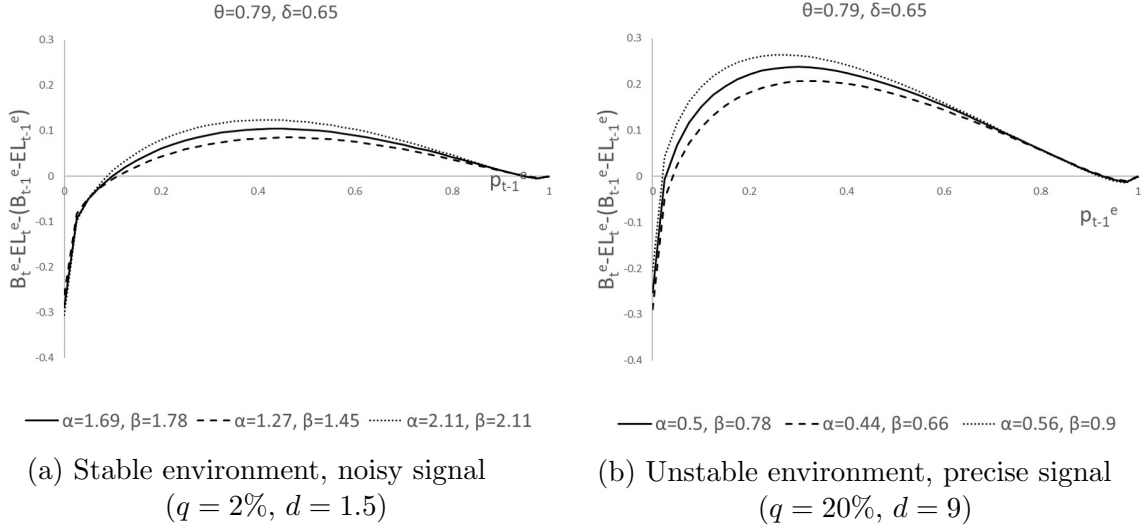


Figure A.8: Change in the risk premium as a function of prior probability of regime shift,  $p_{t-1}^e$  when the regime shift is desirable.

Using the decomposition in (2.3.2) and the equations for each component in (A.2.1) and (A.2.3), we obtain specific predictions for under- and overreaction in pricing judgments and present them graphically in Figure A.9 as a function of the prior probability of regime shift  $p_{t-1}^e$ . We obtained the plots in Figure A.9 by adding up the graphs from Figures A.6 and A.8.

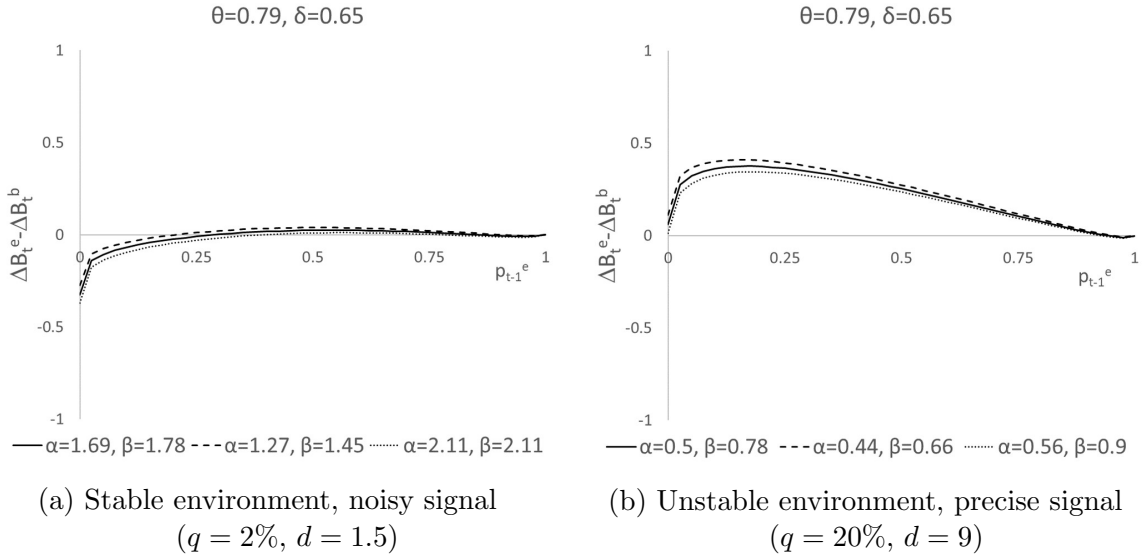


Figure A.9: Under- and overreaction in pricing decisions

Keeping in mind that  $\Delta B_t^e - \Delta B_t^b < 0$  implies overreaction and  $\Delta B_t^e - \Delta B_t^b > 0$  implies underreaction, our model predicts the change in empirical pricing judgments to be closer to the change in Bayesian risk-neutral judgments when the environment is stable and signals are noisy. When the environment is unstable and signals are precise, we predict pricing judgments

to exhibit underreaction.

