UNIVERSITY OF SOUTHAMPTON
FACULTY OF LAW, ARTS, AND SOCIAL SCIENCES
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BEHAVIORAL ECONOMICS AND ITS APPLICATIONS IN FINANCE

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ABSTRACT

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BEHAVIORAL ECONOMICS AND ITS APPLICATION IN FINANCE

by Mohammad Mehdi Mousavi

Traditional theories in economics state that people make their decisions in order to maximize their utility function and all the relevant constraints and preferences are included and weighted appropriately. In other words, in standard models, it is usually assumed that decision makers are fully rational. However, some studies in behavioral economics and finance suggest that individuals deviate from standard models. Behavioral economic models try to make standard models more realistic by modifying these assumptions. This thesis focuses on some applications of behavioral economics in three chapters.

Chapter 1 focuses on individuals' deviations from standard preferences. Based on standard models, individuals have the same preferences about future plans at different points in time and the discounting factor between any two time periods is independent of when utility is evaluated. However, robust laboratory experiments show choice reversal behavior in humans and animals.

The aim of chapter 1 is to find an approach for measuring the decision makers' awareness of choice reversal by analyzing demand for commitment. We use the data from an experimental study by Casari (2009) to measure the awareness of the self-control problem. Also, the welfare implications of introducing a commitment device are studied in this chapter.

The results show that decision makers are partially aware of their self-control problems. Moreover, introducing a costless commitment device can increase the total welfare of the studied population. This increase depends on individuals' awareness of future choice reversal.

The aim of chapter 2 is to analyze stock price movements as a result of fundamental or technical shocks under a heterogeneous agents model (HAM). In this study, it is assumed that the market involves heterogeneous agents that have different rules for trading and that prices are endogenously determined through interactions between these agents. I use the numerical simulation method to examine changes in the prices as the result of fundamental shocks. The result of this chapter indicates that increasing heterogeneity in technical trading strategies could lead to more price oscillations, which is consistent with the excess volatility in stock prices.

The aim of chapter 3 is to predict stock price movements under a new HAM. I use the HAM framework proposed in the previous chapter. The value added by this chapter is estimating stock prices in a heterogeneous agent environment where chartists use different moving average trading strategies. I use monthly data from S&P 500 from 1990 until 2012 and discuss the forecasting ability of the model. The results of this chapter show that the presented model has a better one-step ahead, out-of-sample forecasting power compared with Boswijk et al. (2007) and Chiarella et al. (2012).

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DECLARATION OF AUTHORSHIP

I, Mohammad Mehdi Mousavi

declare that this thesis entitled

” Behavioral Economics And Its Applications In Finance”

and the work presented in it are my own and has been generated by me as the result of my own original research. I confirm that:

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7. None of this work has been published before submission

Date: March 2013

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Chapter 1
The Awareness Of Self-Control

1.1 Introduction

Consider a decision maker who prefers a larger-later than a smaller-sooner reward. However, as time passes and the sooner-smaller reward becomes immediate, she reverses her choice and picks the immediate reward. For example, consider a student who has decided to participate in a pre-exam session class the next morning at 8 o'clock, but when the morning arrives she prefers to stay in bed and enjoy more sleep. These sorts of actions are known as choice reversal actions, diminishing impatience, the self-control problem and present bias. Robust laboratory experiments show choice reversal behavior in humans and animals. Read and Leeuwen (1998) asked individuals if they preferred fruit or chocolate to have for the next week. Although 74% chose fruit at the time they were asked, when the future came they reversed their choices and 70% chose chocolate. There is also evidence of choice reversal and present bias in economics and financial issues. For instance, the median individual is indifferent between \$15 now and \$20 in one month, which requires an annual rate of 345%; however, she is indifferent about $15 now and $100 10 years later, which requires an annual rate of 19% (Thaler 1981). Intertemporal preferences with these features show the self-control problem and diminishing impatience. When decision makers evaluate outcomes in a distant future, such as quitting smoking, they plan to act patiently. However, when the future becomes close, they act impatiently.

Diminishing impatience behavior has been discussed in the literature by two approaches. On one side of the argument, some studies explain diminishing impatience (present bias effect) by introducing an uncertain exponential discounting model (Sozou 1998, Azfar 1999, Halevy 2008, Dusgopta and Maskin 2005). In those studies, the origin of choice reversal is the risk that any future reward contains. On the other side of the argument, some previous works indicate that the presence of diminishing impatience behavior is due to the temptation generated by dynamically inconsistent preferences. As a result, individuals' awareness of diminishing impatience can lead to demand for a commitment device (Strotz 1995; Elster 1979; Akerlof 1991; O'Donoghue and Rabin 1999).

Although both sides of the argument agree on the shape of the discounting function (hyperbolic and quasi-hyperbolic discounting functions), the origin of such behavior is quite different in each of the approaches. One way to distinguish between the origins of choice reversal behavior is looking at the decision maker's demand for flexibility and commitment devices. If the origin of diminishing impatience is only risk (and not temptation), individuals should be unwilling to commit (Casari

2009). There is also experimental evidence that shows the existence of demand for commitment (Casari 2009). Some researchers have found that people are partially aware of their self-control problems, but there is a lack of experimental studies that qualitatively estimate the individual's awareness of the self-control problem in the literature.

The aim of this research is to evaluate the decision maker's awareness of choice reversal behavior by analyzing demand for commitment and flexibility. This means measuring the awareness of the self-control problem. I also use the data from an experimental study by Casari (2009) to measure the awareness of the self-control problem and also evaluate the welfare increase or decrease of introducing a commitment device.

The rest of this research is organized as followed. In Section 2, two approaches to model choice reversal are explained. Section 3 presents a model which shows how it is possible to measure the awareness of the self-control problem. Section 4 uses the mentioned method in section 3 on the experimental data from Casari (2009). In section 5, we evaluate the welfare implications of introducing a commitment device. Sections 6 and 7 contain the results and conclusions are followed in section 8.

1.2 Explaining Choice Reversal

In this section, two approaches for explaining choice reversal behavior are reviewed.

1.2.1 Hyperbolic and Quasi-hyperbolic Discounting Model

According to the quasi-hyperbolic discounting model, in order to model choice reversal behavior, consumption between present and future is discounted higher than any two future periods. O'Donoghue and Rabin (2001) and Laibson (1997) formalized these preferences using the (α, β) preferences model based on Strotz (1956) and Akerlof (1991). By labelling u_t as the per period utility and U_t as the overall utility at time t

$$U_t = u_0 + \beta\alpha u_1 + \beta\alpha^2 u_2 + \beta\alpha^3 u_3 + ... + \beta\alpha^t u_t$$

In this model, α is the time-consistent discounting factor and β is the factor for present bias. Utility between u_0 and u_1 is discounted with $\beta\alpha,$ while the discounting rate between u_t and u_{t+1} $(t \neq 0)$ is α. If $\beta \leq 1 \Rightarrow \beta\alpha \leq \alpha,$ i.e. based on the quasi-hyperbolic discounting model, consumption between present and future $\frac{u_1}{u_0}$ is discounted higher than any two future periods $\frac{u_{t+1}}{u_t}$ $(t > 0)$.

Expectations About Future Preferences

O'Donoghue and Rabin (2001) modelled individuals' expectations about their self-control parameters as follows

$$\hat{U}_t = u_0 + \hat{\beta}\alpha u_1 + \hat{\beta}\alpha^2 u_2 + \hat{\beta}\alpha^3 u_3 + ... + \hat{\beta}\alpha^t u_t$$

According to the above formula, $\hat{\beta}$ is the decision maker's estimation of β. Based on the individual's awareness of the self-control parameter $(\hat{\beta})$, she can be

1. Fully naïve: If an individual is a fully naive decision maker, her expected utility function does not contain the self-control parameter ($\hat{\beta}$=1).

2. Sophisticated: If an individual is a sophisticated decision maker, her estimated self-control parameter is exactly equal to the real self-control parameter ($\hat{\beta} = \beta$).

3. Partially naive: If an individual is partially naive, her estimated self-control parameter is lower than the real self-control parameter ($\beta < \hat{\beta} < 1$), i.e. she underestimates her self-control problem.

1.2.2 Choice Reversal and Uncertain Hazard Rates

In the uncertain hazard rate model, the bias for present (diminishing impatience) is explained by the risk that future rewards contain. Any future reward contains at least two kinds of risks, namely the probability of the mortality of the recipient in the future and the probability that the promise of the future reward is broken. Sozou (1998) modelled the exponential discounting based on an uncertain hazard rate. In this model, $s(\tau)$ is the discounting factor for the delay of τ, and $v(t)$ is the value function at present. λ is assumed to be a constant but unknown parameter, which indicates the hazard rate and is drawn from the probability distribution $f(\lambda)$. Based on this model, it is possible to reproduce the hyperbolic discounting function for a specific $f(\lambda)$. This means that the hyperbolic discounting function can be explained by the exponential discounting model under uncertainty.

$$v(\tau) = v(0) \times s(\tau)$$
$$s(\tau) = \int_0^{\infty} f(\lambda) \exp(-\lambda\tau) d(\lambda)$$
$$\text{if } f(\lambda) = \tfrac{1}{k} \exp(-\lambda/k) \Rightarrow \int_0^{\infty} f(\lambda) \exp(-\lambda\tau) d(\lambda) = \tfrac{1}{1+k\tau}$$

Moreover, experimental evidence shown by Keren and Roelofsma (1995) and Weber and Chapman (2005) indicates that when an immediate reward is involved with risk, present bias (diminishing impatience) decreases. The table below shows the result when people choose first between A and B and then between C and D. Please note that in this table, p is the probability that a reward contains. For example expected payoff of choosing option A when $p = .5$ is $100 \times .5 = 50$.

	$p = 1$	$p = .9$	$p = .5$
A.100 now	.82	.54	39
B. 110 in 4 weeks	.18	.46	.61
C. 100 in 26 weeks	.37	.25	.33
D.110 in 30 weeks	.63	.75	.67

Table 1: From Halevy (2008)

Halevy (2008) suggested a functional representation to explain this evidence. In his representation, the only source of diminishing impatience is the uncertainty that a future reward contains. He claims that if non-constant pure time preferences were the major source of diminishing impatience, present bias should not weaken so drastically once explicit risk (which affects only certainty effect) has been introduced. The suggested model converges to the quasi-hyperbolic discounting model; however, unlike the quasi-hyperbolic model, the only source of present bias is uncertainty (Halevy 2008).

By assuming that both uncertainty and temptations can be sources of diminishing impatience, I aim to measure the awareness of future choice reversal.

1.3 The Model

To motivate the model, consider an agent who faces a choice in which she can choose between two options (A and B) at t=0. First option (A) promises a sooner and smaller (SS) reward at $t = 1$ and noting at $t = 2$. Second option (B) delivers a larger and later (LL) reward at $t = 2$ and nothing at t=1. Suppose that the agent prefers B over A at t=0 but prefers A over B at t=1. This action is known as choice reversal or self-control problem. Now the question is whether the decision maker is aware (at t=0) that she might be tempted at t=1? If the decision maker is aware of her self-control problem, does she have demand for a commitment device?

1.3.1 Setup

Suppose the decision maker's true intertempral preferences are given by a quasi-hyperbolic discounting utility function

$$U_t = u_0 + \beta\alpha u_1 + \beta\alpha^2 u_2 + \beta\alpha^3 u_3 + ... + \beta\alpha^t u_t \qquad (1)$$

where $\alpha \leq 1$ is her discount factor and $\beta \leq 1$ is the present bias parameter (O'Donoghue et al 2001). T is her time horizon. To show how this model indicates choice reversal, consider the example in motivation part for second time. Suppose each option (A or B) promises the following rewards in the future.

$$A : u_0 = 0, u_1 = SS, u_2 = 0$$

$$B : u_0 = 0, u_1 = 0, u_2 = LL$$

Based on equation (1) the player's preferences at t=0 (U^0) can be obtained as

$$U_A^0 = u_0 + \beta\alpha u_1 + \beta\alpha^2 u_2 = 0 + \beta\alpha SS + 0 = \beta\alpha SS$$

$$U_B^0 = u_0 + \beta\alpha u_1 + \beta\alpha^2 u_2 = 0 + 0 + \beta\alpha LL = \beta\alpha^2 LL$$

Similarly, the agent's preferences at t=1 (U^1) are

$$U_A^1 = u_1 + \beta\alpha^1 u_2 = SS + 0 = SS$$

$$U_B^1 = u_1 + \beta\alpha^1 u_2 = 0 + \beta\alpha LL = \beta\alpha LL$$

It is assumed that α, β, SS and LL are exogenous variables.

Claim 1A necessary and sufficient condition for choice reversal behavior is $\frac{SS}{\alpha} < LL < \frac{SS}{\alpha\beta}$

Proof. The agent prefers B at t=0 if and only if $U_B^0 > U_A^0 \Leftrightarrow LL > \frac{SS}{\alpha}$. Similarly, she prefers A at $t = 1$ if and only if $U_A^1 > U_B^1 \Leftrightarrow LL < \frac{SS}{\alpha\beta}$. ■

Now consider a situation in which the proposed choice offers a flexibility option. Meaning that if the player has chosen B at t=0 but prefers A at t=1, she can reverse her choice and choose A. Now the question is to what extent the agent is aware that she might be tempted at t=1 and reverse her choice?

To incorporate uncertainty over future utilities, I make the standard assumption that the agent maximizes her expected discounted utility. For instance, suppose that at t=0 the agent expects to be tempted at $t = 1$ (and revers her choice from B to A) with probability $\hat{p}$ and not to be tempted at t=1 with probability $(1 - \hat{p})$. Therefore, expected utility of choosing B at $t = 0$ when the game has a flexibility option (denoted by $U^0_{B_f}$) is

$$E(U^0_{B_f}) = \hat{p}U^0_A + (1 - \hat{p})U^0_B = \hat{p}\beta\alpha SS + (1 - \hat{p})\beta\alpha^2 LL$$

Definition 1 An agent is fully sophisticated if she meets necessary and sufficient condition for choice reversal behavior and her $\hat{p} = 1$, fully naive if $\hat{p} = 0$ and partially sophisticated if $0 < \hat{p} < 1$.

Now suppose that the agent can choose to play the game with flexibility option (being able to choose A at t=1 even if she has chosen B at t=0) or play the game with commitment device. If the agent choose to play the game with commitment device, she can not revers her choice at t=1. The aim of proposing commitment device in the game is helping the agent to deal with the temptation at t=1. Moreover if the agent chooses commitment device, she will not have the flexibility (V_f). In other words, choosing commitment device has a implicit cost which is loosing the flexibility option. Therefore, expected utility of choosing B at $t = 0$ when the agent uses commitment device (denoted by $E(U^0_{B_C})$) is $E(U^0_{B_C}) = \beta\alpha^2 LL - V_f$.

