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Schumpeterian dynamics

and financial market anomalies

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Schumpeterian Dynamics and Financial Market Anomalies

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Abstract

In this paper we try to put together both the dynamics of the endogenous evolution of an industry and the corresponding dynamics on the capital market. The first module of our modelling efforts is the endogenous evolution of the industry based on the micro-behaviour of boundedly rational agents. They strive to undertake entrepreneurial actions and found new firms. Thereby, the role of knowledge diffusion is emphasized. The second module, the capital market module, will also be represented by boundedly rational agents. They read the data of the real side of the economy – induced by the real economy module – interact with other investors and eventually derive their investment decisions. The cognitive process will be modelled using a neural network approach.

Keywords: neural networks, financial markets, entrepreneurship, endogenous evolution
JEL-Classification: O3, M13, G11, D84.

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1. Introduction

Schumpeterian dynamics focus on the pattern of growth and structural change in capitalistic economies. Its main emphasis is put on the disruptive effects of innovation on the real economy. In this context the role of the financial sphere is often only touched or even neglected. However, financial markets do have a crucial and reinforcing effect on the dynamics of the real economy and vice versa.

The aim of our paper is to merge the Schumpeterian dynamics, occurring in the real sphere of a high technology sector, such as ICT, with the financial dynamics, characterizing the corresponding capital or stock market. Contrary to Perez (2003), who systemized the link between both sides in a more descriptive and historical perspective, we try to develop a general theoretical analysis, using two modules of modelling.

In order to represent the real economy, we construct a model of entrepreneurship and industrial dynamics, whose main features have been developed by Grebel/Pyka/Hanusch (2003) and Grebel (2004). The real economy is represented by an entrepreneurial economy. New firms drive the innovation dynamics within a new technology sector. The dynamics show the stylized facts of an industry life cycle which will feed back into the capital market module. The information relevant for investment decisions come from the three layers of the industrial dynamics model: the performance of individual firms, the market structure and the macroeconomic evolution.

The capital market module derives from Kugler/Sommer/Hanusch (1996). An artificial capital market, modelled via a neural network (e.g. Zimmermann, 1994), will reflect the investment behaviour of heterogeneous, bounded rational actors (investors). They differ in their cognitive capabilities and have to make a choice (Arrow, 1964) between secure investments and shares of companies working in a new, innovative high technology market, such as the ICT sector.
Because of the lack of experience and information (Ohlson, 1987) in new markets, investors cannot calculate present values of firms' future cash flows. Instead, investors have to appraise a firm's competitiveness and prospects under true uncertainty (Knight, 1921). The more, decisions will be contingent to the investors' interaction and learning process influenced by their psychology (Kahneman/Tversky, 1979; Tversky/Kahneman, 1992). Thus, the behavioural dynamics of investors, the way they collect and process information, the way they

react to changing situations on the market making final decisions is incorporated into the model.

The two modules will be brought together in a simulation study; yet, this work is still in progress. In this way, we could manage to combine the dynamic evolution of an innovation-driven real economy and financial markets taking into account feedback effects. As a result, investors' behaviour is put into a dynamic context of an industry life cycle. The modular design of our framework will allow investigating several scenarios of different types of investors such as sophisticated versus naive investors, etc. Conclusively, we will shed some light on the psychological aspects of investment behaviour, illustrated as an interactive process of heterogeneous agents and inducing the phenomenon of euphoric stock market phases.

2. The Dynamic Model of the Real Economy

2.1 Heterogeneous Actors

To represent the real economy we draw on Grebel/Pyka/Hanusch (2003) and Grebel (2004). It is a micro-based simulation study which considers boundedly rational agents that strive to found a firm subject to various economic aspects. Actors are heterogeneous in their endowments. Each actor is characterized by a certain amount of resources such as financial funds, fc_{it} (financial funds component of individual *i* at time *t*), their individual cumulated human capital, cc_{it} (capability component of individual *i* at time *t*), and a psychological profile which may boost or inhibit entrepreneneurial behaviour, ec_{it} (entrepreneurial component of individual *i* at time *t*), respectiviely, i.e. it decides over an individual's propensity to entrepreneurial actions. Consequently, the actor looks as the following:

$$a_{it} = \{w_i, \{ec_{it}, cc_{it}, fc_{it}\}\}$$

Knowledge Diffusion

The additional component w_{it} in the vector a_{it} describing the actor denotes new knowledge about a new technology. For simplicity, it is a dichotomous variable taking values 1 or 0 saying that the individual either knows the functioning of the new technology thinking to be able to use the new technology to found a new firm, or that the individual just does not know how to use the new technology.[1] The diffusion of knowledge is a time-consuming process which has a crucial influence on the endogenous evolution of an industry: the faster the diffusion of knowledge the higher expectations may be in terms of economic prospects; since only few firms will be found at an early stage, and the market still is in an emerging phase. With a slow rate of knowledge diffusion firms will be formed gradually step by step without the possibility of bandwagon effects occurring. To model the diffusion of new technological knowledge, the actors are arranged on a Torus. Doing this, each actor has the same number of neighbours to interact with. Via individual interaction the knowledge will be transmitted through the society, whereby the rate of diffusion is determined by the actors' absorptive capacities.

The Networking Process

While the process of knowledge diffusion goes on, the actors activated, those who know about and how to use the new technology, think of forming a firm. Besides a self-evaluation of whether he is capable of running a business or not, the social network plays an important role. In case the individual happens to meet the "right people", people who he thinks to be adequate and willing to support a new business venture, the actual decision to found a firm is more likely to be made.[2] The networking process is modelled via a random permutation process taking into account the uncertainty in finding adequate co-founders.

The Founding Threshold

As a third aspect in the entrepreneurial founding decision a macro-economic aspect has to be considered, too. The economic opportunities of a new technology's potential have to be evaluated by the actors. This is what we call market sentiment in general. Actors interpret the empirical data of a new emerging market. High growth rates, return on sales, the entry rate of new firms, and the number of exits that have occurred up to a certain point in time. The more positively those data is read, the lower the psychological barrier is to found a firm. Furthermore, the founding threshold represents the micro-macro feedback effects within the model. Actors behave according to the market data as well as they influence the market data by their entrepreneurial actions.

[1] As an example one may think of someone who becomes acquainted with new information and communication technologies (ICT) and thinks of forming an E-commerce business.

[2] As an empirical fact, there is more than just one individual involved in a firm-founding process.

The Firm

The firm consists of the total endowments (financial funds, capabilities, etc.) actors bring into the firm. Since all actors are boundedly rational, it is very unlikely that an optimal composition of a firm's endowment is formed. This is the outcome of the entrepreneurial decision-making process. The relative fitness on the market is determined by the balance of a firm's endowment. A lack of competencies, of knowing the business, in managerial skills, etc. might not be compensated by financial funds. The start-up firm can be ill-chosen in size, whereby a solid, sustainable growth of a firm might be a better strategy.

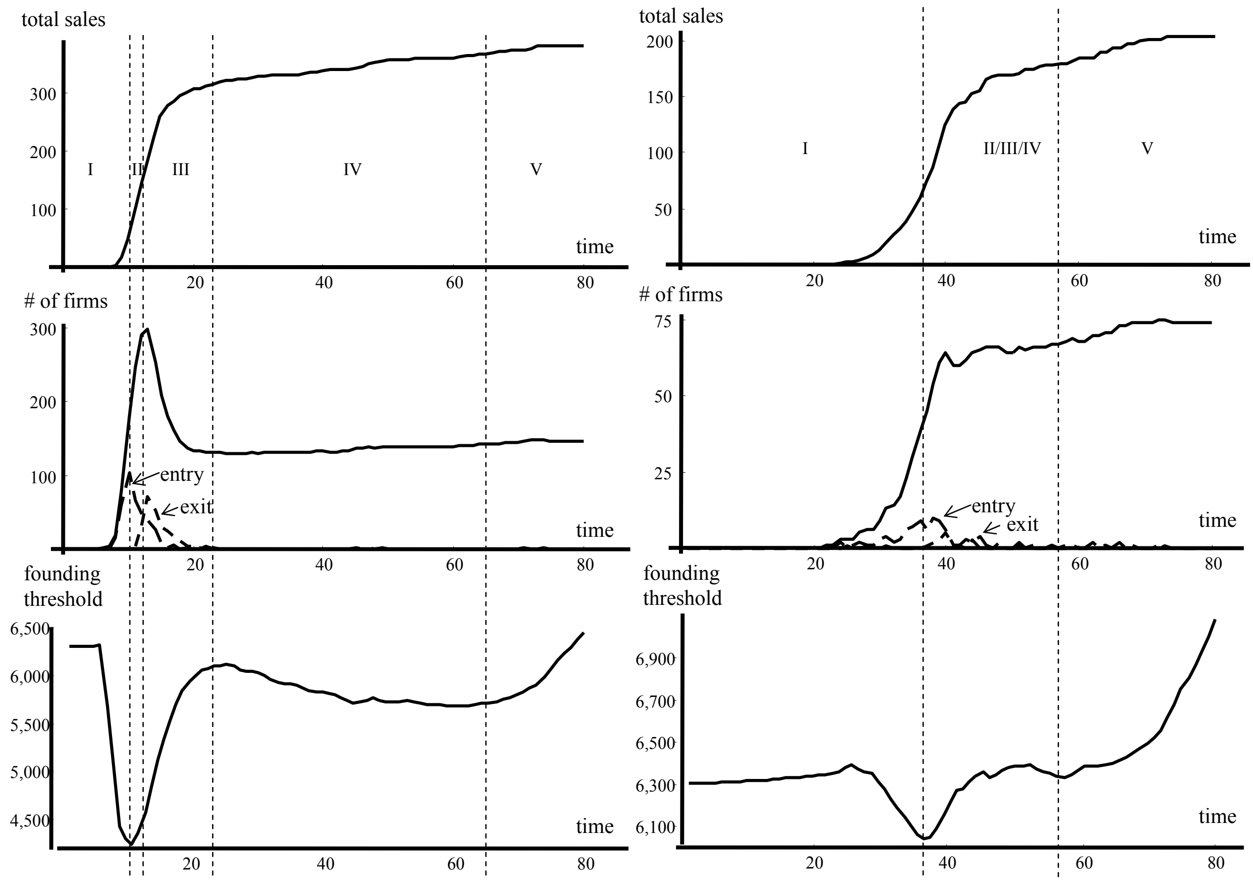
Technically, a firm's competitiveness is derived from the endowments actors incorporated into the firm. The selection process, which drives the dynamics of the market and the industry in a broader sense, is implemented in the model by using a heterogeneous oligopoly, which especially takes into account the heterogeneity of firms.