### A.3 A model for buyers under dreaded regime shift in the asset market setting

In the asset market setting, buyers report their willingness to pay for the asset that yields a positive pay-off (\$1) in the “Good” regime and no payoff in the “Bad” regime. When the regime shift is dreaded, buyers consider the decision given in Figure A.10, where  $B_t$  is the empirical (reported) willingness to pay for the asset in period  $t$ .

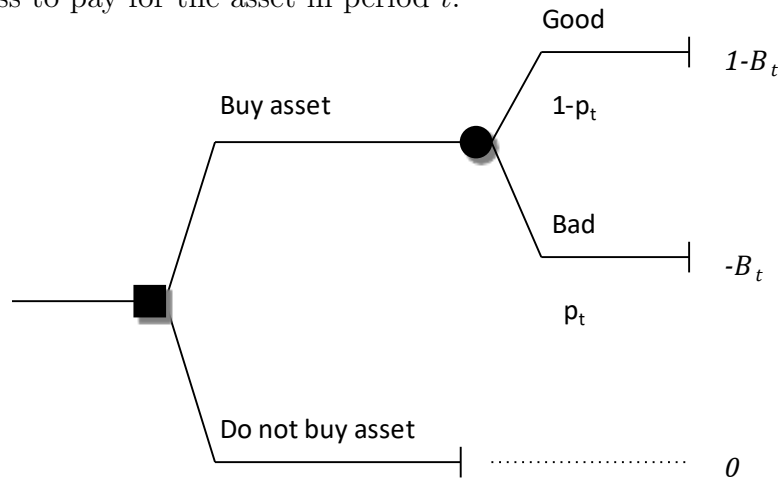


Figure A.10: Lottery asset buyers face under a dreaded regime shift,  $P(\text{regime shift in period } t) = p_t$ .

We continue to define the empirical change in pricing judgments as  $\Delta B_t^e = B_t^e - B_{t-1}^e$ . The Bayesian risk-neutral change in pricing judgments is given by  $\Delta B_t^b = EV_t^b - EV_{t-1}^e = 1 - p_t^b - (1 - p_{t-1}^e) = p_{t-1}^e - p_t^b$ , where  $EV_{t-1}^e \geq 0$  and  $EV_t^b \geq 0$  represent the expected value of the asset when the expectation is calculated using the prior and Bayesian probability of regime shift respectively. We again take the measure of under- and overreaction in pricing judgments to be  $\Delta B_t^e - \Delta B_t^b$  and separate the effect of system neglect and the change in risk premium as follows:

$$\Delta B_t^e - \Delta B_t^b = B_t^e - B_{t-1}^e - (EV_t^b - EV_{t-1}^e) = \underbrace{B_t^e - EV_t^e - (B_{t-1}^e - EV_{t-1}^e)}_{\text{change in risk premium}} + \underbrace{(EV_t^e - EV_t^b)}_{\text{effect of system neglect}} \quad (\text{A.3.1})$$

where  $EV_t^e = 1 - p_t^e$ .

To interpret this measure, note that we have  $B_t^e - B_{t-1}^e < 0$  and  $EV_t^b - EV_{t-1}^e < 0$  because both the empirical pricing decision and the expected value of the asset for a Bayesian risk-neutral agent decrease upon receipt of a signal indicative of a dreaded regime shift. Then,  $\Delta B_t^e - \Delta B_t^b > 0$  implies that the decrease in empirical pricing decisions is higher than the decrease in the Bayesian expected value which indicates overreaction. Using a similar argument, one can see that  $\Delta B_t^e - \Delta B_t^b < 0$  indicates underreaction.

We again study the effect of system neglect and the change in risk premium separately.