Suppose that the commitment device is costly and the maximum cost that the agent is ready to pay is M (units of utility) at t=0. In other words, paying M units of utility at t=0, makes the agent indifferent between playing the game with or without the commitment. So

$$E(U^0_{B_C}) - M = E(U^0_{B_f}) \Leftrightarrow \beta\alpha^2 LL - M - V_f = \hat{p}\beta\alpha SS + (1-\hat{p})\beta\alpha^2 LL \Leftrightarrow \hat{p} = \frac{M+V_f}{\beta\alpha^2 LL - \beta\alpha SS} \qquad (2).$$

Equation (2) states that, if we know M, V_f, α and β (these variables are assumed to be exogenous) for the agent, it is possible to find out her awareness about choice reversal behavior (please note that LL and SS are exogenous variables).

1.3.2 Example

Sara has decided to wake up early on Sunday morning to participate in a pre-exam group study. But in the morning, she is tempted to sleep and not participate in the group study session. Let u_1 be the utility of having more sleep on Sunday morning and u_2 the utility of participation in the pre-exam study group. Assume that she decides on Saturday night (let's call it t=0). Options A and B show the utility streams of not precipitating and participating in class, respectively

$A : u_1 = 4 \, , u_2 = 0$

$B : u_1 = 0 \, , u_2 = 6$

Let's assume that $\alpha = 1$ and $\beta = 1/2$

At t=0 (decision making time), she would prefer to participate in the class, because

$U_A = \beta\alpha u_1 + \beta\alpha^2 u_2 = (1/2 \times 1 \times 4) + (1/2 \times 1 \times 0) = 2$

$U_B = \beta\alpha u_1 + \beta\alpha^2 u_2 = (1/2 \times 1 \times 0) + (1/2 \times 1 \times 6) = 3$

$U_A < U_B$

But based on the assumed numbers, the quasi-hyperbolic discounting model indicates how she will change her mind on Sunday morning after waking up (not getting up) because

$U_A = u_1 + \beta\alpha u_2 = (4) + (1/2 \times 1 \times 0) = 4$

$U_B = u_1 + \beta\alpha u_2 = (0) + (1/2 \times 1 \times 6) = 3$

$U_A > U_B$

It may be worth showing that the exponential discounting function under certainty ($f_E(D) = e^{-KD}$) can not explain the choice reversal behavior in the above example.

$$U_A = e^{-KD} \times u_1 + e^{-KD} \times u_2 = 4e^{-k}$$

$$U_B = e^{-KD} \times u_1 + e^{-KD} \times u_2 = 6e^{-2k}$$

Sara chooses option B at t=0$\Leftrightarrow U_A < U_B \Leftrightarrow 6e^{-2k} > 4e^{-k} \Leftrightarrow k < \ln\frac{3}{2}$. But she changes her decision at t=1. So

$$U_A = e^{-KD} \times u_1 + e^{-KD} \times u_2 = 4$$

$$U_B = e^{-KD} \times u_1 + e^{-KD} \times u_2 = 6e^{-k}$$

Sara chooses option A at t=1$\Leftrightarrow U_A > U_B \Leftrightarrow 6e^{-k} < 4 \Leftrightarrow k > \ln\frac{3}{2}$.

Now, I aim to find the decision maker's awareness of the self-control problem, based on her preferences for commitment. The important assumption here is that there is no uncertainty in future rewards. Let's label $\hat{p}$ as the probability that the decision maker assigns to her choice reversal. If $\hat{p} = 1$, it means that Sara (in example 1) is fully (and correctly) aware that she will be tempted at $t = 1$ and will reverse her choice, which was decided at $t = 0$. Assume that, by observing decision maker behavior, we know $\beta(= 1/2)$ is the correct present bias parameter, which explains choice reversal. Sara can use a free commitment device (ask her mother to wake her up tomorrow using any means!) – using the commitment device results in $\hat{p}$ being zero. By labelling expected utility of choosing option B under a commitment device as U_c and expected utility without a commitment device as U (since there is no uncertainty in the model, I assume that value of flexibility is zero) we get

Utility gain by choosing option A at time 1 and $2u_{1,2}^A$

Utility gain by choosing option B at time 1 and $2u_{1,2}^B$

$$E_{t=0}(U) = \hat{p}u^A + (1-\hat{p})u^B = \hat{p}\alpha\beta[u_1^A + u_2^A] + (1-\hat{p})\alpha^2\beta[u_1^B + u_2^B]$$

$$E_{t=0}(U) = \hat{p}\alpha\beta u_1^A + (1-\hat{p})\alpha^2\beta u_2^B$$

$$E_{t=0}(U_c) = \alpha^2\beta u_2^B$$

$if \;\; U_c > U \Rightarrow$ she prefers to use the commitment device.

Now, assume that the commitment device is costly and the maximum *utility* that Sara is ready to sacrifice for the commitment is M then

$$M = \hat{U}_c - \hat{U} \Rightarrow M = \alpha^2\beta u_2^B - [\hat{p}\alpha\beta u_1^A + (1-\hat{p})\alpha^2\beta u_2^B]$$
$$\Rightarrow \hat{p} = \frac{M}{\alpha^2\beta u_2^B - \alpha\beta u_1^A}$$

In example 1, $\beta = 1/2, \alpha = 1, u_1^A = 4, u_2^B = 6 \Rightarrow \hat{p} = M$

So, if Sara is ready to pay 1 units of utility $\Rightarrow \hat{p} = 1$(fully sophisticated decision maker)

Note that because $0 \leq \hat{p} \leq 1$, the maximum amount of payment for commitment is when $\hat{p} = 1$ and equals $\alpha^2\beta u_2 - \alpha\beta u_1$. If a decision maker is ready to pay more, she overestimates the self-control parameter.

1.4 Measuring $\hat{p}$

In order to estimate the awareness of the self-control problem $(\hat{p})$, it is essential to find α, β and demand for the commitment of each individual. As it is mentioned before, in this study we use the results of the experiment of Casari (2009) to measure $\hat{P}$ based on the presented model in this chapter.

1.4.1 Experimental Setup And Results Of Experiment Of Casari (2009)

Casari (2009) has studied the time preferences of 120 subjects recruited from the undergraduate population of Jaume I University of Castellon, Spain. Each subject faced a series of choices between a smaller-sooner payment (SS) and a larger-later (LL) payment with delays between 2 days and 22 months. Choices were divided into three parts: a first part to measure impatience, a second part to detect choice reversal, and a third part to assess preferences for commitment and flexibility.

In part one, each decision has four parameters: The amount of the two possible payments and their delays. Both payment amounts were held constant throughout the procedure at 100€ and 110€. The goal of part one was to elicit an approximate measure of impatience D* by fixing the delay of the smaller-sooner payment at 2 days, SS= (100€, 2 days), and varying the delay D of the larger-later payment, LL= (110€, D), up and down until the subject was approaching indifference between the two payments. For example, consider a subject who selects LL= (110€, 10 days) over SS= (100€, 2 days), but chooses SS over LL=(110€,17 days). In this example, the point of the switch from LL to SS narrows the subject's indifference point between the two options to a delay between 10 and 17 days. Thus, D*=17 is the approximate measure of impatience (Casari 2009).

In part two, both rewards are added with a front-end delay (FED*) in order to detect possible choice reversals. The smaller-sooner reward maintains a consistent delay of FED*+2 days and the larger-later reward maintains a delay of FED*+D* days, which ensured throughout part two that the waiting time difference between SS and LL was constant. The remaining parameters of the decisions were unchanged (Casari 2009).

Part three includes decisions aimed at measuring the preferences for commitment and flexibility. These choices had two peculiarities. First, instead of only two alternative payments, each decision could involve either three or four. Second, each decision comprised two choices that took place on two separate days: one on the day of the experimental session and the other through e-mail at a later date, sometimes months later. In part three, a subject could either commit immediately to the larger-later reward {LL} or postpone the choice between a larger-later reward and a smaller-sooner reward {LL, SS}. The commitment strictly eliminated the possibility of later choosing another option: in particular, once made, it irreversibly ruled out the possibility at a future date of opting for SS. On the contrary, postponing the choice allowed a subject to wait exactly FED* days and send an e-mail stating a preference for either LL or SS. The amount and delays of payments were structured in a way to resemble those decisions already made in parts one and two. In particular, in the lab, a subject faced SS=(100€, FED*+2) versus LL=(110€, FED*+D*). Remember that the subject faced the same decision in part two, and those who reversed their choices choose LL. A commitment for LL at the time of the lab session shows an awareness of the future temptation to choose SS (Casari 2009). In the next part, we model each part of the experiment using the present model in this chapter.

The main results founded in the experiment of Casari (2009) can be summarized as follow

1. Among the 120 subjects, the median willingness to wait for 110€ over 100€ was 14 days.

2. 78 subjects reversed their choice when adding a front-end delay (FED).

3. The median subject that reversed her choice did so with a FED of 42 days.

4. There is a strong positive correlation between never having tried to stop smoking and doing choice reversal.

5. About 60% of those who reversed their choice did commit.

6. About 14% of those who reversed their choice were willing to pay for flexibility.

7. Under the assumption that subjects reversed their choices because of their preferences, at least half of them were sophisticated and not naïve.

1.4.2 Part 1

In part one, each decision has four parameters: The amount of the two possible payments and their delays. Both payment amounts were held constant throughout the procedure at 100€ and 110€. By using the data from the first part and modelling it with the quasi-hyperbolic discounting model, we get (labelling V as the value of each option and assuming a risk-neutral utility function)

SS = (100,2) $\Rightarrow V_{SS} = 100$

LL = (110,D*) $\Rightarrow V_{LL} = 110 \times \beta \times \delta^{D^*}$

D* has been increased to tempt the decision maker to choose $\Rightarrow V_{SS} > V_{LL} \Leftrightarrow$ $110 \times \beta \times \delta^{D^*} < 100$.

1.4.3 Part 2

In part two, both rewards are added with a front-end delay (FED*) in order to detect possible choice reversals. The smaller-sooner reward maintains a consistent delay of FED*+2 days and the larger-later reward maintains a delay of FED*+D* days, which ensured throughout part two that the waiting time difference between SS and LL was constant. By modelling part two based on quasi-hyperbolic discounting, we get

SS = (100,FED*+2) $\Rightarrow V_{SS} = 100 \times \beta \times \alpha^{(FED^{*}+2)}$

LL = (110,FED*+D*) $\Rightarrow V_{LL} = 110 \times \beta \times \alpha^{(FED^{*}+D^{*})}$

$V_{LL} > V_{SS} \Rightarrow 110 \times \beta \times \delta^{(FED^{*}+D^{*})} > 100 \times \beta \times \delta^{(FED^{*}+2)}$.

From the inequalities from part one and two, we get

1. $100 > 110 \times \beta \times \alpha^{D^{*}}$

2. $100 \times \beta \times \alpha^{FED^{*}} < 110 \times \beta \times \alpha^{FED^{*}+D^{*}}$

$$\Rightarrow \frac{100}{110} < \beta < 1\ ,\ 1 > \alpha > \sqrt[D^{*}]{\frac{100}{110}}$$

Up to this point, the discounting elements (α, β) for quasi-hyperbolic and hyperbolic discounting are measured.

1.4.4 Part 3

Part three includes decisions aimed at measuring the preferences for commitment and flexibility. More precisely, Subjects should choose between two options. Each question in part three aims to detects demand for commitment, demand for costly commitment or demand for flexibility.

Part 3, Question 1

Option A ={ss=(100,FED*+2) or LL=(110,FED$^* + D^*$}

Option B={LL(110,FED$^* + D^*$)}

If a decision maker choose option B, she sacrificed the utility of having flexibility for a commitment device. By labelling the value of the flexibility option as V$_f$ and V$_{A,B}$, the values of each option A and B are

(where p is the probability that the individual estimates she might change her choice in the future)

$$V_A = (\hat{p} \times \beta \times \alpha^{,FED^*+2} \times 100) + [(1-\hat{p}) \times \beta \times \alpha^{FED^*+D^*} \times 110]$$

$$V_B = \beta \times \alpha^{FED^*+D^*} \times 110 - V_f$$

If the individual prefers option B to A : $V_B > V_A \Leftrightarrow \hat{p} > \frac{-V_f}{100 \times \beta \times \alpha^{FED^*} - 110 \times \beta \times \alpha^{FED^*+D^*}}$

If the individual prefers option A to B : $V_B < V_A \Leftrightarrow \hat{p} < \frac{-V_f}{100 \times \beta \times \alpha^{FED^*} - 110 \times \beta \times \alpha^{FED^*+D^*}}$

Please note that, here we have assumed that agents have risk neutral utility functions. This assumption has been made to find the minimum of $\hat{p}$. For details see appendix.

Part 3, Question 2

Option A ={SS=(100,FED*+2) or LL=(110,FED$^* + D^*$}

Option B={LL(110-2,FED$^* + D^*$)}

If a decision maker chooses option B, she sacrifices the utility of having flexibility and pays $2 \times \alpha^{FED^*+D^*}$ € for the commitment device.

By using quasi-hyperbolic discounting, we get

$$V_A = (\hat{p} \times \beta \times \alpha^{,FED^*+2} \times 100) + [(1-\hat{p}) \times \beta \times \alpha^{FED^*+D^*} \times 110]$$

$$V_B = \beta \times \alpha^{FED^*+D^*} \times 108 - V_f$$

$$V_B > V_A \Leftrightarrow \hat{p} > \frac{-2\times\beta\times\alpha^{FED^*+D^*} - V_f}{100\times\beta\times\alpha^{FED*} - 110\times\beta\times\alpha^{FED^*+D^*}}$$

$$V_B < V_A \Leftrightarrow \hat{p} < \frac{-2\times\beta\times\alpha^{FED^*+D^*} - V_f}{100\times\beta\times\alpha^{FED*} - 110\times\beta\times\alpha^{FED^*+D^*}}$$

Based on the decision maker's choices in questions 1 and 2 of part 3, they can be divided into four categories. For instance, category BA means that the decision maker has chosen option B in question 1 and option A in question 2. Therefore, if the individual prefers option B in questions 1 and 2 in part 3, we get (based on the quasi-hyperbolic discounting function)

$\frac{-2\times\beta\times\alpha^{FED^*+D^*}-V_f}{100\times\beta\times\alpha^{FED*}-110\times\beta\times\alpha^{FED^*+D^*}} < \hat{p} < 1.$

Further, if the decision maker has chosen A and B in questions 1 and 2, respectively, it is not possible to find any positive $\hat{p}$ to explain this choice. In other words, this model predicts that the decision maker will not choose A,B because there is no $\hat{p}$ to model that choice (she will not sacrifice the value of flexibility for the commitment in question 1, while she is ready to pay the value of flexibility and $2\times\beta\times\alpha^{FED^*+D^*}$€ for the commitment in question 2). The minimum, maximum and average p̂ are described in the table below. Table 1 is based on a quasi-hyperbolic model.

table 2: $\hat{p}$, based on quasi-hyperbolic discounting model (risk neutrality is assumed).

