EXPLORING FIRMS FINANCIAL DECISIONS BY HUMAN AND ARTIFICIAL AGENTS

Towards an Assessment of Minsky's Financial Instability Hypothesis

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Keywords: Firms financial decision, Experimental economics, Heuristic optimization, Differential evolution.

Abstract: In this paper we take the first step of a project aimed at assessing Minsky's Financial Instability Hypothesis. Differently from a number of existing studies, our aim is to tackle the issue by combining two approaches: experimental and computational economics. The main goal of this paper is in fact to build artificial agents whose behavior mimic that of experimental agents. Two are the results worth to be mentioned. First, the heuristic approach could provide for a valid alternative micro-foundation for the financial decisions of entrepreneurs. Secondly, financial behaviors could mainly depend on the volatility of demand and on the accuracy of demand forecasts instead of depending on the business cycle phases as usually pointed out by models inspired by Minsky's economic thought.

1 INTRODUCTION

This work is an effort toward the goal of assessing if, under which conditions and in what extend the Financial Instability Hypothesis (FIH) (Minsky, 1974; Minsky, 1975; Minsky, 1982; Minsky, 1986) could be judged as valid. It is only right to tell that this goal is very ambitious due to the several "ingredients" used in the FIH. This paper focuses on what we think to be the essential ingredient: the entrepreneur behavior. Our intention is to build artificial agents whose behavior is similar to that of real agents. With artificial entrepreneurs in our hand, we intend to study in future works the properties of aggregate variables derived from a simulated economy populated by a high number of such artificial entrepreneurs.

The paper is organized as follows. In section 2 we build a simple microeconomic structure which ease the monitoring of the financial aspects of the firm. This structure is submitted to selected people in a set of laboratory experiments described in section 3. In section 4 we build an artificial agent whose behavioral rules are economically grounded. The parameters of the artificial agents are endogenously established in section 5 by using the differential evolution algorithm. Section 6 gives conclusions and discusses future research opportunities.

2 THEORETICAL BACKGROUND

The financial aspects of a firm are surveyed by a balance sheet in which debt (B) and equity (A) are liabilities facing the capital endowment (K). To ease the monitoring of the financial part, we use a very simple production function: $y = K$.

The economic aspects of firms are described by the economic result equation given by

$$\pi_{j,t} = y_{j,t} - c_{j,t}^p - c_{j,t}^f \qquad (1)$$

where $y_{j,t}$ is production of entrepreneur j at time t and $c_{j,t}^p$ and $c_{j,t}^f$ denotes production and financing costs respectively. Price are not involved because we assume subjects have not "money illusion".

We will now give details on the production and financing costs.

Production Costs.   The market value of a unit of input is denoted by $\hat{w}$. However, the final cost for the firm depends on adjustment costs as we explain hereafter.

In each period, the market gives a "spontaneous" level of demand ($y_{j,t}^*$) for a firm. The production must be made before the level of $y_{j,t}^*$ is known.[1] The

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[1]This is how uncertainty, which is an essential element in Minsky's thought, is introduced in our framework.

task of an entrepreneur is that of making a good forecast for the "spontaneous" level of demand. In fact, wrong forecasts (both shortages and excesses) causes a "fast" adaptation of quantities which in turn implies additional costs (Bagliano and Bertola, 2004, p. 48).[2] It is common to model these adjustment costs using convex functions (Koeva, 2009); in this paper we will use a quadratic function: $\beta((y_{j,t} - y_{j,t}^*)/y_{j,t}^*)^2$. The total cost of a unit of input for the entrepreneur is thus

$$w_{j,t} = \hat{w} + \beta \left(\frac{y_{j,t} - y_{j,t}^*}{y_{j,t}^*} \right)^2$$

where β is a parameter which regulates the relevance of adjustment costs. Consequently, production costs can be written as

$$c_{j,t}^p = y_{j,t} w_{j,t} = \hat{w} y_{j,t} + \beta y_{j,t} \left(\frac{y_{j,t} - y_{j,t}^*}{y_{j,t}^*} \right)^2.$$

Financing Costs. They are given by
$$c_{j,t}^f = r_B B_{j,t} + r_A A_{j,t}$$

where r_B is the interest rate charged by the bank and r_A the reward for shares holders.