*Effect of system neglect:* The difference between expected values calculated using empirical and Bayesian probabilities of regime shift is equal to  $EV_t^e - EV_t^b = (1 - p_t^e) - (1 - p_t^b) = -(EL_t^e - EL_t^b)$ . Thus, the analysis for system neglect in this setting is the same as the analysis in §1.2 but has the opposite sign.

*Change in risk premium:* We first note that the pricing decision,  $B_t$ , in the dreaded regime shift condition should satisfy the following:

$$0 = w(p_t)V(-B_t) + (1 - w(p_t))V(1 - B_t).$$

Using the same power value function as in (1.2.5) and the probability weighting function in (1.2.6), we obtain  $\left(\frac{B_t}{1 - B_t}\right)^\theta = \frac{1}{\lambda\delta} \left(\frac{1 - p_t}{p_t}\right)^\gamma$ . Using this equality we can write the DM's risk premium as

$$B_t - EV_t^e = \frac{y}{1 + y} - (1 - p_t),$$

where  $y = (\lambda\delta)^{-\frac{1}{\theta}} \left(\frac{p_t}{1 - p_t}\right)^{-\frac{\gamma}{\theta}}$ . Thus,  $B_t - EV_t^e$  depends on the parameters  $\theta$ ,  $\gamma$ , and on the product  $\lambda\delta$ .

In the dreaded shift condition, where the regime can only shift from the “Good” state to the “Bad” state, we again take period  $t - 1$  without loss of generality and plot the difference  $B_{t-1} - EV_{t-1}^e$  as a function of the probability of regime shift,  $p_t$ , in Figure A.11. We take  $\theta = 1.14$ ,  $\gamma = 0.7$  and consider a range of values for  $\delta\lambda$  consistent with our analysis in Appendix A.1. This figure shows that individuals are risk averse ( $B_{t-1} < EV_{t-1}^e$ ) except when the probability of regime shift is very high.

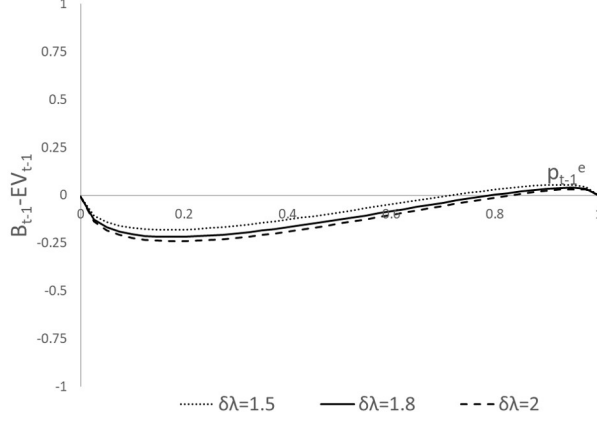


Figure A.11: Risk premium,  $B_{t-1} - EV_{t-1}^e$ , as a function of probability of regime shift  $p_{t-1}$ .

The change in risk premium in this setting is

$$B_t - EV_t^e - (B_{t-1} - EV_{t-1}^e) = \frac{y_t}{1 + y_t} - (1 - p_t^e) - \left( \frac{y_{t-1}}{1 + y_{t-1}} - (1 - p_{t-1}^e) \right) \quad (\text{A.3.2})$$

where  $y_t = (\delta\lambda)^{-\frac{1}{\theta}} \left( \frac{p_t^e}{1-p_t^e} \right)^{-\frac{\gamma}{\theta}}$  as above. To see how this difference behaves as a function of the prior empirical probability,  $p_{t-1}^e$ , we use (1.2.3) to calculate  $p_t^e$  as a function of  $p_{t-1}^e$  and obtain Figure A.12. For a Bayesian risk-neutral DM, note that this change in risk premium would always be equal to 0. However, Figure A.12 predicts that DMs become less risk averse ( $B_t - EV_t - (B_{t-1} - EV_{t-1}) > 0$ ) after observing a signal indicative of regime shift for most prior probabilities except those that are close to 0.

Using the decomposition in (A.3.1), we obtain specific predictions for under- and overreaction in pricing judgments and present them graphically in Figure A.13 as a function of the prior probability of regime shift  $p_{t-1}^e$ .

The predictions for in this setting are qualitatively the same as the predictions in our other settings in that we expect underreaction in unstable environments with precise signals and overreaction in stable environments with noisy signals when the prior probability of regime shift is low. For high probability of regime shift, we expect to find no difference in our measure across the two environments.