		$\hat{p}$
1	A,A	$0 < \hat{p} < \frac{-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}}$
2	A,B	$\frac{-2\times\beta\times\alpha^{FED^*+D^*}-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}} < \hat{p} < \frac{-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}}$
3	B,A	$\frac{-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}} < \hat{p} < \frac{-2\times\beta\times\alpha^{FED^*+D^*}-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}}$
4	B,B	$\frac{-2\times\beta\times\alpha^{FED^*+D^*}-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}} < \hat{p} < 1$

It just is left to measure V_f.

Part3, Question 3

Question 3 is designed to estimate individuals' demand for flexibility. If the decision maker prefers to have flexibility, she needs to sacrifice 2€ (at time FED* or FED*+D*)

Option A ={SS=(100-2,FED*) or LL=(110-2,FED* $+ D^*$}

Option B={LL(110,FED$^{*}+D^{*}$)}

By modeling the value of each options based on the quasi-hyperbolic discounting model we get

$$V_A = (\hat{p} \times \beta \times \alpha^{,FED^{*}+2} \times 98) + [(1-\hat{p}) \times \beta \times \alpha^{FED^{*}+D^{*}} \times 108]$$

$$V_B = \beta \times \alpha^{FED^{*}+D^{*}} \times (110) - V_f$$

If the decision maker chooses option A (B) then

$$V_A \gtreqless V_B \Leftrightarrow V_f \lesseqgtr p(-98 \times \beta \times \alpha^{FED^{*}} + 108 \times \beta \times \alpha^{FED^{*}+D^{*}}) + 2 \times \beta \times \alpha^{FED^{*}+D^{*}}$$

As can be seen, the value of flexibility is related to $\hat{p}$, and it is not possible to estimate the exact V_f. Table 3 shows how we estimate the value of flexibility based on the decision maker's choice in question 3. Please note that, under this setup it is not possible to find the value of flexibility exogenously. In the next sections we will provide sensitivity analysis of results regarding to changes in V_f.

Table 3: Estimation of V_f , using Quasi-hyperbolic discounting function (risk neutrality is assumed).

1	V_f	Estimated V_f
A	$V_f > p(-98\beta\alpha^{FED^{*}} + 108\beta\alpha^{FED^{*}+D^{*}}) + 2\beta\alpha^{FED^{*}+D^{*}}$	$2\beta\alpha^{FED^{*}+D^{*}}$
B	$V_f < p(-98\beta\alpha^{FED^{*}} + 108\beta\alpha^{FED^{*}+D^{*}}) + 2\beta\alpha^{FED^{*}+D^{*}}$	$1\beta\alpha^{FED^{*}+D^{*}}$

Based on the decision makers' choices for questions 1, 2 and 3 in part three, they can be divided into eight categories (see Table 3). For example (A,B,A) means the decision maker has chosen option A in question 1, option B in question 2 and option A in question 3. In four categories, no real number for p̂ can be found based on the inequalities gained from the quasi-hyperbolic discounting model. This means that the proposed model cannot explain the decision maker's behavior who has chosen (A,B,A), (A,B,B), (B,A,A) and (B,B,A).

Table 4: Pooling table 1 and 2 .Estimating p̂ based on quasi-hyperbolic discounting (risk neutrality is assumed).

	average $\hat{p}$	average $\hat{p}(V_f$ is replaced)
AAA	$1/2(\frac{-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}})$	$1/2(\frac{-2\times\beta\times\alpha^{FED^*+D^*}}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}})$
AAB	$1/2(\frac{-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}})$	$1/2(\frac{-\beta\times\alpha^{FED^*+D^*}}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}})$
ABA	NA	NA
ABB	NA	NA
BAA	NA	NA
BAB	$\frac{-\beta\times\alpha^{FED^*+D^*}-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}}$	$\frac{-2\times\beta\times\alpha^{FED^*+D^*}}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}}$
BBA	NA	NA
BBB	$1/2(\frac{-2\times\beta\times\alpha^{FED^*+D^*}-V_f}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}}+1)$	$1/2(\frac{-3\times\beta\times\alpha^{FED^*+D^*}}{100\times\beta\times\alpha^{FED^*}-110\times\beta\times\alpha^{FED^*+D^*}}+1)$

1.5 Welfare Implications

The aim of this section is to examine if proposing a commitment device to decision makers increases their welfare. To answer this question, I assume that commitment is available for decision makers in two ways

1. Voluntary costless commitment: individuals can choose to have the commitment or not (question 1 in part 3).

2. Voluntary costly commitment: individuals can choose to have the commitment or not, but if they want to commit, they must pay for it (question 2 in part 3).

To evaluate the welfare increase or decrease as a result of the commitment, we begin by analyzing question 1 in part 3 of the mentioned experiment (Casari 2009). Decision makers should choose between options A and B. As in the previous parts, let's assume a risk-neutral utility function (U (M) =M, where M is the money associated with each of the options). Moreover, let $\hat{p}$ be the probability that the decision maker estimates for temptation in the future (choosing SS in option A). As mentioned before, there is always an implicit cost of commitment, which is losing the flexibility option. Here, the cost of the commitment device refers to the explicit cost that decision makers should pay to have the commitment device.

1.5.1 Part 3, Question 1

In question 1 of part 3, there is a voluntary costless commitment device (choosing option B instead of option A)

Option A ={ss=(100,FED*) or LL=(110,FED$^*+D^*$}

Option B={LL(110,FED$^*+D^*$)}

$$E_{t=0}(A) = \hat{p} \times (100 \times \beta \times \alpha^{FED^*}) + (1 - \hat{P}) \times (110 \times \beta \times \alpha^{FED^*+D^*})$$

$$E_{t=0}(B) = (110 \times \beta \times \alpha^{FED^*+D^*}) - V_f$$

So, $E\{QUESTION1\}$ is

$$\max[\{\hat{p}\times(100\times\beta\times\alpha^{FED^*})+(1-\hat{P})\times(110\times\beta\times\alpha^{FED^*+D^*})+V_f\},\{(110\times\beta\times\alpha^{FED^*+D^*})\}]\geq\{\hat{p}\times(100\times\beta\times\alpha^{FED^*})+(1-\hat{P})\times(110\times\beta\times\alpha^{FED^*+D^*})+V_f\}$$

The question is how much does this voluntary costless commitment device increase the decision maker's welfare. The answer to this question depends on which option the decision maker has chosen in the question. More precisely, the answer depends on $\hat{p}$ and V_f. If the decision maker has chosen option B, then the welfare increase (let's call it WI) due to the voluntary commitment is

$$WI_i=[\{(110\times\beta\times\alpha^{FED^*+D^*})\}-\{\hat{p}\times(100\times\beta\times\alpha^{FED^*})+(1-\hat{P})\times(110\times\beta\times\alpha^{FED^*+D^*})+V_f\}]$$

Further, it is easy to show the relation between WI and $\hat{P}, V_f$

$$\frac{\delta(WI)}{\delta(p)}=-(100\times\beta\times\alpha^{FED^*})+(110\times\beta\times\alpha^{FED^*+D^*})$$

From question 1 of part 1, we know that $\alpha>\sqrt[D^*]{\frac{100}{110}}\Rightarrow\frac{\delta(WI)}{\delta(p)}>0$. This means that the higher the $\hat{P}$ the more welfare the commitment brings for the decision maker. By contrast, because $\frac{\delta(WI)}{\delta(V_f)}<0$, the higher V_f is, the less welfare the commitment brings for the decision maker. Similarly, if the decision maker has chosen option A $\Leftrightarrow WI=0$

Now, it is possible to compute the welfare effect in the studied population (Casari 2009). Assume that the number who have chosen option B in question 1 in part 3 is N_1 and the rest ($N-N_1$) have chosen option A . Because we have measured $\hat{p}$ and V_f for each decision maker in the previous sections, it is now possible to compute the total welfare increase as a result of the costless voluntary commitment

$$\sum_{i=1}^{N} WI_i = \sum_{1}^{N-N_1} 0 + \sum_{i=1}^{N_1}[\{(110\times\beta\times\alpha_i^{FED_i^*+D_i^*})\} - \{\hat{p}_i\times(100\times\beta\times\alpha_i^{FED_i^*}) + (1-\hat{p}_i)\times(110\times\beta\times\alpha_i^{FED_i^*+D_i^*}) + V_{f_i}\}]$$

The welfare increase based on question 1 of part 3 is summarized in the table below.

	$N-N_1$	N_1	N
	30	48	78
WI	0	90.7	90.7

Thus, the voluntary costless commitment increases the total utility of subjects by 90.7 units

It is possible to use the same method to find the welfare implications of introducing a costly commitment. For example

option A ={ss=(100,FED*) or LL=(110,FED* $+ D^*$}

option B={LL(108,FED* $+ D^*$)}

$$\sum_{i=1}^{N} WI_i = \sum_{1}^{N-N_1} 0 + \sum_{i=1}^{N_1}[\{(108\times\beta\times\alpha_i^{FED_i^*+D_i^*})\} - \{\hat{p}_i\times(100\times\beta\times\alpha_i^{FED_i^*}) + (1-\hat{p}_i)\times(110\times\beta\times\alpha_i^{FED_i^*+D_i^*}) + V_f\}]$$

	N-N_1	N_1	N
	68	10	78
Total WI	0	15.84	15.84

Therefore, the voluntary costly commitment increases the total utility of subjects by 15.84 units.

1.6 Results

The first table of the results shows the number of decision makers in each category. As mentioned before, in four categories it is not possible to find any feasible number for $\hat{p}$. This means that the model used in this research cannot explain those decision makers' behavior who have chosen (A,B,A), (A,B,B), (B,A,A) and (B,B,A). Overall, the model cannot explain the behavior of four out of 78 decision makers. As the table shows, the majority of individuals' behavior (based on three questions of part 3) is consistent with the model.

Table 5 : Numbers of decision makers in each category.

		Number of decision makers.
1	A,A,A	1
2	A,A,B	25
3	A,B,A	2
4	A,B,B	2
5	B,A,A	0
6	B,A,B	38
7	B,B,A	0
8	B,B,B	10
	total	78

Table 5 indicates the average p̂ using the quasi-hyperbolic discounting and hyperbolic discounting models, respectively. As the table shows, the average awareness of the self-control problem using the quasi-hyperbolic discounting model (hyperbolic discounting model) is 34% (33%). This means that decision makers in this experiment on average are partially aware of future choice reversal and the self-control problem. In other words, they think that they might be tempted in the future to change the decision they have made with probability of 34%.

Table 6: Estimated p̂ for the sample under hyper and quasi-hyperbolic functions

	Quasi hyperbolic	Hyperbolic
$\min \hat{p}$	.1791068	.1671707
Std.Dev	.1845694	.1804574
$\max \hat{p}$	.5066707	.4939568
Std.Dev	.264532	.2893877
$ave\ \hat{p}$	.3428887	.3305637
Std.Dev	.2230062	.2303776

1.7 Characteristics of subjects and $\hat{P}$

The aim of this section is to examine if there is a relation between characteristics of subjects and $\hat{P}$. Table 7 shows the relation between individuals' characteristics and awareness about self-control problem based on the OLS regression method. It should be mentioned that due to the presented models in this research, the awareness about choice reversal is measured by the willingness to pay for the commitment device (choosing option B in questions 1 and 2 of part 3). Casari (2009) run a logit regression model to find if the sophistication is related to the decision makers characteristics. In that study, individuals are divided into sophisticated and naive (binary variable) categories, and a logit regression is used. In this experiment, I found the degree of sophistication or naiveté. As a result, we have continuous numbers for the variable ($\hat{p}$) and therefore it is possible to use an OLS regression model. In Table 6, the regressors are

1. avealpha: the average discounting factor (α) for each individual, which is generated from the results of questions in parts 1 and 2.

2. earlya: measure of impatience, D^*, which is generated from the results of questions in parts 1 and 2.

3. front_earlyb: choice reversal time: FED^*.

4. amale: dummy variable, male or female: male=1 female=0.

5. lcreditaccess: Belief about personal access to credit :1=at least 90%, 2=at least 75%, 3=at least 50% , 4=less than 50%

6. smokerntq: smoker never tried to quit

7. smokertqu: smoker unsuccessfully have tried to quit.

8. Category: Individuals' choices for option B in questions 1, 2 and 3 in part 3 of the experiment.

Table 7: Quasi hyperbolic model

	(1)
VARIABLES	*P*
avealpha	-1.42
	(-0.50)
earlya	-.0000778
	(-0.26)
front_earlyb	.0000784
	(0.89)
amale	.0203703
	(1.55)
lcreditaccess	-.0048222
	(-0.84)
smokerntq	.0153102
	(1.10)
smokertqu	.030058 *
	(1.73)
strangerisk	-.00674
	(-1.12)
fmayor	.0009018
	(0.11)
category	.3660715 ***
	(37.95)
Observations	74
R-squared	0.911

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As this table shows, there is a positive relation between awareness of choice reversal and having tried to quit smoking unsuccessfully. In other words, smoker who unsuccessfully have tried to quit, are more aware about self-control problem.

1.7.1 Sensitivity Analysis Of Regression Results With Respect To V_f.

The aim of this part is to analyze the sensitivity of the regression results with respect to estimated values of V_f. As it is mentioned before, $\hat{p}$ (the awareness about self control problem) is related to V_f (value of flexibility). Also based on tables 2 and 3, our formula for measuring the V_f is dependent on $\hat{p}$. As a result, the only way we could measure $\hat{p}$ was to find an approximate value for V_f. Since in our model it is not possible to find V_f exogenously, it is a reasonable to analyze sensitivity of the regression results with respect to estimated values of V_f. To do so, we have increased the estimated V_f by 20 and 10 percents ($\hat{p}_2$ and $\hat{p}_3$ respectively) for individuals who has choose option A in section 3 of part 3. Similarly we have decreased the estimated V_f by 20 and 10 percents ($\hat{p}_2$ and $\hat{p}_3$ respectively) for individuals who has choose option B in section 3 of part 3. Table 8 shows the results of regression with respect to the changes in estimating V_f.