Making substitutions, using the definition of equity ratio ($a := A/K = A/y$) in equation (1) and dividing by $K_{j,t}$ we obtain the return on investment (*roi*: $\rho_{j,t} := \pi_{j,t}/K_{j,t}$ which with our production function is equal to $\pi_{j,t}/y_{j,t}$):

$$\rho_{j,t} = 1 - w - \beta \left(\frac{y_{j,t} - y_{j,t}^*}{y_{j,t}^*} \right)^2 +$$
$$- r_B(1 - a_{j,t}) - r_A a_{j,t}. \qquad (2)$$

$\rho_{j,t}$ (as well as $\pi_{j,t}$) reaches a maximum when $y_{j,t} = y_{j,t}^*$ and it gets negative when $y_{j,t}$ greatly differs from $y_{j,t}^*$.

Let us specify a number of aspects of financial management. In our simplified model, the financial aspects can be managed in two occasions within a production cycle: when the production is set, and when the economic result is obtained. Given the production function we have assumed, changes in the production capacity modify the financial structure due to the balance sheet identity $K_{j,t} = B_{j,t} + A_{j,t}$. In particular, equity base is not allowed to change when K is updated so that $\Delta K = \Delta B$ at this stage. The movement of the financial structure is more elaborate when the

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[2]In our case $y_{j,t}^*$ adapts to $y_{j,t}$. Examples of additional costs are: opportunity cost due to the short supply when $y_{j,t} < y_{j,t}^*$ and advertising costs to increase $y_{j,t}^*$ when $y_{j,t} > y_{j,t}^*$.

economic result is obtained. Let us start from the observation that the economic result (π) can be positive (profit) or negative (loss). When a profit is realized, it can be used to refund the bank and reduce debt. The entrepreneur decision in this case in to set the level of ΔB in the range $[-\pi, 0]$ (that is $-\pi \leq \Delta B \leq 0$). The residual amount $\pi + \Delta B$ is withdrawn from the enterprise and is employed in the entrepreneur's private purposes. In this case, K remains the same so that $\Delta A = -\Delta B$. When a loss is suffered we have two cases depending on the fact that $\pi \geq -A$ or $\pi < -A$. In both cases, the loss wears out assets ($\Delta K = \pi$), however, when $\pi \geq -A$, equity base is enough to face the loss and the firm survives: K and A are both reduced by π and the balance sheet identity is still verified while A is still positive. But, when $\pi < -A$, the equity base is not enough to face the loss, and consequently the bailout procedure is activated. In any case, when a loss is suffered, the entrepreneur cannot reduce debt.

3 HUMANS

Our first step is to obtain data from humans. To this aim we have written a computer code, which computes values according to the microeconomic structure described in the previous section. The code also generates a Graphical User Interface (see figure 1) with which selected experimental subjects interacts. The experimental subjects are endowed with a forecasting service whose reliability can change and must be assessed by the decision makers. In other words experimental subjects should evaluate when the forecasting service helps fighting the uncertainty of setting $y_{j,t}$ before $y_{j,t}^*$ is known.

EXPERIMENT WITH BAILOUT COST EQUAL TO 1%					
TIME 27					
REPORT ON DEMAND					
time	24	25	26	27	28	29
forecast	10739	11715	9408	10278		
choice	11000	10600	10500			
demand	10663	11042	9776			
error	337	-442	724			
REPORT ON FINANCIAL AND ECONOMIC SITUATION					
stoks	assets	debt	equity	% debt		
	10500	10020	480	95.43		
flows	profit	max. prof.	roi	roi (average)	# bailouts	score
	408	926	3.88 %	3.19 %	5	-1.81 %
PRODUCTION CHOICE					
choice						
DEBT REDUCTION CHOICE					
choice						
EQUITY REDUCTION CHOICE					
choice						
BAILOUT: SET NEW VALUES FOR YOUR FIRM					
assets		equity				

Figure 1: The graphical user interface used by the experimental subjects.