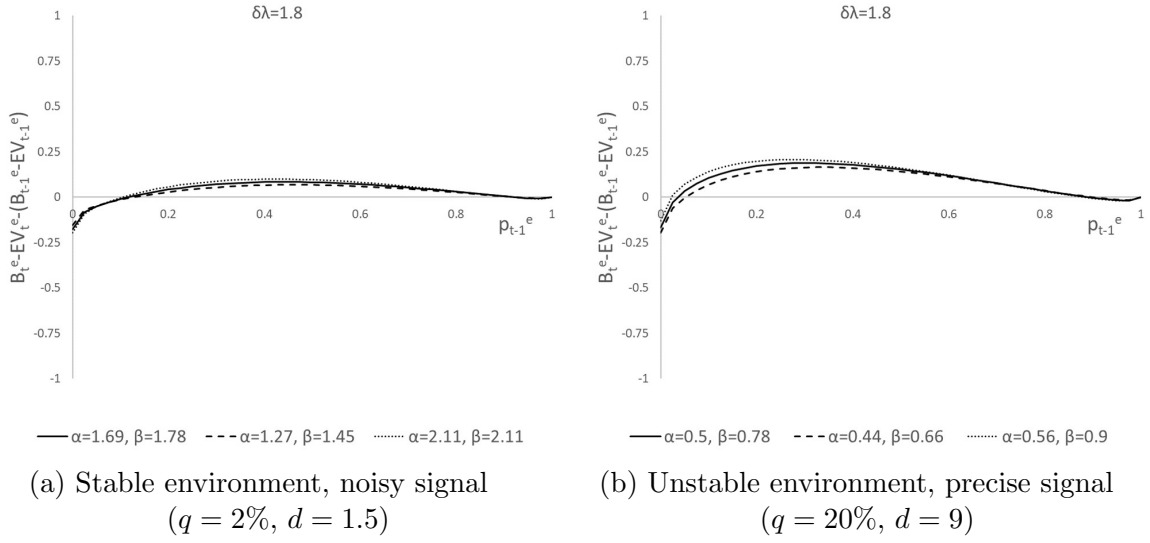


Figure A.12: Change in the risk premium as a function of prior probability of regime shift,  $p_{t-1}^e$ , for buyers

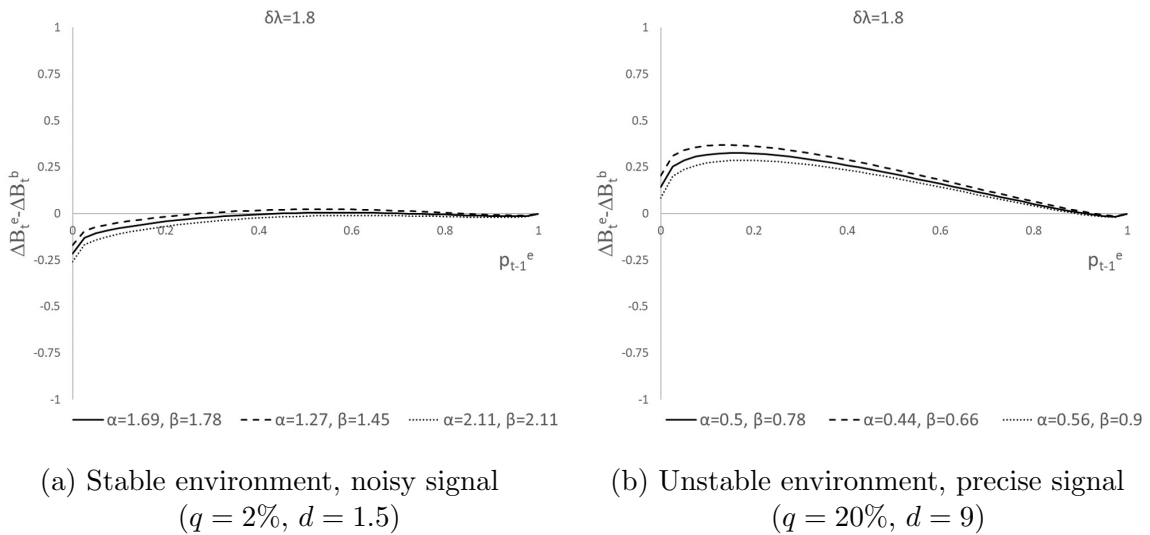
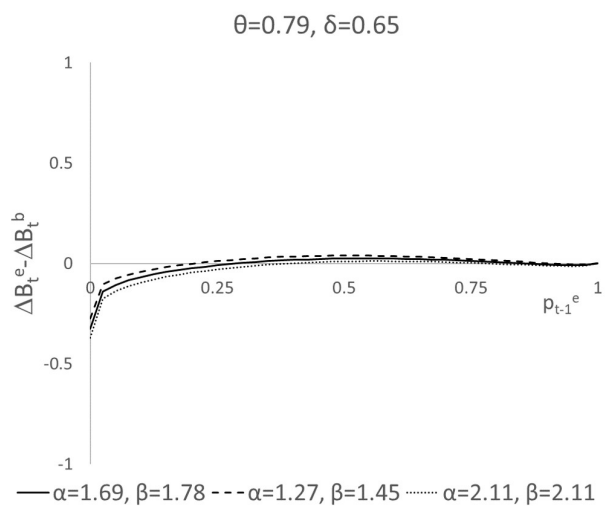