Table 8: Quasi hyperbolic model

VARIABLES	$\hat{p}_2$	$\hat{p}_3$
avealpha	-2.112249	-1.870868
	(-0.65)	(-0.61)
earlya	.0000209	-.000022
	(0.06)	(-0.07)
front_earlyb	.0000928	.000091
	(0.93)	(0.97)
amale	.021675	.021749
	(1.56)	(1.56)
lcreditaccess	-.0046349	-.0047576
	(-0.72)	(-0.78)
smokerntq	.0191987	.0172544
	(1.22)	(1.16)
smokertqu	.030058 *	.0306748 *
	(1.59)	(1.67)
strangerisk	-.00774	-.0071929
	(-1.12)	(-1.12)
fmayor	.0009818	.0009414
	(0.11)	(0.11)
category	.360715 ***	.359 ***
	(32.95)	(35.02)
Observations	74	74
R-squared	0.951	.911

Robust t-statistics in parentheses
*** p$<$0.01, ** p$<$0.05, * p$<$0.1

As these table show, there is still a positive relation between awareness of choice reversal and having tried to quit smoking unsuccessfully. So, 10 and 20 percent increase or decrease in the estimated value of flexibility does not change the regression results. Moreover, the mean of $\hat{p}$ stays fairly constant at 33 percent.

1.7.2 Additional Insight Derived With The Proposed Model Comparing With Results Of The Experiment Of Casari (2009)

In this chapter we have introduced a model to measure the awareness of future choice reversal. In the related literature, individuals are divided into three categories regarding their awareness about choice reversal, they are known as sophisticated, partially sophisticated and naive. Unlike the similar studies about awareness of choice reversal, in this study we introduced a model to find a continuos measurement for awareness about future choice reversal. This approaches help us to find a degree of sophistication. In section 5, we have shown that, this approaches can help us to measure the welfare increase (or decrease) as a result of introducing a commitment device.

Finally, finding a continuos variable for awareness about choice reversal creates some new regression results. As tables 6-8 show, there is still a positive relation between awareness of choice reversal and having tried to quit smoking unsuccessfully. This finding is different with regression results of Casari(2009) which finds a positive relation between awareness of choice reversal and having never tries to quite smoking.

1.8 Conclusion

Diminishing impatience behavior has been discussed in the literature by two approaches. On one side of the argument, some studies have explained diminishing impatience (present bias effect) by introducing an uncertain exponential discounting model (Sozou 1998, Azfar 1999, Halevy 2008, Dusgopta and Maskin 2005). In those studies, the origin of choice reversal behavior is the risk that any future reward contains that the immediate reward does not. On the other side of the argument, some previous studies claim that diminishing impatience is a result of the temptation generated by dynamically inconsistent preferences. These studies show that the observed behavior is consistent with the hyperbolic and quasi-hyperbolic discounting functions (Laibson 1997; Thaler and Shefrin 1981).

Both sides of the argument agree on the shape of the discounting function (hyperbolic and quasi-hyperbolic), However, the origin of such behavior is quite different in each of the approaches. One way to find the origin of choice reversal behavior is looking at the decision makers' demand for flexibility and commitment devices. There is also experimental evidence that shows the existence of demand for commitment (Casari 2009)

In this research, I showed how it is possible to examine the origin of present bias behavior by analyzing the demand for commitment and flexibility devices. It was also shown how it is possible to measure the decision makers' awareness of choice reversal behavior. I used data from an experimental study by Casari (2009) to estimate the awareness of the self-control problem. The results indicate that decision makers are partially aware of their self-control problems (using hyperbolic discounting and quasi-hyperbolic discounting). Based on Table 6, there is a positive relation between awareness of choice reversal and having tried to quit smoking unsuccessfully. In other words, smoker who unsuccessfully have tried to quit, are more aware about self-control problem. However, belief about personal access to credit has a negative relation with $\hat{p}$.

Moreover, according to section 5 of this research, proposing a voluntary commitment device can increase welfare. This increase depends on individuals' awareness of the self-control problem. Based on the experimental data considered in this research, introducing a voluntary commitment device increases the welfare of the studied population.

Chapter 2
Stock Price Movements In A Heterogeneous Agent Model

2.1 Introduction

Is it possible to model stock price movements? Economists have long been interested in that question. One of the most influential theories about the predictability of stock price movements was stated by Fama (1970). The theory known as the EMH and states that because market participants are fully rational, any stock price prediction will be applied by the investors until it loses its predictability power. Therefore, stock price movements can be model by a Random Walk process. Some observed evidence in stock markets is not consistent with the "full rationality" assumption of the EMH (Hommes 2006) such as high daily trading volume, excess volatility (Shiller 1981, 1989), overreaction (Thaler 1980), some skewness, excess kurtosis, fat tails and power low behavior in returns. See Pagan (1996) and Lux (2004). Also, various studies show the predictability power of technical analysis, which uses past price movements to predict future prices (see Pesaran and Timmermann 1994, 1995).

As this evidence is not in line with the EMH, Heterogenous Agent Models (HAMs) have emerged in financial economics literature. See the recent surveys by Lux(2004), Hommes (2006), LeBaron(2006) and Chiarella et al (2009). Basically these models explain the dynamics of financial asset prices by interaction between heterogeneous agents who have a different attitude to risk and trading strategies.

One class of HAMs exhibit that the fraction of each type of investors would change according to the predictability power of their trading strategy. In particular, Brock and Hommes(1997,1998) introduced an Adaptive Belief System model of financial markets. According to this model, market is populated by heterogenous agents who use different types of investing strategies. If one particular strategy generates more profit than the others, investors will convert to use the more profitable strategy. The resulting non-linear dynamic systems is able to show a wide range of complex price behavior from local stability to high order cycles and chaos (See Brock and Hommes, 1998 and Hommes, 2002).

The other class of heterogenous agent models are computational oriented models (LeBaron, 2006). These models can also generate the stylized facts of financial markets. Since this class of models assume more realistic market features such as wealth constraint or no-short-selling, they face the problem of too many parameters and too many degree of freedom(Chiarella, He and Pellizari, 2012).

The aim of this research is to model stock price movements as a result of fundamental or technical shocks under a heterogeneous agents' structure. Basically this chapter is based on theoretical research done by Chiarella, He and Hommes (2006) (here after CHH 2006). In this study, I assume that the market involves heterogeneous agents that use different rules for trading and that prices are endogenously determined through interactions between these agents. I use the HAM framework by CHH 2006. In the CHH 2006 model, the market involves two types of traders: chartists, who use a moving average trading strategy, and fundamentalists. The difference between this study and the CHH 2006 model is heterogeneity in the chartist group which was left for future works. As it is suggested in CHH 2006, heterogeneity in chartist group can make the HAMs more realistic. This means that chartists use different technical trading rules. More precisely, chartists are assumed to use moving average strategies with different time lengths.

It should be mentioned that, Chiarella, He and Pellizzari (2012)(here after CHP 2012) have extended the work of CHH in a Double Action Market frame work. They use simulation to analyze the stock price movement base CHH.

In this chapter we use the theoretical work of CHH and use the simulation methods in CHP but not in double auction market frame work.

2.2 The Model

As mentioned before, I use the model introduced in CHH 2006 and aim to model more demand variety by allowing heterogeneity even in the chartist group. More precisely, it is assumed that chartists use moving average strategies (one of the most popular technical trading strategies) with different lengths. In this study, the same notations as CHH 2006 are used to facilitate the comparison between the proposed model and CHH 2006.

It is assumed that there is just one risky asset in the market and the price (market price) at time t is p_t, which is adjusted with a market maker scenario rather than a Walrasian approach. This means that the market maker adjusts prices relative to the total excess demand of all market investors. So

$$p_{t+1} = p_t + \mu . D_t \qquad (1)$$

where D_t is the aggregate excess demand of all market participants and μ is the speed of the adjustment of the market maker to aggregate excess demand. Aggregate excess demand can be divided into two groups: demand of fundamentalists and demand of chartists. Further, it is assumed that the demand of fundamentalists is homogeneous, whereas the demand for chartists is heterogeneous. In other words, there is just one type of fundamentalist but H different types of chartists with H different technical strategies. The aggregate excess demand of $H+1$ different participants is

$$D_t = (N_t^f D_t^f + \sum_{i=1}^{H} N_t^{C_i} D_t^{C_i}) \qquad (2)$$

The total number of investors in the market is fixed at N . N_t^f is the number of fundamentalists with excess demand D_t^f at time t and $N_t^{C_i}$ is the number of chartists who use technical trading strategy i and have excess demand $D_t^{C_i}$. Now, it is useful to derive the fraction of each type of trader in the market

$$n_t^f = \frac{N_t^f}{N} \qquad , \qquad n_t^{C_i} = \frac{N_t^{C_i}}{N} \qquad (3)$$

Where n_t^f is the fraction of fundamentalists with excess demand D_t^f at time t, and $n_t^{C_i}$ is the fraction of chartists who use technical strategy i and have excess demand $D_t^{C_i}$.

By substituting (2) and (3) into equation (1), we get

$$p_{t+1} = p_t + \tfrac{\mu}{N}(N_t^f D_t^f + \sum_{i=1}^{H} N_t^{C_i} D_t^{C_i})$$

$$p_{t+1} = p_t + \mu(n_t^f D_t^f + \sum_{i=1}^{H} n_t^{C_i} D_t^{C_i})^1 \qquad (4)$$

Following CHH2006 and Beja and Goldman (1980), fundamentalists' excess demand can be written as

$$D_t^f = \alpha(p_t^* - p_t) \qquad (5)$$

where p_t^* is the fundamental price, which is assumed to be an exogenous variable, and α is the fundamentalists' sensitivity to the difference between the fundamental price and the market price. Despite the demand of fundamentalists, the demand of chartists is heterogeneous and depends on which technical trading strategy they use. It is assumed that the used technical trading strategy is moving average; however, chartists are different with respect to the lengths they use for computing

[1] Please note that μ in this equation stands for μ/N, but for simplicity in notations it is written as μ.

the moving average. Therefore, the excess demand of chartist i who uses a moving average with length L_i is

$$D_t^{C_i} = h(p_t - ma_t^{L_i}) \qquad (6)$$

Where h is the sensitivity of the chartist to the difference between the market price and moving average. $ma_t^{L_i}$ is the moving average of length L_i and is calculated as

$$ma_t^{L_i} = \frac{1}{L_i}\sum_{i=0}^{L_i-1} p_{t-i} \qquad (7)$$

In this research, we select $h(x)$ as a concave function similar to Chiarella (1992)

$$h(x) = \tanh(ax)$$

In this model, the fraction of investors using strategy i changes according to the profit (U) that the strategy i has generated. These profit functions have a memory element, and η is the weight of profit generated by each trading strategy at $t-1$. So

$$U_{f,t} = \pi_{f,t} + \eta\pi_{f,t-1} \qquad (8)$$

$$U_{C_i,t} = \pi_{C_i,t} + \eta\pi_{C_i,t-1} \qquad (9)$$

$$\pi_{f,t} = D^{f}_{t-1}(p_t - p_{t-1}) - sD^{f}_{t-1} \qquad (10)$$

$$\pi_{C_i,t} = D^{C_i}_{t-1}(p_t - p_{t-1}) - sD^{C_i}_{t-1} \qquad (11)$$

Where $sD^{C_i}_{t-1}$ and sD^{f}_{t-1} are the costs associated with excess demand at time $t-1$ and s is the transaction cost of trading one share of the asset. As in CHH 2006, it is assumed that the proportion of each type of investor evolves according to the Gibbs probabilities (Manski and McFadden 1981)

$$n_{f,t} = \frac{e^{\beta U f,t}}{e^{\beta U_{f,t}} + \sum_{i=1}^{H} e^{\beta U_{c_i},t}} \qquad (12)$$

$$n_{C_i,t} = \frac{e^{\beta U_{C_i},t}}{e^{\beta U_{f,t}} + \sum_{i=1}^{H} e^{\beta U_{c_i},t}} \qquad (13)$$

where $\beta > 0$ is the intensity of choice, measuring how quickly investors switch between two strategies. For example, if $\beta = 1$ and there is one type of chartist and one type of fundamentalist who make the same profit, $U_{f,t} = U_{C,t}$, then the proportion of fundamentalists and chartists would be equal ($n_{f,t} = n_{C_i,t} = 1/2$). However, if $U_{f,t}$ is bigger than $U_{c,t}$, then some chartists will change their trading strategies to the fundamental strategy and vice versa. The speed of this conversion depends positively on β. If $\beta = 0$, then the proportion of each type of investors is fixed and equals to $\frac{1}{2}$.

Now, by putting equations (6) and (5) into equation (4) and using (12) and (13) for changes in the proportions, we get a nonlinear system of difference equations for stock price movements as follows

$$p_{t+1} = p_t + \mu[n_{f,t}\alpha(p^* - p) + \sum_{i=1}^{H} n_{c_i,t} h(p - \frac{1}{L_i}\sum_{i=0}^{L_i-1} p_{t-i}]$$

$$n_{f,t} = \frac{e^{\beta U f,t}}{e^{\beta U_{f,t}} + \sum_{i=1}^{H} e^{\beta U_{c_i},t}} \tag{14}$$

$$n_{C_i,t} = \frac{e^{\beta U_{C_i},t}}{e^{\beta U_{f,t}} + \sum_{i=1}^{H} e^{\beta U_{c_i},t}}$$

We are interested in simulating system (14) when p^* (i.e. the fundamental price) changes, namely finding the dynamic behavior of stock price movements as a result of these fundamental changes.

2.3 Example Of Empirical Evidence

CHP 2012 have considered some descriptive statistics of daily returns of major European stock indices such as, German DAX, French CAC and English FTSE. They have studied the indexes for two non-overlapping periods of 8 years (1992-1999 and 2000-2007). Table 1 summarizes some descriptive statistics.

Period	Index	Max	Min	Sd	Skew	Kurt
1992-1999	CAC	0.06098	-0.05627	0.012074	-0.11737	4.72
	DAX	0.05894	-0.06450	0.011938	-0.37973	6.10
	FTSE	0.05440	-0.04140	0.009199	0.04947	5.37
2000-2007	CAC	0.07002	-0.07678	0.013961	-0.09272	5.96
	DAX	0.07553	-0.06652	0.015492	-0.04577	5.74
	FTSE	0.05904	-0.05589	0.011292	-0.17404	5.87

TABLE 1. From Chiarella, He and Pellizzari (2012). Descriptive statistics of the returns of three European indexes.