Simulation Results

The simulation runs show specific patterns in the endogenous evolution of an industry. Figure 1 shows two scenarios of an industry's evolution subject to different rates of knowledge diffusion. Total sales of the industry draw a sigmoid shape. This holds for both scenarios. In the fast diffusion case, the number of firms on the market is overshooting, and, after a shake-out phase, remains at a certain level. The diagrams at the bottom depict the founding threshold, i.e. the market sentiment, the mental barrier of actors who found a firm. And again, we observe euphoric (fast diffusion) and less euphoric (slow diffusion) market sentiment.

Figure 1: Simulation results of the endogenous evolution of an industry considering

(a) fast knowledge diffusion and (b) slow knowledge diffusion.



Aside from the aggregate data, this model also delivers firm specific data such as sales, profits, and relative competitiveness (determined by the firms balance in endowments), etc.[3]

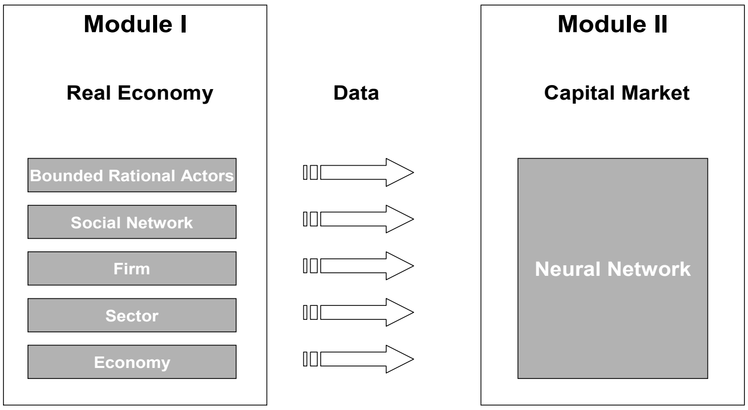
In a further step, the data output of this model will serve as input data feeding into the neural network model, which will be explained in the following.

Figure 2 shows the basic arrangement of the two interacting modules. Module I generates data by the endogenous evolution of an industry. Module II reads in this data in order to build the capital market onto the real economy module. Although this definitely is an interactive process between both modules, we confine ourselves to a one-way influence from the real economy onto the financial market neglecting repercussions from the financial market onto the real economy.[4]

[3] Details can be found in Grebel (2004) and Grebel/Pyka/Hanusch (2003).

[4] Certainly, to make the link between the real economy and the capital market requires a going public process. But for simplicity, we will not discuss this aspect, here.

Figure 2: The two modules put together.