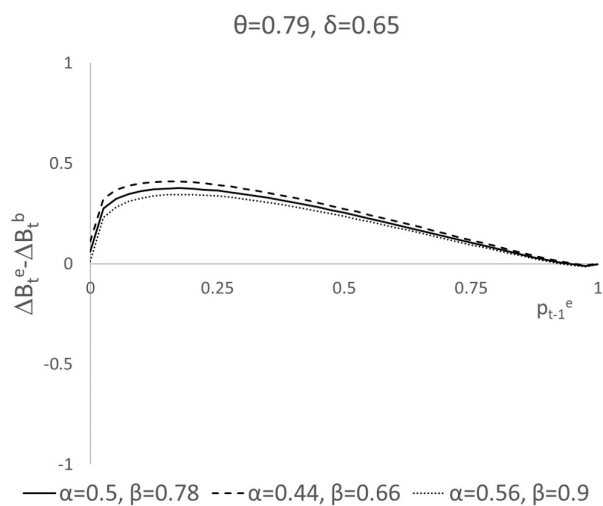
Figure A.13: Under- and overreaction in pricing decisions for buyers in the asset market setting

# Appendix B

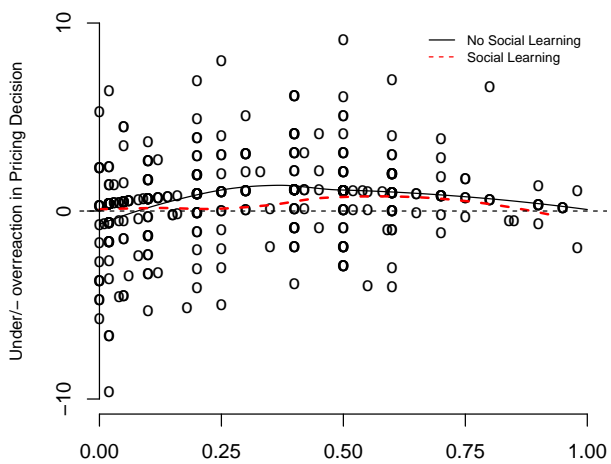
## B.1 Under- overreaction in pricing decisions under desirable regime shift



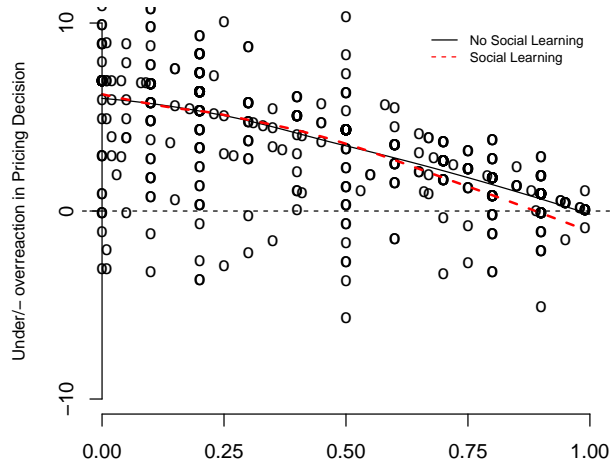
(a) Stable environment, noisy signal  
 ( $q = 2\%$ ,  $d = 1.5$ )  
 Model Prediction



(b) Unstable environment, precise signal  
 ( $q = 20\%$ ,  $d = 9$ )  
 Model Prediction