The aim of this chapter is to reproduce some stylized facts of the stock market. More precisely, we are interested to reproduce fat tails, positive excess kurtosis in returns and excess volatility of market prices relative to fundamental prices.

2.4 Simulations

2.4.1 Parameter Selection.

We discuss in this section the results obtained by simulations of the model previously described. For each parameter set we run the market 1000 times for T = 250 trading days, about one year. Similar to CHP 2012 the choice of the parameters is guided by the values that were used in CHH 2006 but still required some trial-and-error to get realistic time series, as in the most of agent-based models. The parameters are listed in Table 2. For the local robustness of our results with respect to slight changes in β and α, we have run the simulations with different values of α, β.

Parameter	Value	Description
α	$\frac{60}{100}, \frac{65}{100}, \frac{70}{100}$	Reaction coefficient for fundamentalists
a	1	Reaction coefficient for chartists
η	$.2$	Profit smoothing parameter
μ	1	Reaction coefficient of market maker
c	$.1$	Cost of transaction
β	$\frac{3}{10}, \frac{4}{10}$	Intensity of switching
L	$5, 20, 50$	Length of moving average window
Types of chartists	$1, 2, 3$	

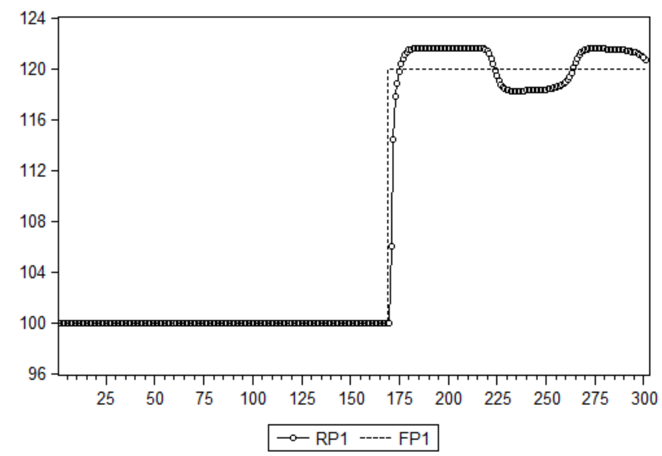
Table 2. Parameters Selection

2.4.2 Fundamental Prices Has A Single Shock

This section examines stock price dynamics by using numerical simulations. It is assumed that there are three types of technical traders and one type of fundamental trader. The first type of chartist uses long moving average strategies (i.e. they use a 50-day moving average strategy). The second type uses medium moving average strategies (20 days) and the last type evaluates short moving average strategies (5 days). The aim of this part is to assess the dynamic behavior of market prices when the fundamental price changes. Consider a situation when the fundamental price increases from 100 to 120 at time t=170. We run the simulation for 250 days (one trading year). In order to measure market price fluctuations around the fundamental price (p^*), the sum of squared differences between the market (p) and fundamental prices is calculated. Thus, the difference between market and fundamental prices (D) is calculated as

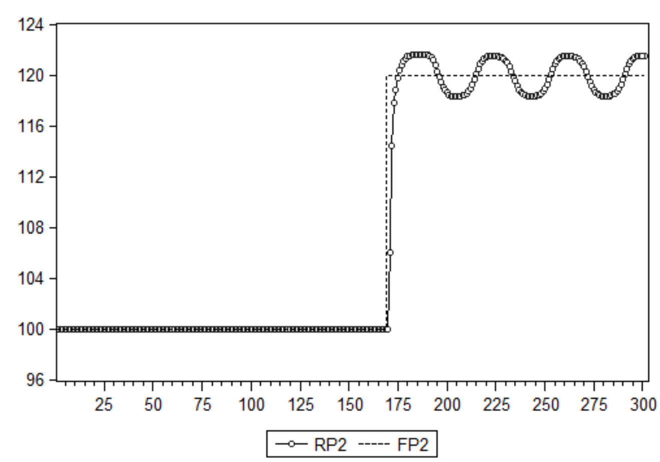
$$D = \sum_{i=1}^{N}(p_t - p_t^*)^2.$$

In Figures 1–3, the solid lines show the fundamental prices (fp) and the market prices if there were only fundamentalists in the market. The dashed lines indicate the market prices (rp) when the market is populated by fundamentalists and just one type of chartist using 50, 20 or 5 day moving average strategies. In figures 4-7 we have increased the variety of chartists in our model and assumed that there are three types of chartists in the market. The aim of this section is to find out the effects of chartists heterogeneity in fluctuations of market prices as a results of changes of fundamental prices.



Case1: one type of chartists 50 (alpha=.6,beta=.3)

2



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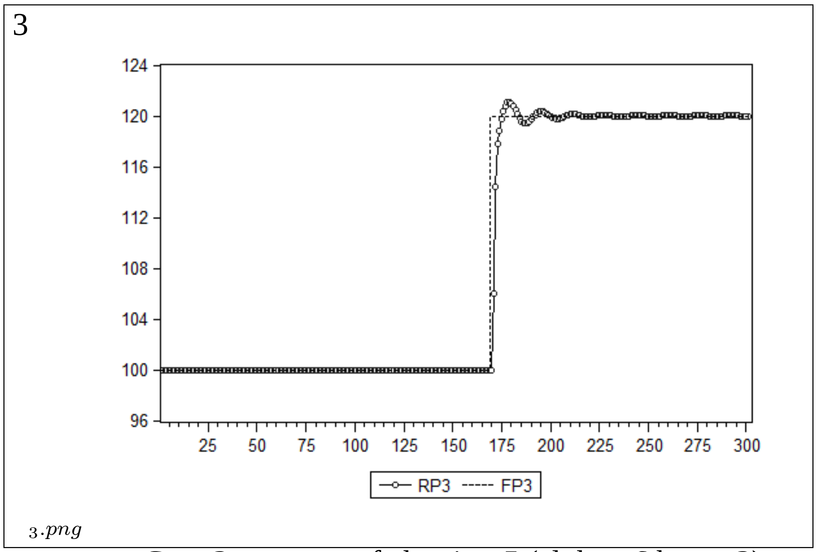
Case 2: one type of chartists 20 (alpha=.6,beta=.3)

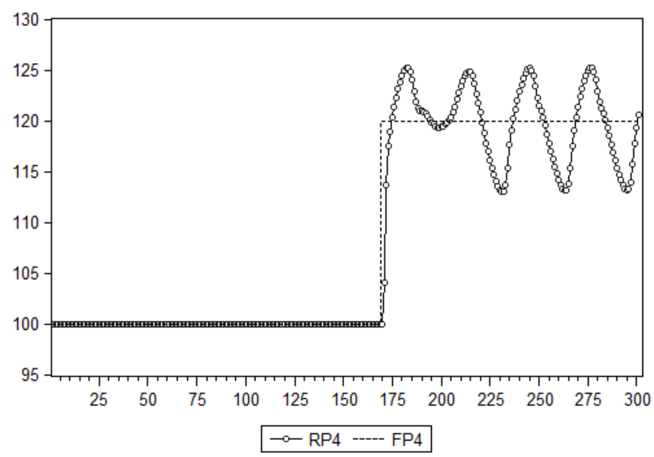


Case 3:one type of chartists 5 (alpha=.6,beta=.3)

At t=170, the fundamental price increases to 120. At this time, the demand of fundamentalists is positive since the fundamental price has increased. Moreover, the demand of chartists is positive because the excess demand of fundamentalists has raised market prices. At the first intersection between the fundamental and market prices, the excess demand of fundamentalists is zero, but there is positive excess demand for chartists, which leads to an increase in the market price. After the fundamental price changes, whenever the market price moves toward the fundamental price, the excess demand of fundamentalists and chartists has the same sign. However, as the market price moves above or below the fundamental price, the excess demand of fundamentalists and chartists has a negative relation. This dynamic leads to oscillations in market prices. In the next case, the heterogeneity between chartists is increased to assess if more heterogeneity can lead to more oscillations.

The stability conditions for this dynamic system are not the aim of this research, however, as these figures (and parameter D) show (table 3), when market participants use moving average strategies with longer time lengths, market prices indicate more fluctuations. Please note that this finding is consistent with the results in CHH 2006.

4



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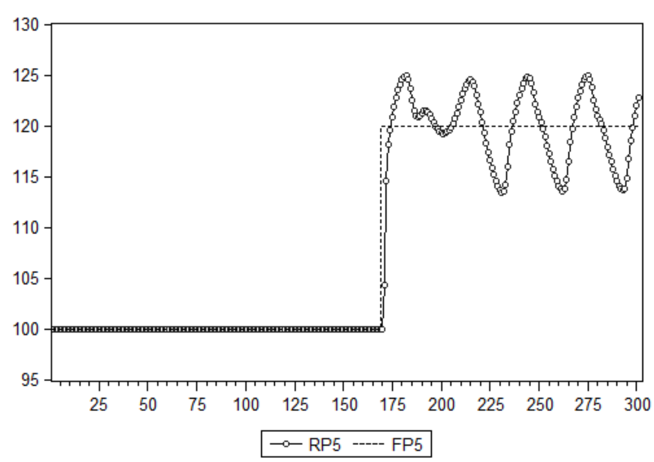
Case 4: three types of chartists 50,20,5 (alpha=.6,beta=.3)

5



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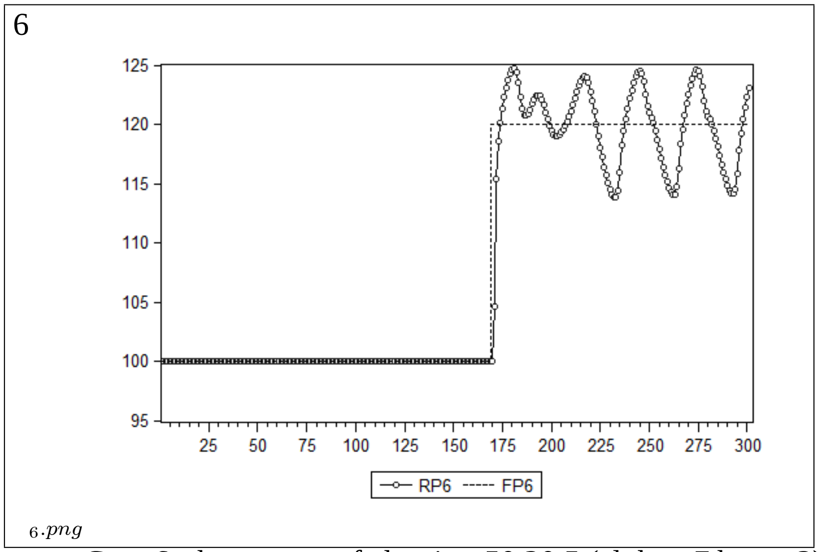
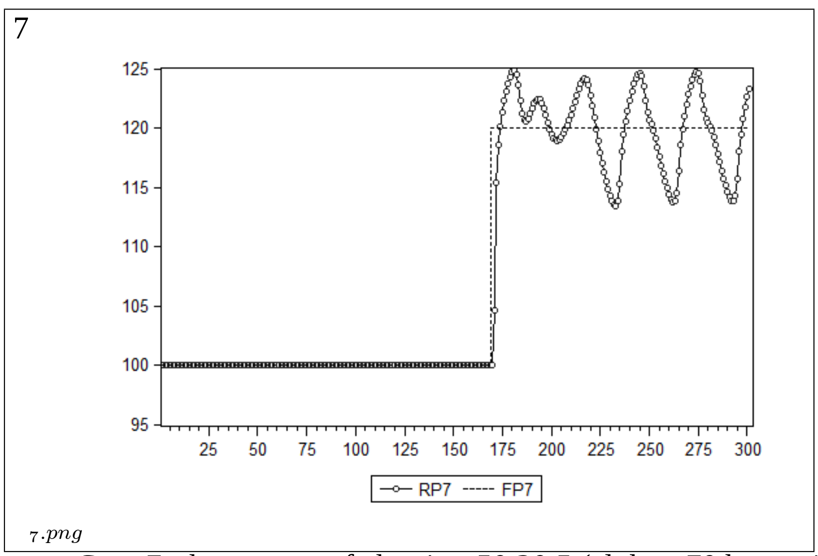
Case 5: three types of chartists 50,20,5 (alpha=.65,beta=.3)



Case 6: three types of chartists 50,20,5 (alpha=.7,beta=.3)



Case 7: three types of chartists 50,20,5 (alpha=.70,beta=.4)

These simulations show that increasing heterogeneity in the chartist group leads to more volatility in stock prices (when the other parameters are fixed). By comparing figures 1-3 with figures 4-7, we can see more fluctuations in market prices.

Table below presents maximum, minimum, standard deviation, skewness, kurtosis and D of these 7 simulations. As this table shows, the parameter D is higher in cases 4-7 than cases 1-3. As it is mentioned before, this parameter captures the volatility of market prices relative to fundamental prices. Moreover, according to this table, there is a fair amount of skewness and kurtosis in distribution of returns.

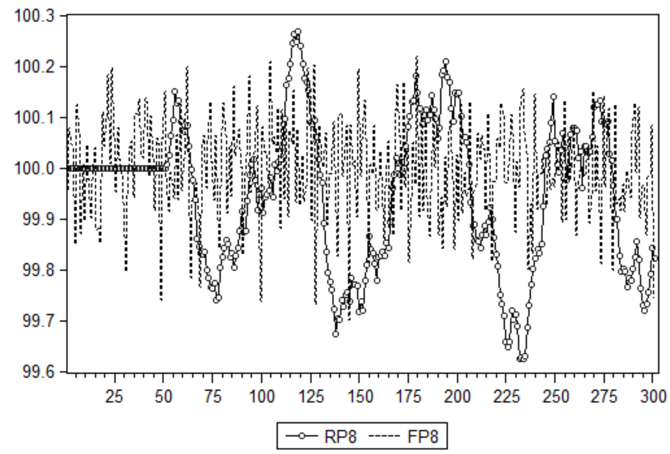
	max	min	std	skew	kurt	D
case1	0.076262	-0.004089	0.005849	10.80621	126.9705	2.99
case2	0.076262	-0.003936	0.005920	10.40489	120.8296	2.80
case3	0.076262	-0.002780	0.005821	10.97500	129.5415	2.12
case4	0.088292	-0.009449	0.007395	6.492935	70.55668	8.35
case5	0.093129	-0.009828	0.007512	7.139933	81.32840	7.30
case6	0.097624	-0.010152	0.007632	7.770150	92.04206	6.52
case7	0.097624	-0.011120	0.007773	7.417906	85.80368	6.82

Table 3. Descriptive Statistics

2.4.3 Fundamental Prices Follow a Random Walk

As in the previous part, it is assumed that there are three types of technical traders and one type of fundamental trader. The aim of this part is to examine the dynamic behavior of market prices when the fundamental price follows a random walk. Simulations are run for 1000 times for 250 days (one trading year) and the other parameters are fixed. Similar to the previous section, we have run the first simulations (figures 8-10) with one types of chartists using 50,20 and 5 days moving average strategies. Next we have run the simulations with three types of chartists (Figures 11-14) to see the effects of heterogeneity in chartists on dynamics of market prices.