We assign to the agent the goal of maximizing a score given by

$$score_{j,t} = \langle \rho \rangle_{j,t} - O_{j,t}c^O \qquad (3)$$

where $\langle \rho \rangle_{j,t}$ denotes the average *roi* up to time t, $O_{j,t}$ is the number of bailouts until time t and c^O is a parameter representing the bailout cost. This goal takes care of two aspects: *i)* maximize the entrepreneurs reward and *ii)* minimize the number bailouts. This gives a key role to the equity ratio. In fact, a high level of the ratio favors the achievement of *ii)* while it makes harder the achievement of *i)* because of $r_A > r_B$.

Table 1: Experiments standard deviations.

e	σ	$\tilde{\sigma}$
B1a	0.02	0.03
B1b	0.02	0.05
B1c	0.02	0.1
B2a	0.03	0.04
B2b	0.04	0.05
B2c	0.05	0.06

Experiments Settings. Being our main goal to understand agents' behavior over the business cycle, we generate an oscillating sequence of demand. We call it the benchmark pattern of demand and we denote it $\hat{y}_t$. We obtain it as

$$\hat{y}_t = (1 + \cos(0.2t)0.25)10000 \qquad t \in \{0, 1, 2, ...\}.$$

Each experiment (lower script e) is characterized by a time series of demand generated as follows:

$$y^*_{e,t} = \hat{y}_t(1 + x_{e,t}\sigma_{e,t}),$$

where $x_{e,t}$ is the realization of a standard gaussian random variable and $\sigma_{e,t}$ denotes the standard deviation. To diversify each experiment we extract sub-series of length 60 changing in each experiment the starting point. The forecast series is obtained as

$$\tilde{y}_{e,t} = y^*_{e,t}(1 + \tilde{x}_{e,t}\tilde{\sigma}_{e,t}),$$

where $\tilde{x}_{e,t}$ is again the realization of a standard gaussian random variable. The standard deviation $\tilde{\sigma}_{e,t}$ regulates the accuracy of forecast. The latter is crucial for the performance of agents. In fact, if $\tilde{\sigma}_{e,t} = 0 \; \forall t$, the experimental subjects shall set the production at the same level of the forecast. In this way s/he will always realize the maximum profit and the bailout procedure will never be activated. At high levels of $\tilde{\sigma}_{e,t}$, the standard deviation of demand ($\sigma_{e,t}$) assumes a great importance. In fact, if $\sigma_{e,t}$ is low, good guesses for the future production could still be obtained extrapolating the trend from past values. When both $\tilde{\sigma}_{e,t}$ and $\sigma_{e,t}$ are high, setting the production is a problematic task because both the forward looking and the backward looking conducts are not reliable. To ease the experiments we use time independent standard deviations in the proposed exercises. The parameters are as follow: $r_B = 0.01$, $r_A = 0.05$, $w = 0.9$, $\beta = 9$, $c^O = 0.01$.

Experiments Composition. Experiments in this paper are characterized by reversible and divisible investments, so that the production can be increased or decreased by an arbitrarily chosen amount. At the beginning, the experimental subjects are asked to go through a training phase (labeled as A) with the goal of discovering the mechanisms at work in the microeconomic structure. To this aim we turn the forecast uncertainty off by setting $\tilde{\sigma} = 0$. When the subjects becomes familiar with the proposed setting they are admitted to the subsequent phase (labeled as B) where forecasts are inexact. Our aim is to analyze two decisions: 1) how experimental subjects set the production and 2) how they set the equity base. Point 1) is achieved by asking the experimental subject to apply in three exercises (labeled as B1a, B1b and B1c) having an increasing $\tilde{\sigma}$. The level of the standard deviation of demand is kept low to avoid bailouts. Concerning point 2) (the management of equity), the experimental subjects apply in three additional exercises (labeled as B2a, B2b and B2c) where both $\tilde{\sigma}$ and σ are high so that bailouts can easily occur.