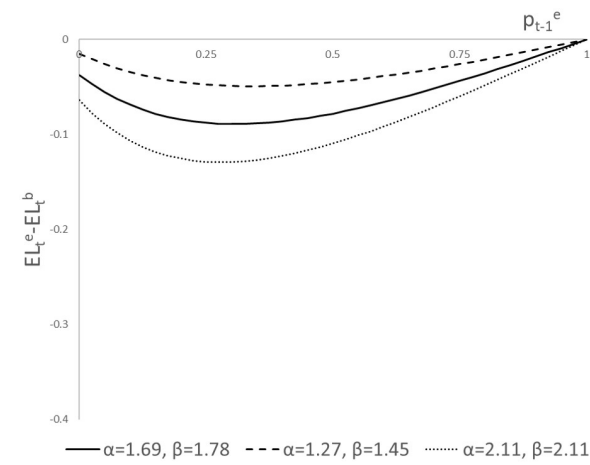
(c) Stable environment, noisy signal  
 ( $q = 2\%$ ,  $d = 1.5$ )  
 Empirical Result



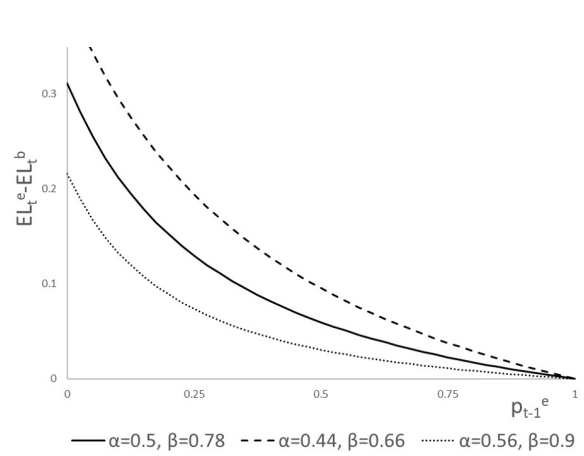
(d) Unstable environment, precise signal  
 ( $q = 20\%$ ,  $d = 9$ )  
 Empirical Result

Figure B.1: Under- overreaction in pricing decisions under desirable regime shift

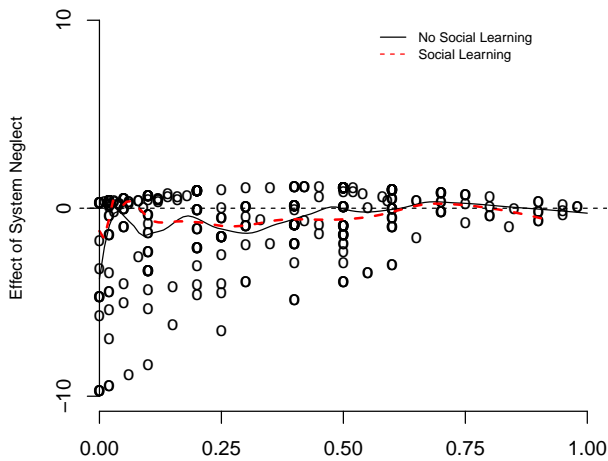
## B.2 Effect of system neglect under desirable regime shift



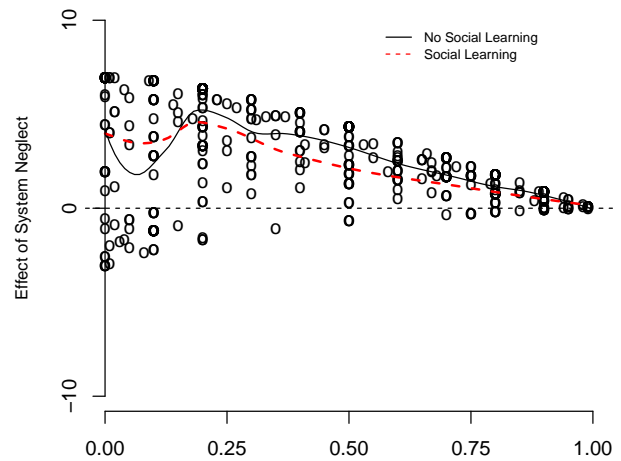
(a) Stable environment, noisy signal  
 $(q = 2\%, d = 1.5)$   
 Model Prediction