8



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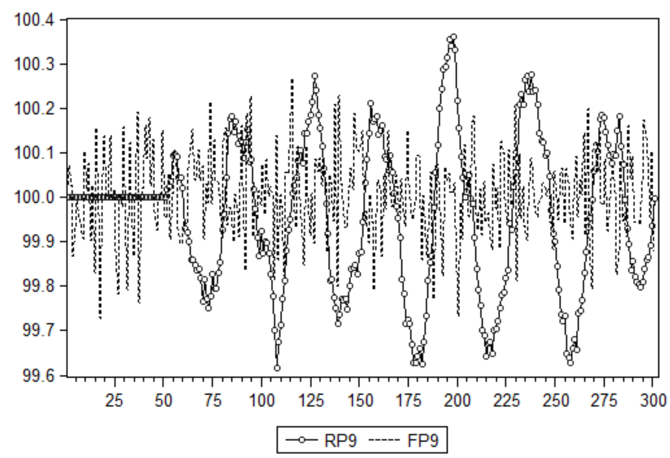
Case 8: there one type of chartists 50 (alpha=.6,beta=.3)

9



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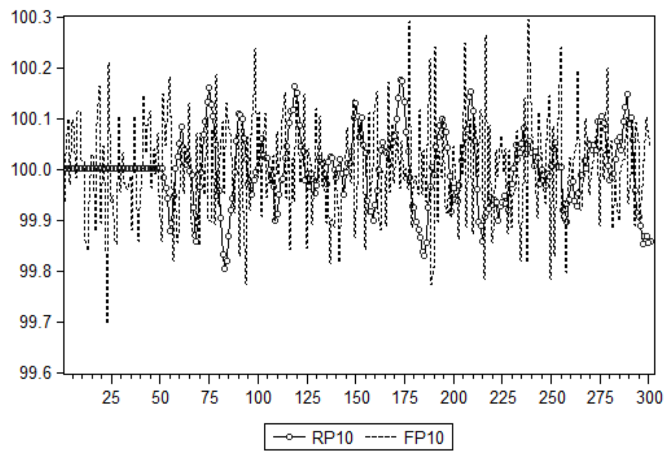
Case 9: there one type of chartists 20 (alpha=.6,beta=.3)

10



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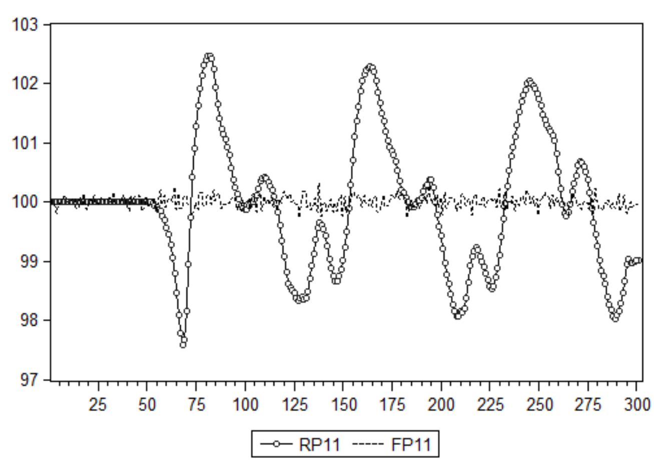
Case 10: there one type of chartists 5 (alpha=.6,beta=.3)

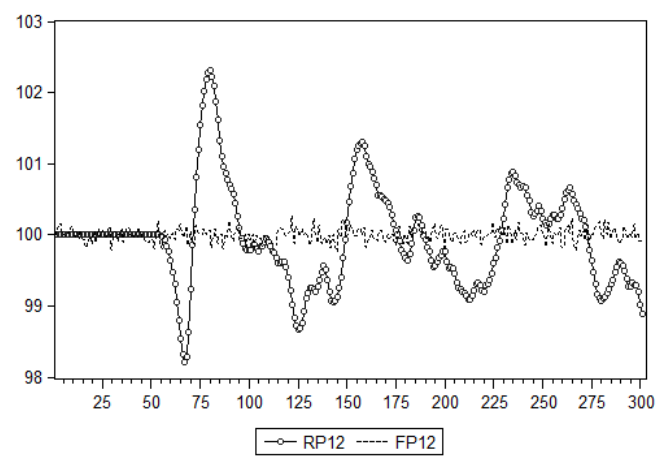
11



11.png

Case 11: three types of chartists 50,20,5 (alpha=.6,beta=.3)

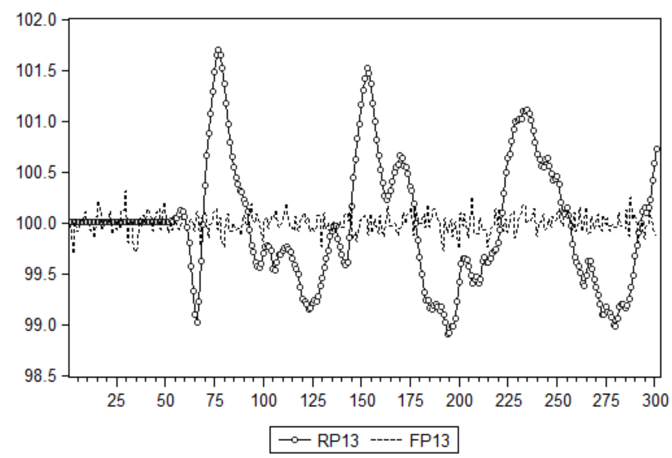
12



$_12.png$

Case 12: three types of chartists 50,20,5 (alpha=.65,beta=.3)

13



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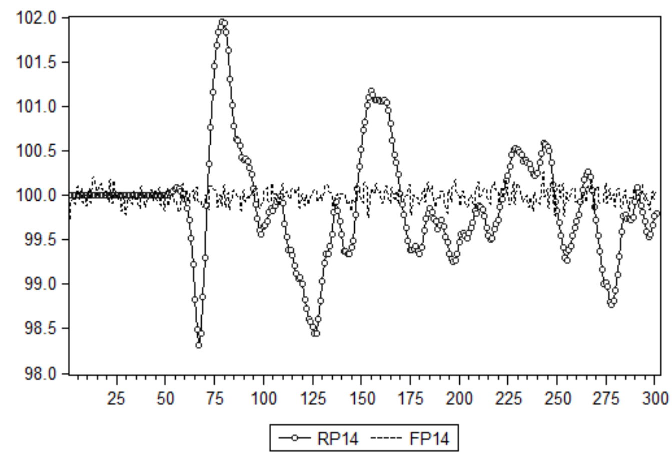
Case 13: three types of chartists 50,20,5 (alpha=.7,beta=.3)

14



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Case 14: three types of chartists 50,20,5 (alpha=.70,beta=.4)

Despite cases 1–3, Figures 8–10 show that when the market is populated by one type of chartist and one type of fundamentalist and fundamental prices follow a random walk, market prices and fundamental prices move together. This finding is the same as in CHH 2006 and it is not consistent with the findings in actual stock market such as excess volatility.

Figures 11-14 shows the case when heterogeneity in trading strategies increases; here, market prices indicate more volatility as a result of the changes in fundamental prices. So it can be concluded that our extended work of CHH 2006 can capture not only the finding in CHH 2006, but also is able to reproduce the excess volatility which one of the most controversial anomalies of stock markets.

Table 4 shows the results of these simulations (figures 8-14). As this table shows, similar to table 3, the parameter D is higher in cases 10-14 than cases 8-

10. As it is mentioned before, this parameter captures the volatility of market prices relative to fundamental prices. Also, according to this table, there is a fair amount of skewness and kurtosis in distribution of returns.

	Max	Min	STD	Skew	Kurt	D
case 8	0.001065	-0.000870	0.000319	0.114363	3.462582	2.40
case 9	0.001193	-0.001152	0.000408	0.041243	3.050976	2.19
Case 10	0.000748	-0.001012	0.000326	-0.380547	3.349227	1.24
case 11	0.008271	-0.003770	0.001740	1.251187	6.476243	20.40
case 12	0.006572	-0.002901	0.001265	1.510904	8.537888	17.60
case 13	0.004261	-0.002478	0.001065	0.668808	4.478898	15.28
case 14	0.006120	-0.004148	0.001301	0.791044	5.903242	16.80

Table 4. Descriptive Statistics

2.5 Conclusion

In this paper, the effects of changes in fundamental prices on market prices were studied. This research followed the work of Chiarella et al. (2006) and considered a market populated by heterogeneous investors using different trading strategies. The new aspect of this research is allowing chartists to use different time lengths for calculating the moving average strategy. The time series analysis of changes in fundamental prices was studied in two scenarios.

The first scenario considers a stock market when there is a single shock to fundamental prices. In this scenario, the proposed HAM indicates oscillations in market prices (Figures 1–3). Moreover, when heterogeneity in the market (letting chartists use moving average strategies with different time lengths) is increased, market prices fluctuate more around fundamental prices.

In the second scenario, fundamental prices follow a random walk. In this condition, when the market is populated by one type of fundamentalist and one type of chartist (who use 50-, 20- or 5-day moving average strategies), fundamental prices and market prices move closely together (Figures 8–10). This result is not consistent with the findings in actual markets such as excess volatility (Shiller 1985). However, increasing heterogeneity in the chartist group leads to higher fluctuations in actual prices in response to fundamental changes (Figures 11-14).

In future works, it might be possible to add different technical trading rules such as pricing channels or genetic algorithms to assess if the volatility of actual prices increases. It might also be possible to use the proposed HAM for real data to compare the predictability power of this model and known models such as ARCH and GARCH.

Chapter 3
Estimation of Stock Price Movements Based On HAM

3.1 Introduction

This section continues on from chapter 2. In the previous chapter, it was shown that increasing heterogeneity in the chartist group results in more fluctuations in response to a fundamental shock. This result was based on numerical simulations. The contributions of this paper are twofold: First, we predict stock prices based on a HAM in which there is heterogeneity in the chartist group. Second, we compare a measure of fitness and the forecasting ability of the presented model with similar studies using HAMs. We use monthly data of S&P 500 from 1990 until 2012.

As mentioned in the previous chapter, HAMs are able to capture extreme movements in asset prices, thereby explaining excess volatility. Excess volatility states that fluctuations in market prices are too large to be justified by changes in fundamental prices (Shiller 1981). This difference in fluctuations is the main motivation to study stock markets under HAMs. Because in HAMs, it is assumed that the market is populated by different agents. For example, chartists believe that the stock price trend will continue, while fundamentalists expect the prices to return to fundamental prices. The existence of these two types of beliefs in the market will create fluctuations around fundamental prices. This aspect of HAMs has motivated the recent literature to estimate such models. For example, Gilli and Winker (2003) and Jong et al. (2011) documented the existence of behavioral heterogeneity in foreign exchange markets. Boswijk et al. (2007) found a similar result in the stock market. Chiarella et al. (2012) used a regime switching model to estimate behavioral heterogeneity in the stock market. Most of these mentioned studies assume that chartists use one type of technical trading strategy. However, in this study we assume that chartists use different technical trading strategies.

This research is organized as follows. Section 2 describes the HAM (similar to in chapter 2), while section 3 presents the results of the empirical estimation of the model. In section 4, the forecasting accuracy of the model is evaluated by comparing it with the models proposed by Boswijk et al. (2007) and Chiarella et al. (2011). In section 5, we analyze how the elements of our HAM change over time. Concluding remarks are presented in section 6.

3.2 Model

As mentioned before, we use the model introduced in CHH 2006 and aim to make it more heterogeneous by allowing heterogeneity even in the chartist group. More precisely, we assume that chartists use one of the most popular technical analyses (moving average with different lengths). The idea behind introducing heterogeneity in the chartist group comes from chapter 2. In chapter 2, it was shown that when heterogeneity in the chartist group increases, stock prices show higher fluctuations in response to a fundamental shock. This finding is in line with some evidence in stock markets such as excess volatility (Shiller 1989).

In this model, it is assumed that there is just one risky asset in the market and that the real market price at time t is p_t, which is adjusted with a market maker scenario rather than a Walrasian approach. So,

$$p_{t+1} = p_t + \mu(D_t) \qquad (1)$$

where D_t is the aggregate excess demand of all market participants and μ is the speed of the adjustment of the market maker to aggregate excess demand. It is useful to mention that in this research we use “stock price”, “actual price” and “market price” with the same meaning, which is the revealed price of an asset. Aggregate excess demand can be divided into two groups: demand of fundamentalists and demand of chartists. Further, it is assumed that the demand of fundamentalists is homogeneous. In other words, there is just one type of fundamentalist, whereas there are H different types of chartists with H different technical strategies. Therefore, the aggregate excess demand for H+1 different participants is

$$D_t = (N_t^f D_t^f + \sum_{i=1}^{H} N_t^{C_i} D_t^{C_i}) \qquad (2)$$

The total number of investors in the market is fixed at N. N_t^f is the number of fundamentalists with excess demand D_t^f at time t, while $N_t^{C_i}$ is the number of chartists who use technical strategy i and have excess demand $D_t^{C_i}$. Now, it is useful to derive the proportion of each type of trader in the market

$$n_t^f = \frac{N_t^f}{N} \quad , \quad n_t^{C_i} = \frac{N_t^{C_i}}{N} \qquad (3)$$

By substituting (2) and (3) into equation (1), we get

$$p_{t+1} = p_t + \frac{\mu}{N}(N_t^f D_t^f + \sum_{i=1}^{H} N_t^{C_i} D_t^{C_i})$$

$$p_{t+1} = p_t + \mu(n_t^f D_t^f + \sum_{i=1}^{H} n_t^{C_i} D_t^{C_i}) \qquad (4)$$

Following CHH 2006 and Beja and Goldman (1980), fundamentalists' excess demand can be written as

$$D_t^f = \alpha_1(p_t^* - p_t) \qquad (5)$$

where p_t^* is the fundamental price and α_1 is the fundamentalists' sensitivity to the difference between the fundamental and market prices. For estimation purpose, the long-term fundamental price (p_t^*) can be derived from the static Gordon growth model (Gordon, 1959), so that $p_t^* = dt(1+g)/(r-g)$, where dt is the dividend flow, g is the average growth rate of dividends and r is the average required return (or the discount rate). Following Fama and French (2002), we assume that r equals to the sum of the average dividend yield y and the average rate of capital gain$x$, that is$r = y + x$. The Gordon model then implies that x is equal to g. Consequently,

$p_t^* = dt(1+g)/y.$

Hence p_t^* is equal to the current dividend times a constant multiplier $(1+g)/y$, which is also called the fundamental price to cash flow ratio.