Standard deviations of the various experiments are reported in table 1.

Results. Among the numerous subjects we have contacted, at the time of writing this paper eight of them have reached a good knowledge of the model and consequently they have been admitted to the experiments of phase B. Summary statistics from their performances are reported in table 2. In line with the notation above, in the table, j indexes experimental subjects, e experiments, $\langle \rho \rangle$ denotes the average *roi* and O the number of bailouts.

Looking at table 2 we can say that humans' performances gradually deteriorate when the standard deviations increase. Except in a number of occasions, the average *roi* decreases, while the number of bailouts increases when standard deviations increase.

Replicating the humans' performance by an artificial agent is a task addressed in the remainder of the paper.

4 ARTIFICIAL AGENT

In this section we will discuss on how to built an artificial agent able to move in the same framework submitted to humans. Our aim is to make the performances of the artificial agent as close as possible to these of humans. We adopt in this paper the results of recent studies which show how the heuristic approach can be a solid foundation of the smartness and adaptability of human decision making (Gigerenzer et al.,

Table 2: Results from experiments. j indexes experimental subjects, e experiments, $\langle \rho \rangle$ denotes the average *roi* (percentage) and O the number of bailouts.

| | $j=1$ | | $j=2$ | | $j=3$ | | $j=4$ | | $j=5$ | | $j=6$ | | $j=7$ | | $j=8$ | |
e	$\langle \rho \rangle$	O	$\langle \rho \rangle$	O	$\langle \rho \rangle$	O	$\langle \rho \rangle$	O	$\langle \rho \rangle$	O	$\langle \rho \rangle$	O	$\langle \rho \rangle$	O	$\langle \rho \rangle$	O
B1a	8.25	0	8.53	0	6.26	0	8.35	0	8.11	0	8.54	0	7.02	1	7.55	0
B1b	7.25	1	8.02	0	7.29	1	7.91	0	7.44	0	7.56	0	6.9	0	5.87	0
B1c	7.65	0	7.84	0	5.78	3	8.1	0	7.7	0	7.85	1	7.23	0	2.94	5
B2a	5.48	3	7.43	1	7.33	0	7.98	0	7.53	0	6.79	1	5.63	1	6.66	1
B2b	6.61	2	7.08	1	6.43	1	5.85	3	6.13	1	4.7	2	5.6	1	4.2	4
B2c	4.23	3	5.75	3	4.16	4	5.92	2	6.58	0	4.44	2	1.5	5	5.32	1

2011).

As pointed out above, in this paper agents move in a context of reversible and divisible investments and they take two decisions: 1) the amount of production, and 2) the level of equity ratio. We analyze them in the following sections. Before starting, let us give a comment on the notation. To be rigorous, we should use $x_{j,e,t}$ to denote agent's j variable x at time t of experiment e. However, we are building a prototype artificial agent so that the j is dropped in what follows and $x_{e,t}$ intend variable x of the artificial agent at time t of experiment e.

4.1 The Production Choice

The decision on production is made by taking into account some information from the past and the forecast. We denote the information set on which the decision is based with $I_{e,t} = \{y^*_{e,t-N} \ldots, y^*_{e,t-1}, \tilde{y}_{e,t}\}$. A different way to pose the problem is to use growth rates. The growth rate of a variable x at time t is $g_{x_t} := (x_t - x_{t-1})/x_{t-1}$. The agent's choice variable is now $g_{y_{e,t}}$, and s/he sets the production according to

$$y_{e,t} = (1 + g_{y_{e,t}})y^*_{e,t-1}.$$

We assume $g_{y_{e,t}}$ to be set as a linear function of the variables in $I_{e,t}$:

$$g_{y_{e,t}} = s^u_{1,e,t} g_{y^*_{e,t-N+1}} + s^u_{2,e,t} g_{y^*_{e,t-N+2}} + \cdots + s^u_{N,e,t} g_{\tilde{y}_{e,t}}. \quad (4)$$

The agent's problem has been transformed into the one of choosing the $\mathbf{s}^u_{e,t} := \{s^u_{n,e,t}\}$ coefficients with $n \in \{1, 2, \ldots, N\}$.