(b) Unstable environment, precise signal  
 $(q = 20\%, d = 9)$   
 Model Prediction



(c) Stable environment, noisy signal  
 $(q = 2\%, d = 1.5)$   
 Empirical Result



(d) Unstable environment, precise signal  
 $(q = 20\%, d = 9)$   
 Empirical Result

Figure B.2: Effect of system neglect under desirable regime shift

### B.3 Change in risk premium under desirable regime shift

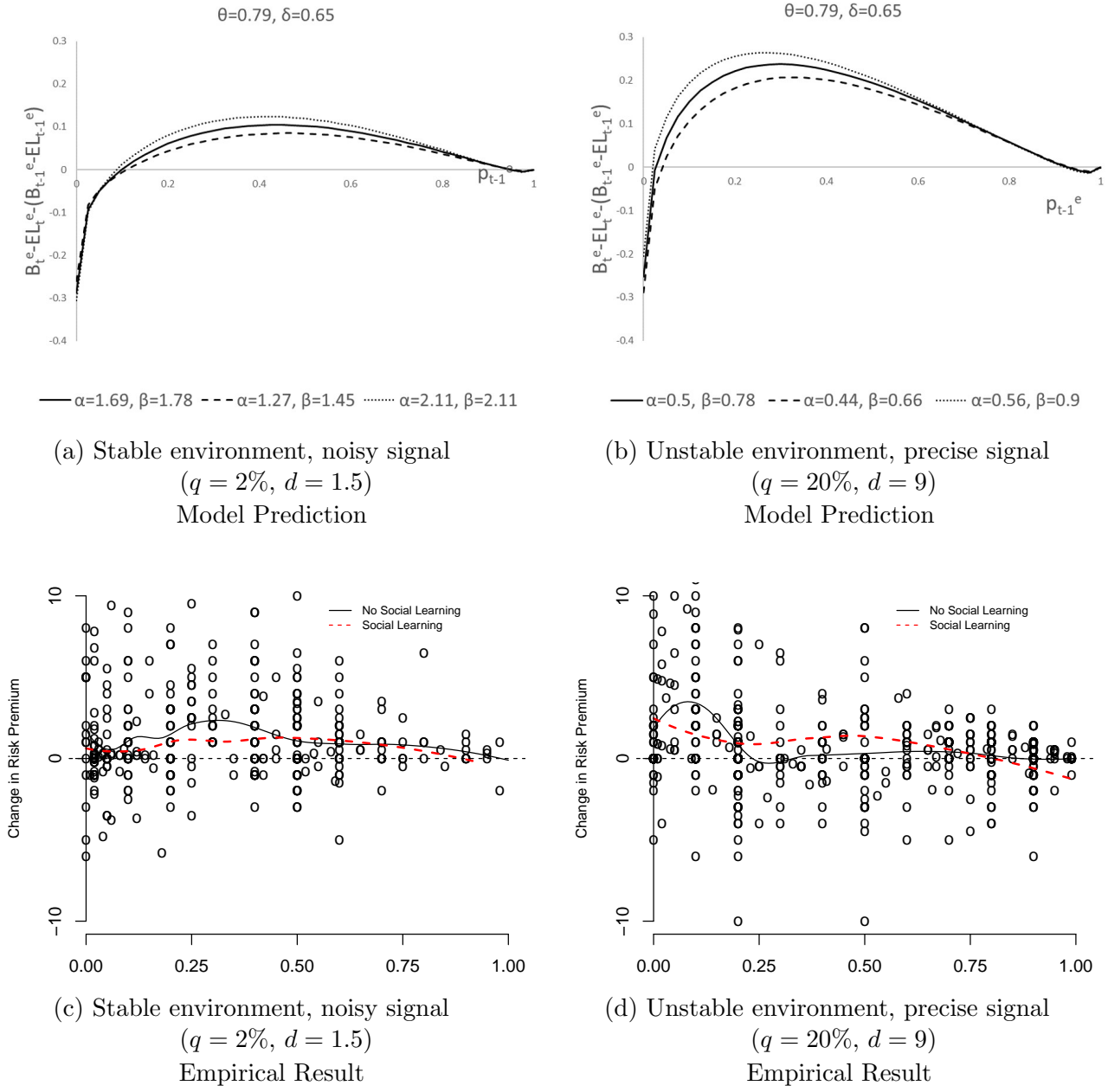


Figure B.3: Change in risk premium under desirable regime shift