Despite the demand of fundamentalists, the demand of chartists is heterogeneous and depends on which technical trading strategy they use. Since the use of various moving average strategies is popular with financial market participants (Chiarella et al. 2006), we assume that the technical trading strategy is a moving average. However, chartists are different with respect to the lengths they use for computing the moving average. The excess demand of chartist i who uses a moving average with length L_i is

$$D_t^{C_i} = \alpha_2(p_t - ma_t^{L_i}) \qquad (6)$$

Where α_2 is the sensitivity of chartists to the difference between the market price and the moving average. $ma_t^{L_i}$ is the moving average of length L_i and this is calculated as

$$ma_t^{L_i} = \frac{1}{L_i}\sum_{i=0}^{L_i-1} p_{t-i} \qquad (7)$$

In this model, the proportion of investors using strategy i changes according to the profit that strategy i has generated. These profits are written as

$$\pi_{f,t} = D^{f}_{t-1}(p_t - p_{t-1}) \qquad (8)$$

$$\pi_{C_i,t} = D^{C_i}_{t-1}(p_t - p_{t-1}) \qquad (9)$$

$$\pi_{n,t} = D^{n}_{t-1}(p_t - p_{t-1}) \qquad (10)$$

Consider any type of investor who believes in higher prices in the future. This results in having positive demand: if future prices go up, he or she makes a positive profit. However, if the price goes down, he or she makes a negative profit. As in CHH 2006, we assume that the proportion of each type of investor evolves according to the Gibbs probabilities (Manski and McFadden 1981)

$$n_{f,t} = \frac{e^{\beta\pi f,t}}{e^{\beta\pi f,t} + \sum_{i=1}^{H} e^{\beta\pi c_i,t}} \qquad (11)$$

$$n_{C_i,t} = \frac{e^{\beta\pi c_i,t}}{e^{\beta\pi f,t} + \sum_{i=1}^{H} e^{\beta\pi c_i,t}} \qquad (12)$$

The fact that investors' proportions change according to the profitability of their strategies comes from the bounded rationality assumption in HAMs. This means that investors are boundedly rational they will discover more profitable strategies. In this setting, β is the speed of conversion to the more profitable strategy. Simply, If $\beta = 0$, investors are not rational to any degree. By contrast, a high positive number for β indicates a high degree of rationality for investors. Now, putting equations (6) and (5) into equation (4) and using (11) and (12) for changes to the proportions, we obtain a nonlinear system of difference equations for stock price movements.

$$\begin{aligned} p_{t+1} - p_t &= \mu[n_{f,t}\alpha_1(p_t^* - p_t) + \sum_{i=1}^{N} n_{c_i,t}\alpha_2(p_t - \tfrac{1}{L_i}\sum_{i=0}^{L_i-1} p_{t-i})] \\ n_{f,t} &= \frac{e^{\beta\pi f,t}}{e^{\beta\pi}f,t + \sum_{i=1}^{H} e^{\beta\pi c_i,t}} \\ n_{C_i,t} &= \frac{e^{\beta\pi c_i,t}}{e^{\beta\pi}f,t + \sum_{i=1}^{H} e^{\beta\pi c_i,t}} \end{aligned} \tag{13}$$

3.3 The Empirical Estimation Of The Model

3.3.1 Data

Figure 1 shows the monthly S&P 500's real fundamental prices (dashed lines) based on the static Gordon model and real actual prices (solid lines) from 1990 to 2012. We use S&P 500 monthly data from Shiller (2005). For a fair evaluation of prices over time and non-stationarity problem, the nominal values of both fundamental and market prices are discounted by the CPI and converted into real values. As this graph shows, the stock price deviates from its fundamental value between 2000 and 2003 during which time the dot-com bubble burst, and between 2008 and 2009 when the credit crunch unfolded. The price commoves with the fundamental value broadly during 2003 to 2007 when the financial market is booming. However, the most noticeable point is that fluctuations in fundamental prices are much less than fluctuations in actual prices.

1

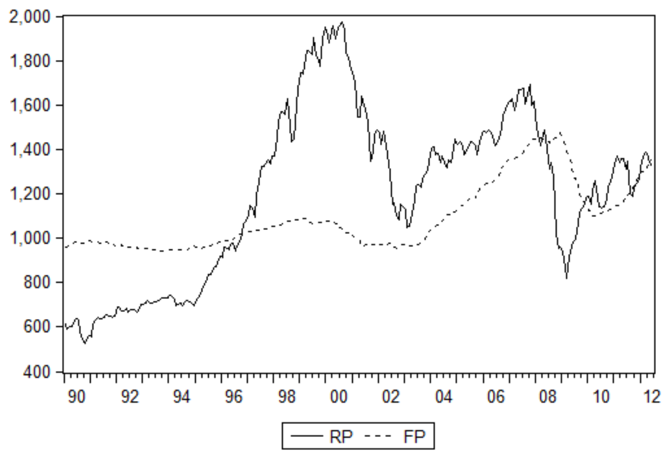

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Figure 1

Table 1 presents the summary statistics for the fundamental and real prices of the S&P 500 for the studied period.

$Table$ 1: statistics of fundamental and real prices

	Fundamental prices	Actual prices
Mean	1419.16	1392.28
STDEV	196.36	239.70
Max	1788.10	1986.95
Min	1155.10	822.72

3.3.2 Estimation Results

This section presents the regression results of the system of equation 13. Since the aim of this research is to investigate the effects of introducing heterogeneity into the chartist group, we use the nonlinear least squares method to estimate the system of equation 13 under three different scenarios. In the first scenario, it is assumed that there is one type of fundamentalist and one type of chartist. Chartists use 1-, 5- or 10-month moving average strategies. Table 2 indicates the results.[2]. In this table, Model 1.1 shows the results when chartists use a 1-month moving average strategy, while Models 1.2 and 1.3 present the results for the situations in which chartists use 5- and 10-month moving average strategies, respectively.

Table 2

Variable	β	α_1	α_2	$\log -likelihood$	AIC
Model 1.1	-0.000168	0.009232	0.459348	-1404.784	10.54520
p-value	0.428	0.502	0.000	-	-
Model 1.2	$5.70E-05$	0.020088	0.270573	-1392.285	10.57034
p-value	0.866	0.226	0.023	-	-
Model 1.3	$4.14E-05$	0.026422	0.174175	-1366.837	10.57789
p-value	0.874	0.118	0.012	-	-

Based on Table 2, Model 1.3 has the highest log-likelihood ratio. This indicates that estimating the system of equation 13 under homogeneity in the chartist group can fit the data better when it is assumed that chartists use a 10-month moving average strategy. It should be mentioned that, based on Model 1.3, β is not significant; however, α_2 is highly significant and α_1 is weakly significant.

In the second scenario, it is assumed that there is heterogeneity in the chartist group. More precisely, it is assumed that there are two types of chartists in the market. In Model 2.1, one type of chartist uses a 1-month moving average strategy, while the other type uses a 10-month moving average strategy. Similarly, Model 2.2 assumes that chartists use 1- and 5-month moving average strategies and Model 2.3 assumes

[2] Please note that α_1 and α_2 in all the regression results stand for $\mu\alpha_1$ and $\mu\alpha_2$ in the system of equation 13.

that chartists use 5- and 10-month moving average strategies. Table 3 shows the regression results under the second scenario.

Table 3

Variable	β	α_1	α_2	log $-likelihood$	AIC
Model 2.1	$-4.23E-05$	0.036623	0.244483	-1365.288	10.56593
p-value	0.818	0.138	0.003	-	-
Model 2.2	$-2.85E-05$	0.026886	0.296647	-1390.856	10.55952
p-value	0.925	0.272	0.004	-	-
Model 2.3	$6.96E-05$	0.038628	0.167360	-1366.709	10.57690
p-value	0.8368	0.1231	0.0133	-	-

Finally, in the third scenario there is one type of fundamentalist, but three types of chartists. The first, second and third types of chartists use 1-, 5- and 10-month moving average strategies, respectively. Table 4 presents the results of the regression under the third scenario.

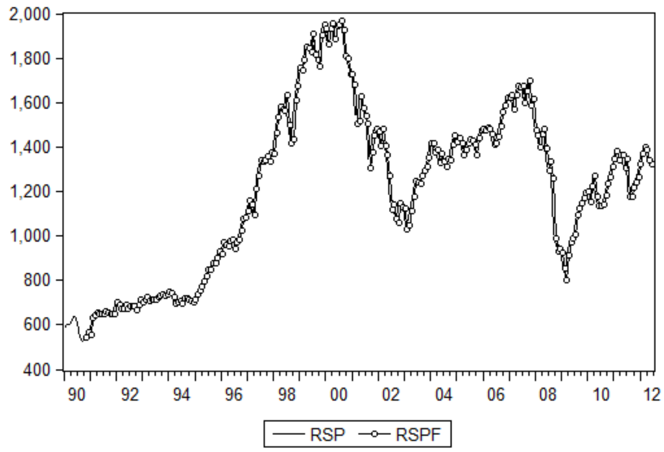
Table 4

Variable	β	α_1	α_2	log $-likelihood$	AIC
Model 3	$1.26E-06$	0.048929	0.209063	-1365.784	10.56976
p-value	0.996	0.144	0.006	-	-

Based on these results, Model 2.1, which includes one type of fundamentalist and two types of chartists who use 1- and 10-month moving average strategies, has the highest log-likelihood ratio. This indicates that the estimating system of equation 13 under heterogeneity in the chartist group can fit the data better than those models with homogeneous chartists. It should be mentioned that based on Model 1.2, β is not significant; however, α_2 is highly significant and α_2 is weakly significant.

Figure 2 demonstrates the fitted value and the one-step ahead prediction based on Model 2.1. In this figure, the solid lines are real stock prices (RSP) and the dots are the one-step ahead forecasted value for RSP. As can be seen, the one-step ahead prediction captures the ups and downs of price movements even when they are extreme.

2



$_16.png$

Figure 2

3.4 Forecasting

The aim of this section is to evaluate the forecasting power of the HAM presented in this research. We compare the in-sample and out-of-sample predictability of the presented model with two similar studies. The first study is the HAM proposed by Boswijk et al. (2007) and the second study is the estimation of behavioral heterogeneity under regime switching by Chiarella et al. (2012). It should be mentioned that Chiarella et al. (2012) compared the forecasting accuracy of their model with that of Boswijk (2007) and found that their model has better out-of-sample forecasting power. Since Chiarella et al. (2012) estimated their model from January 2000 until June 2010 and also re-estimated the model of Boswijk et al. (2007) for this period of time, we estimate our model (model 2.1) for this interval to get a fair comparison. Table 5 indicates the log-likelihood and AIC of the regression results of these three models for the mentioned time interval. In this table, BHM represents the model presented by Boswijk et al., while CHHH is the model by Chiarella et al. and HC (heterogeneous chartists) stands for the model presented in this paper.

Table 5

Model	log-likelihood	AIC
BHM	-649.94	10.783
CHHH	-663.1	10.652
HC	-681.9013	10.87145

In terms of in-sample estimation, the log-likelihood and AIC suggest that the BHM and CHHH models share similar explanatory power to our model over the same sample period.

3.4.1 Out-of-sample predictability

Similar to Chiarella et al (2012), we compare forecasting performance using the root mean square errors (RMSE) and mean absolute error (MAE) for one-step ahead forecasting horizon. The forecasts are based on a rolling estimation window with a fixed sample size, which is 96 observations. We also use the same time interval which is 2000(January)-2010(June) (126 observations). Specifically, we use non-linear least square method to estimate model 2.1 for a rolling estimation window with a fixed sample size which is 96 (8 years of data) and step size of 1 (1 month of data) in our practice. We estimate the model applying the first 96 observations $(p_1, p_2, ..., p_{96})$

and find the one-step ahead price prediction ($\tilde{p}_{97}$). Similarly we use the second 96 observations $(p_2, p_3, ..., p_{97})$ to estimate ($\tilde{p}_{98}$). Such a process is repeated until we use the last window.

$$RMSE = \frac{1}{30} \times \sqrt{\sum_{t=96}^{125} (\hat{p}_t - p_t)^2}, \qquad MAE = \frac{1}{30} \times \sum_{t=96}^{125} |\hat{p}_t - p_t|$$

Table 7 shows the out-of-sample, one-step ahead prediction of Model 2.1 based on rolling window estimation which we compared with the models of Boswijk et al. (2007) and Chiarella et al. (2011).

Table 6

Model	RMSE	MAE
BHM	272	105
CHHH	71	50
HC	54	40

In this table RMSE stands for Root Mean Square Errors and MAE is Mean Absolute Errors. Based on this table, we can conclude that our model (Model 2.1) provides a better one-step ahead prediction in the out-of-sample prediction compared with the models by Boswijk et al. (2007) and Chiarella et al. (2011).

3.5 Estimation Using Different Time Intervals

In this section, we investigate how the coefficients in the presented HAM (Model 2.1) change over different time intervals. We divide the data sample (1990–2012) into two parts. The first part includes the data from January 1990 to December 2007 and the second part includes data from January 2008 to June 2012. The idea behind dividing the data sample into these two periods came from Figure 1. As demonstrated in Figure 1, fundamental prices and real prices have noticeable differences in 1990–2008, but they move closely in 2008–2012. Table 8 shows the results of the regression using Model 2.1 for these two parts.

Table 7

	1990-2008			2008-2012		
	β	α_1	α_2	β	α_1	α_2
Model 2.1	.00	0.01	0.26	.00	0.23	0.44
p-value	0.38	0.31	0.00	0.98	0.09	0.02

As Table 7 shows, during periods in which real prices and fundamental prices move closely together, for example between 2008 and 2012 (see Figure 1), α_1 becomes more significant compared with periods in which fundamental and real prices have more differences, for example between 1990 and 2008.