In our model, the agent achieves the final decision on $y_{e,t}$ by taking two steps:

- determine which one would have been the best achievable solution $\mathbf{s}^*_{e,t} := \{s^*_{n,e,t}\}$;

- use best solutions of the previous periods to decide the $\mathbf{s}^u_{e,t}$ in the current period.

We will go into details in the following paragraphs.

The Best Achievable Solution ($\mathbf{s}^*_{e,t}$). Once $g^*_{y_{e,t}}$ is known, $\mathbf{s}^*_{e,t}$ can be established. A systematic check on all the combinations of s is not possible. We use a *greedy* algorithm to identify a path in the coefficients space which realizes a sequence of improvements bringing to the best achievable solution given the available resources. The starting point of the algorithm is chosen in a set of easily computable aritmetic averages we will refer to as "focal points" (Schelling, 1960; Zuckerman et al., 2007).

Given a parameter called "difference" denoted hereafter with d and the number of addends (N) of the average in (4), we use the notation $\mathbf{F}^d_{R \times N}$ to identify the matrix containing the focal points. R here denotes the number of rows of this matrix. The latter is implicitly chosen when the values of N and d are set. If we set $N = 2$ and $d = 0.5$ we have for example

$$\mathbf{F}^{0.5}_{3 \times 2} = \begin{pmatrix} \mathbf{f}_{1 \times 2, 1} \\ \mathbf{f}_{1 \times 2, 2} \\ \mathbf{f}_{1 \times 2, 3} \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 0.5 & 0.5 \\ 1 & 0 \end{pmatrix}$$

When N is higher, a software able to generate evenly spaced points in the unit simplex (Giulioni, 2011) can be used to obtain $\mathbf{F}$.

Each row of this matrix gives the coordinates of a focal point. We denote with i the row number of F at which a given focal point ($\mathbf{f}_{1 \times N, i}$) can be found.

The first step consists in choosing one of the focal points. Remember this computation is done when $y^*_{e,t}$ is known. Let us denote the column vector of the known growth rates with $\mathbf{g}_{N \times 1, e, t}$. The best performing focal point ($i^*_{e,t}$) is determined by

$$i^*_{e,t} = \min_{i \in \{1, 2, \ldots, R\}} \left| g_{y^*_{e,t}} - \mathbf{f}_{1 \times N, i} \mathbf{g}_{N \times 1, e, t} \right|$$

where $\mathbf{f}_{1 \times N, i} \mathbf{g}_{N \times 1, e, t}$ is the dot product.

Then, the local search starts by iterations which have the following steps:

1. identify a set made up of the starting point and a number of its neighbors;

2. select the best point in the set;

3. if the selected point is equal to the starting point or if the number of iterations reaches a maximum (Z), then stop the search;

else, set the selected point as the new starting point and go to point 1).

Step 1) can be done in several ways. We take a real number ψ and we build a neighborhood by permuting with repetition the elements of $\{-\psi, 0, \psi\}$ and taking them N at a time. We arrange all these in a matrix

$$\mathbf{D}_{3^N \times N} = (\mathbf{d}_{1 \times N, l}) \qquad l \in \{1, \dots, 3^N\}.$$

If we denote with $\mathbf{s}_{1 \times N}^{(z-1)}$ the point selected at iteration $z-1$, the neighbors to be considered in iteration z are gathered in the matrix $(\mathbf{s}_{1 \times N}^{(z-1)} + \mathbf{d}_{1 \times N, l})$. Iterations go on until one of the stopping conditions at point 3) is satisfied.

This process brings us to the best solutions $\mathbf{s}_t^*$

The Used Solution ($\mathbf{s}_t^u$). To let the agent learn and evolve the most reliable focal point, we build a learning classifier system whose rules are the focal points. Based on the previous experience, a score is associated to each rule and at each time step the rule with the highest score is taken as basis to establish the s coefficients to be used in t. We call it the "reference" rule (or reference focal point).

Given a memory length m, the entrepreneur has a set $\{(i_{t-m}^*, \mathbf{s}_{t-m}^*), (i_{t-m+1}^*, \mathbf{s}_{t-m+1}^*), \dots, (i_{t-1}^*, \mathbf{s}_{t-1}^*)\}$ informing on which one was the best focal point in the past.

The reference rule, denoted with i_t^u, can be determined by maximizing a function defined on the set of the best focal points. The function we use is

$$i_t^u = \max_{i \in \{1,2,\dots,R\}} \sum_{z=1}^{m} \delta(i, i_{t-z}^*)$$

where $\delta(\circ, \circ)$ denotes the Kronecker delta function.

Once the reference focal point has been determined, we select the best solutions which was obtained starting from the reference focal point in the previous m periods. The rule to be used in t, $\mathbf{s}_t^u$ is obtained as an average of such points:

$$\mathbf{s}_t^u = \frac{\sum_{z=1}^{m} \mathbf{s}_{t-z}^* \delta(i, i_{t-z}^u)}{\sum_{z=1}^{m} \delta(i, i_{t-z}^u)}.$$

4.2 The Equity Ratio

From equation (2) one can see how the best strategy concerning the level of equity ratio (a) is to keep it at the minimum level (it is because we have assumed $r_A > r_B$). However, as we did for humans, we assign the artificial agent the goal of maximizing the score

(equation 3) which establish the trade off between the level of *roi* and the probability of run up against the bailout procedure.

Because we want the agent to be able to adapt to changing economic conditions we let m^a be the memory length the agent has for the ρ values. At time t, the agent considers the following set of values $\{\rho_{t-m^a} - h, \rho_{t-m^a+1} - h, \rho_{t-m^a+2} - h, \dots, \rho_{t-1} - h, \rho_t - h\}$ where h is a precautionary parameter.

Now consider the sum

$$\Theta_t = \sum_i \delta(-, sign(\rho_{t-i} - h))(\rho_{t-i} - h);$$

we calculate the target level of the equity ratio ($\hat{a}$) as

$$\hat{a}_t = 1 - \exp(\lambda \Theta_t)$$

where λ is a parameter. If $a_{t-1} \neq \hat{a}_t$, the agent manages to reach the target level as fast as possible.

5 HUMANS AND ARTIFICIAL AGENT

In this section we investigate the conditions under which the artificial agent delivers results which are comparable to those of humans.

The artificial agent's behavior depends on the following parameters: Z, m, m^a, h and λ. By using the same framework submitted to humans (the same rules and the same parameters), and assigning to the artificial agent the same task of humans, we let the behavioral parameter of the artificial agent to be selected by the differential evolution algorithm (Storm and Price, 1997). The final step to setup the artificial agent concerns the **F** matrix which depends on N and d. Several trials revealed the simplest choice ($N = 2$ and $d = 1$) as the one which is most suitable to replicate the results of humans.

Table 3: Results from the differential evolution algorithm.

e	$\langle \rho \rangle \%$	O	Z	m	m^a	h	λ
B1a	8.27	0	1	1	$\forall$	$\forall$	$\forall$
B1b	7.37	0	1	5	$\forall$	$\forall$	$\forall$
B1c	7.4	0	1	9	5	4.96	0.6
B2a	6.7	0	1	1	10	5.65	0.75
B2b	6.62	1	7	13	7	2.65	9.31
B2c	4.89	0	4	27	5	3.13	5.02

Table 3 reports the results obtained from running the differential evolution algorithm on the same experiments carried out by humans. Concerning the behavioral parameters of the artificial agent we can divide them in two subsets. Z and m governing the choice of production and m^a, h and λ governing the

Table 4: Scores of Humans and Artificial Agent.