3.5.1 Rolling window Estimation

In the previous section, we have analyzed the time variation in coefficients by separating the sample into some sub-samples. The other method which can be used to find time variations in coefficients is to estimate the model for rolling windows. Specifically, we use non-linear least squares method to regress model 2.1 for a rolling estimation window with a fixed sample size which is 120 (10 years of data) and step size of 24 (2 years of data) in our practice. We estimate the model applying the first 120 observations $(p_1, p_2, ..., p_{120})$ and find the coefficients $(\beta, \alpha_1, \alpha_2)$. Similarly we use the second 120 observations $(p_{25}, p_{26}, ..., p_{144})$. Such a process is repeated until we use the last window which is $(p_{150}, p_{151}, \ldots, p_{269})$. Figures 3 and 4 show the results.

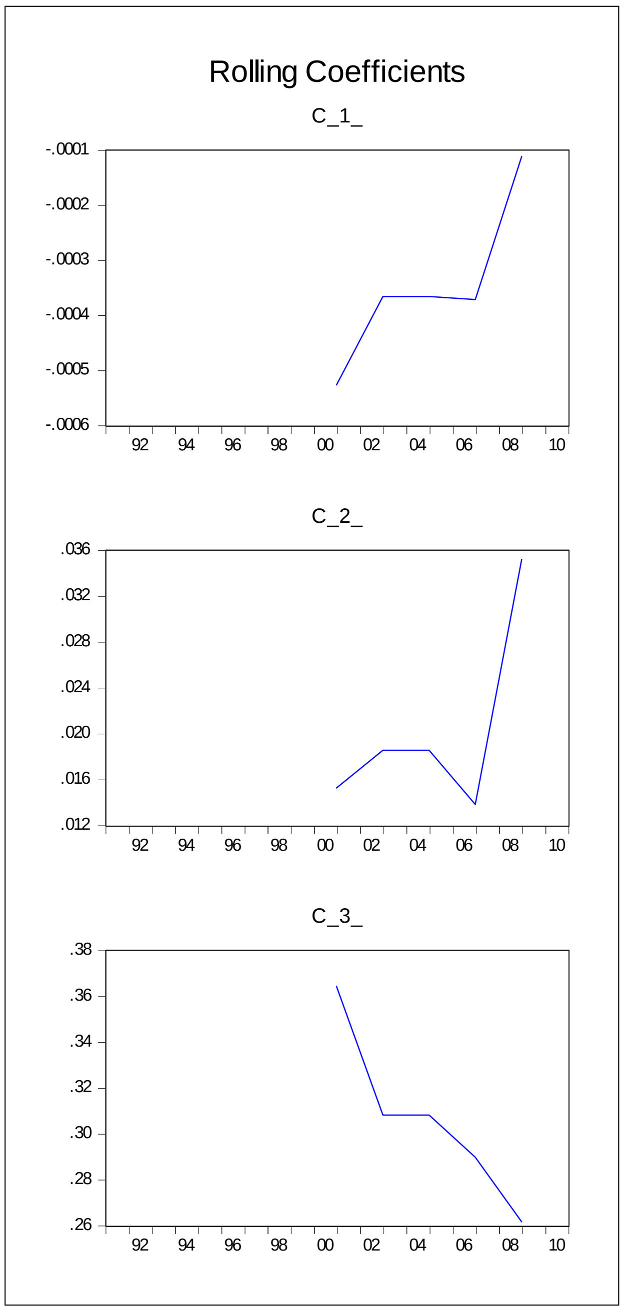


Figure 3 (c1, c2 and c3 stand for $\beta, \alpha_1, \alpha_2$)

Figure 3 shows how the coefficients change thorough time.

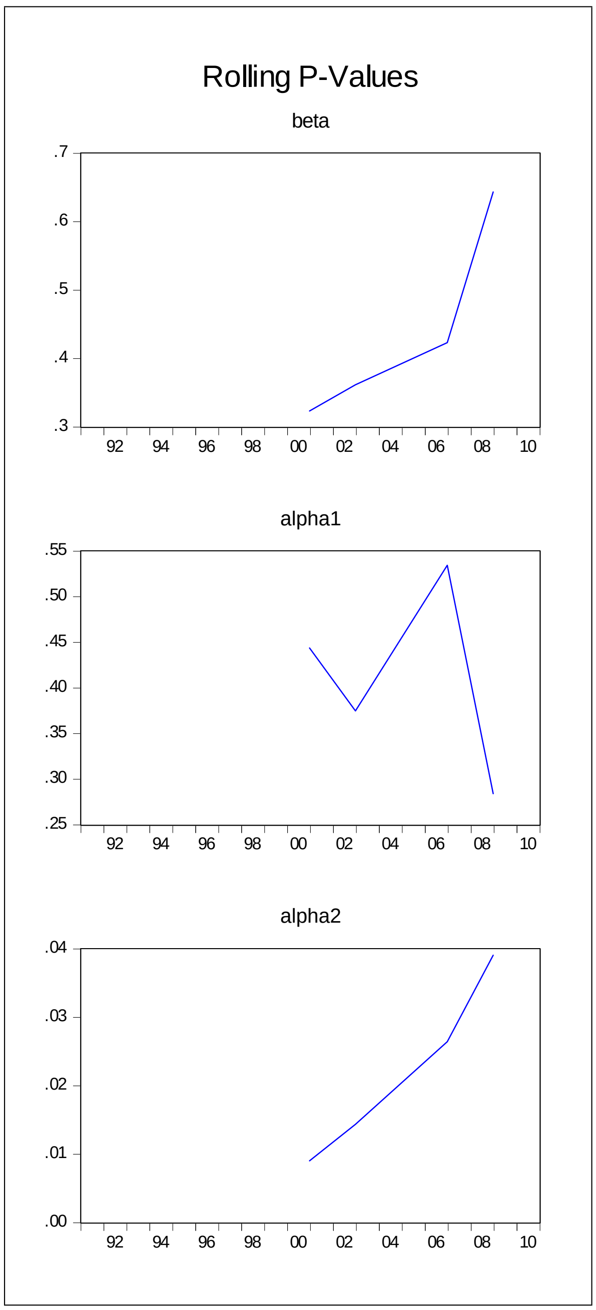


Figure 4

Figure 4 shows how p-values change thorough time. Table 8 shows the movements in the coefficients, real prices and fundamental prices between 2000 and 2009. Basically this table combines results from figure 1 with figures 3 and 4.

	2001-2003	2003-2005	2005-2007	2007-2009
α_1	Increase	Constant	Decrease	Increase
p-value α_1	Decrease	Increase	Decrease	Decrease
α_2	Decrease	Constant	Decrease	Decrease
p-value α_2	Increase	Increase	Increase	Increase
p[7]	Decrease	Increase	Increase	Decrease
fp[8]	Constant	Increase	Increase	Increase
$p \lesseqgtr fp$	$p > fp$	$p > fp$	$p > fp$	$p < fp$

Table 8

Table 8 shows that during periods of time that real prices move toward fundamental prices (2001-2003, 2007-2009), p-value of $\alpha_1(\alpha_2)$ decreases (increases). This result is consistent with the proposed model in this paper. As it was mentioned before, fundamentalists believe that when fundamental prices are lower than real prices, real prices move toward fundamental prices. However chartists believe that real prices continue their previous movements. To explain the results in table 8 in detail, each time interval should be studied separately.

2001-2003

Based on Table 8, during this period, actual prices are decreasing and moving toward fundamental prices. In this condition the presented HAM in this paper indicates that fundamentalist are achieving higher profits than chartists. As figures 3 and 4 show, the estimated HAM for this period shows that $\alpha_1(\alpha_2)$ increases (decreases) and its p-value decreases (increases).

2003-2005

During this period actual and fundamental prices increase almost equally. Despite the previous period actual prices do not converge to the fundamental prices. As figure 4 shows, in this period p-values of α_1 and α_2 both increase.

2005-2007

During this period both fundamental and actual prices increase, however at the end of this period these two prices converge towards each other. Based on figure 4, p-values of $\alpha_1(\alpha_2)$ decreases (increases).

2007-2009

During this period there is a sharp drop in actual prices in 2008. In this period Actual prices fluctuate around fundamental prices and cross it several times. Figures 3 and 4 show that, $\alpha_1(\alpha_2)$ increases (decreases) and its p-value decreases (increases).

3.6 Concluding Remarks

In this research, we studied a new type of HAM to examine if adding heterogeneity in the chartist group could make a better HAM. To do so, we have used S&P 500 monthly data from 1990 to 2012. The presented model is estimated for the data under three scenarios. In the first scenario it is assumed that there is only one type of fundamentalist and one type of chartist. In the second and third scenarios, it is assumed that there is one type of fundamentalist but two and three types of chartists in the market respectively. Log-likelihood ratio of the estimated model under three scenarios, indicates that the HAM that includes two types of chartists and one type of fundamentalist fits the data better than models that include one type of fundamentalist and one type of chartist.

Moreover, The forecasting power of the presented HAM (Model 2.1) was compared with the HAM introduced by Boswijk et al. (2007) and the regime switching model by Chiarella et al. (2012). In terms of in-sample estimation, the log-likelihood and AIC suggest that these two models share similar explanatory power to our model over the same sample period. In order to evaluate out-of-sample predictivity power of our model, we have compared forecasting performance using the root mean square errors (RMSE) and mean absolute error (MAE) for one-step ahead forecasting horizon. The forecasts are based on a rolling estimation window with a fixed sample size, which is 96 observations. Results of this section indicate that our model (Model 2.1) provides a better one-step ahead prediction in the out-of-sample prediction compared with the models by Boswijk et al. (2007) and Chiarella et al. (2011).

Finally, we have analyzed how the coefficients of the presented model change over time. To do so, we have used two methods. In the first method we have divided the data into two sub-samples while in the second method the presented model is estimated for rolling windows. The results of both of methods show that in periods where actual prices move towards fundamental prices, the coefficients for fundamentalists are more significant than situations where those prices have noticeable differences.

Chapter 4
Conclusion

This thesis focused on the applications of behavioral economics in the following order.

4.0.1 Chapter 1

This chapter focuses on individuals' deviations from standard preferences. Based on standard models, individuals have the same preferences about future plans at different points in time and the discounting factor between any two time periods is independent of when utility is evaluated. However, robust laboratory experiments show choice reversal behavior in humans and animals.

Diminishing impatience has been discussed in the literature by two approaches. On one side of the argument, some researchers explain diminishing impatience (present bias effect) by introducing an uncertain exponential discounting model (Sozou 1998, Azfar 1999, Halevy 2008, Dusgopta and Maskin 2005). In those studies, the origin of choice reversal is the risk that any future reward contains that the immediate reward does not. On the other side of the argument, some studies indicate that the presence of diminishing impatience is due to the temptation generated by dynamically inconsistent preferences. As a result of this model, individuals' awareness of diminishing impatience can lead to demand for a commitment device (Strotz 1995; Elster 1979; Akerlof 1991; O'Donoghue and Rabin 1999).

Although both sides of the argument agree on the shape of the discounting function (hyperbolic and quasi-hyperbolic discounting functions), the origin of such behavior is quite different in each of the approaches. One way to distinguish between the origins of choice reversal behavior is looking at the decision maker's demand for flexibility and commitment devices. Some researchers have found that people are partially aware of their self-control problems, but there is a lack of experimental studies that qualitatively estimate the individual's awareness of the self-control problem in the literature.

The results of this chapter show that decision makers are partially aware of their self-control problems. Moreover, introducing a costless commitment device can increase the total welfare of the studied population. This increase depends on individuals' awareness of future choice reversal.

4.0.2 Chapter 2

Chapter 2 presents a behavioral model to analyst stock price movements. In this chapter, the effects of changes in fundamental prices on actual prices were studied. This research followed the work of Chiarella et al. (2006) and considered a market populated by heterogeneous investors using different trading strategies. The new aspect of this research is allowing chartists to use different time lengths for calculating the moving average strategy. The time series analysis of changes in fundamental prices was studied in two scenarios.

The first scenario considers a stock market when there is a single shock to fundamental prices. In this scenario, the proposed HAM indicates oscillations in actual prices (Figures 1–3). Also, when heterogeneity in the market (letting chartists use moving average strategies with different time lengths) is increased, market prices fluctuate more around fundamental prices.

In the second scenario, fundamental prices follow a random walk. In this condition, when the market is populated by one type of fundamentalist and one type of chartist (who use 50-, 20- or 5-day moving average strategies), fundamental prices and actual prices move closely together (Figures 5–7). This result is not consistent with the findings in actual markets such as excess volatility (Shiller 1985). However, increasing heterogeneity in the chartist group leads to higher oscillations in actual prices in response to fundamental changes (Figure 7).

4.0.3 Chapter 3

The aim of this chapter is to predict stock price movements under a new HAM. In this study, it is assumed that the market involves heterogeneous agents that use different rules for trading. Prices are endogenously determined with interactions between these agents. I use the HAM framework proposed in the previous chapter. In the related literature, studies of HAMs with implications of a moving average strategy have only focused on either simulations or analytical derivation methods (Chiarella et al. 2006). The value added by this chapter is estimating stock prices in a heterogeneous agent environment where chartists use different moving average trading strategies. I use monthly data of S&P 500 from 1990 until 2012 and discuss the forecasting ability of the model. To evaluate the forecasting accuracy of the presented model, I compare its out-of-sample and in-sample predictability power with the two studies by Boswijk et al. (2007) and Chiarella et al. (2012).

The results of this chapter can be concluded as follows

- A HAM that includes two types of chartists and one type of fundamentalist fits the data better than models that include one type of fundamentalist and one type of chartist.

- The forecasting power of the presented HAM (Model 2.1) was compared with the HAM introduced by Boswijk et al. (2007) and the regime switching model by Chiarella et al. (2012) and it was shown that the presented HAM (Model 2.1) has better one-step ahead out-of-sample forecasting power.

- Finally, in periods where fundamental prices are close to actual prices, the coefficients for fundamentalists are more significant than situations where those prices have noticeable differences.

Appendix A

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Under the Risk Neutrality assumption, the awareness about self-control problem $(\hat{p}_1)$ is

$$\hat{p}_1 = \frac{V_f}{-100\times\beta\times\alpha^{FED^*}+110\times\beta\times\alpha^{FED^*+D^*}}$$

If we assume the utility function is $U(x) = \sqrt{x}$, the awareness about self-control problem $(\hat{p}_2)$ would be

$$\hat{p}_2 = \frac{V_f}{-\sqrt{100}\times\beta\times\alpha^{FED^*}+\sqrt{110}\times\beta\times\alpha^{FED^*+D^*}}$$

So, if $\alpha > \sqrt[D^*]{\frac{100-\sqrt{100}}{110-\sqrt{110}}} \Leftrightarrow \hat{p}_2 > \hat{p}_1$

Since in our sample the above condition is met, we conclude that in the studied population, agents are on average at least 33 percent aware about self-control problem (table 5).

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