e	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
B1a	8.25	8.53	6.26	8.35	8.11
B1b	6.25	8.02	6.29	7.91	7.44
B1c	7.65	7.84	2.78	8.1	7.7
B2a	2.48	6.43	7.33	7.98	7.53
B2b	4.61	6.08	5.43	2.85	5.13
B2c	1.23	2.75	0.16	3.92	6.58

e	$j=6$	$j=7$	$j=8$	artificial agent
B1a	8.54	6.02	7.55	8.27
B1b	7.56	6.9	5.87	7.37
B1c	6.85	7.23	-2.06	7.4
B2a	5.79	4.63	5.66	6.7
B2b	2.7	4.6	0.2	5.62
B2c	2.44	-3.5	4.32	4.89

choice of financial position. Table 3 shows how Z and m increases with the standard deviations. The behavior of the parameters which regulate the financial decision also changes with the level of standard deviations. For low levels of σ and $\tilde{\sigma}$ (experiments B1a and B1b) the values of these parameters are irrelevant ($\forall$ symbol). When the standard deviations have intermediate levels (experiments B1c and B2a) the value of h is high while that of λ is low. h decreases and λ increases at high levels of the standard deviations (experiments B2b and B2c).

To give a summary of the work done in this paper, we report the scores (equation 3) of humans and artificial agent in Table 4. The performance of the artificial agent is in line with the average score of humans in the initial four experiments. In experiments B2b and B2c, the artificial agent performs better than humans, however a number of the latter still perform similarly (or better) than the artificial agent.

6 CONCLUSIONS

In this paper we take the first step of a project aimed at assessing Minsky's FIH. Our aim is to create avatars whose behavior mimic that of humans.

Here we focus on entrepreneurs whose behavior is the cornerstone of FIH. A result of our analysis is that, beside the traditional approach which assumes rational maximizing subjects, the heuristic approach could also provide for a valid alternative micro-foundation for the financial decisions of entrepreneurs. A second point worth to be mentioned probably provides an element of novelty in the interpretation of Minsky's thought: financial behaviors could mainly depend on the volatility of demand and on the accuracy of demand forecasts instead of depending on the busi-

ness cycle phases as usually pointed out by models inspired by Minsky's economic thought

The potential future developments of our model are many. First of all, the agents' choice under different assumptions on divisibility and reversibility of investment could be analyzed. Second, a statistical analysis of experimental data could lead us to identify a number of heterogeneous avatars. The third extension concerns interaction. It could be investigated how the results change when selected information on the other subjects are given to each experimental subject, and how the situation evolves when credit demands are selected by a real life banker.

The final goal of our project is to build a multi-agent artificial system made up of a large number of different types of avatars interacting with each other and with banks. The model could be used for monitoring how the situation evolves at macroeconomic level and to verify in what extend the FIH could be judged as valid.

REFERENCES

Bagliano, F.-C. and Bertola, G. (2004). *Models for Dynamic Macroeconomics*. Oxford University Press.

Gigerenzer, G., Hertwig, R., and Pachur, T., editors (2011). *Heuristics: The Foundations of Adaptive Behavior*. Oxford University Press, New York.

Giulioni, G. (2011). A Software to Generate Evenly Spaced Points on the Unit N-Simplex. *SSRN eLibrary. Available at* http://ssrn.com/paper=1822002.

Koeva, P. (2009). Time-to-build and convex adjustment costs. International Monetary Fund. Working Paper n. 1.

Minsky, H. P. (1974). The modeling of financial instability: an introduction. In *Modelling and Simulation. Proceedings of the 5th Annual Pittsburg Conference*, pages 267–272.

Minsky, H. P. (1975). *John Maynard Keynes*. Columbia University Press, New York.

Minsky, H. P. (1982). *Can 'It' Happen Again? Essays on Instability and Finance*. M.E. Sharpe, New York.

Minsky, H. P. (1986). *Stabilizing an Unstable Economy*. Yale University Press, New Haven and London.

Schelling, T. C. (1960). *The Strategy of Conflict*. Harvard University Press.

Storm, R. and Price, K. (1997). Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4):341–359.

Zuckerman, I., Kraus, S., and Rosenschein, J. S. (2007). Using focal point learning to improve tactic coordination in human-machine interactions. In *IJCAI'07*, pages 1563–1569.