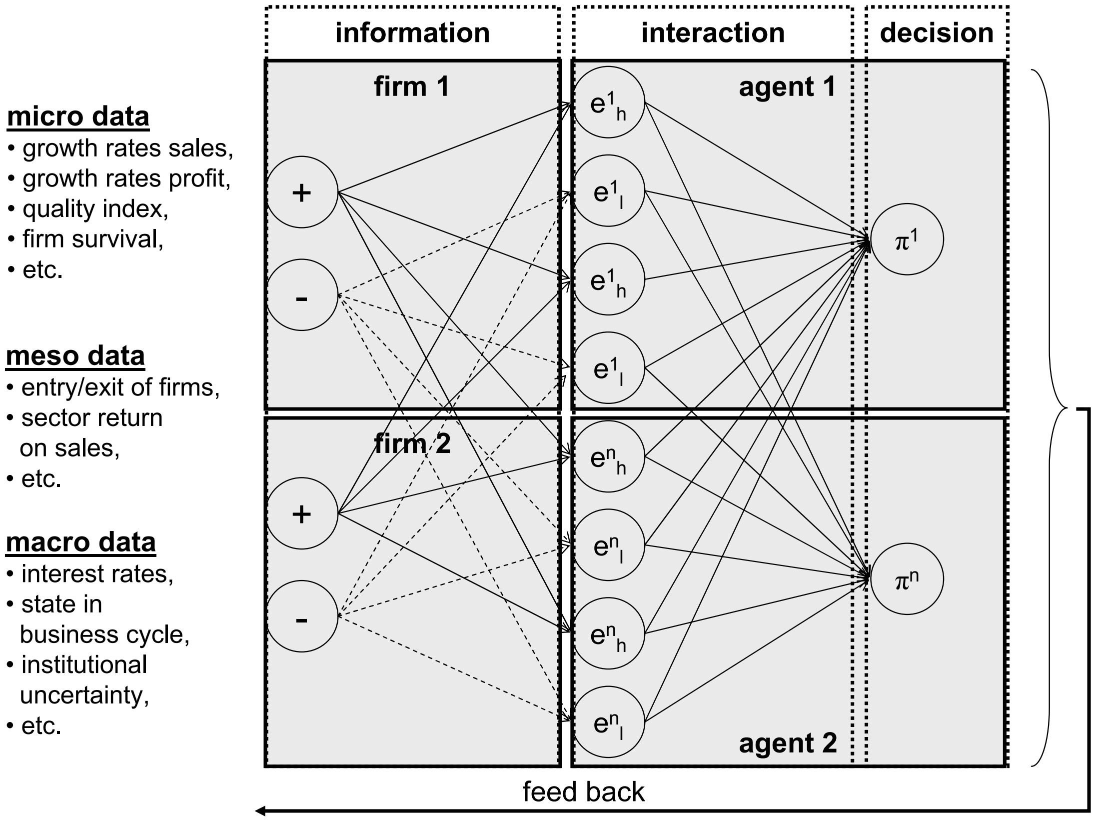
3. The Capital Market

For a first step, we use a simply version of a neural network approach to trace the behaviour of boundedly rational investors. Sommer (1999) develops such a portfolio model expanding the state preference approach from Arrow (1953). Arrow describes the decision-making process of an individual who decides over current, certain consumption and the uncertain return of a portfolio investment. Thereby, the investor maximizes the utility of current consumption and the utility of the expected state-dependent pay-off of the portfolio subject to budget constraints. Sommer transforms Arrow's approach into an *n*-period model applying subjective probabilities (Savage, 1954) in order to describe the formation of expectations. Thereby the resulting market sentiment feeds back into the decisions-making process of investors.

3.1. The neural network approach

The basic idea of the neural network (module II) is depicted in figure 3. As figure 3 shows, each agent i for $i = \{1,\ldots, n\}$ is represented by a multi-layer perceptron (MLP). The information layer perceives the incoming information such as information about the performance of firms (growth rates in sales and profit, quality index, firm survival, etc.) but it also considers meso (entry/exit of firms, sector return on sales) and macro data (interest rates, state in business cycle, institutional uncertainty, etc.).

Figure 3: The configuration of the neural network – agents represented by a multi-layer perceptron.



To recall, this data is produced by module I, the real economy module. Each agent weighs incoming positive as well as negative information (denoted by vertices with a "+" or a "-" respectively). This leads to subjective forecasts of price boundaries in the hidden layer (vertices labelled with e^i_p, with $p = \{h,l\}$, whereby h stands for expected highest price and l stands for expected lowest price). After that, the individual agents interact and compare price boundaries with other agents. Thus, a second weighing process results in π^i, the agent's revealed preferences, the portfolio investment bid. Eventually, the actual share price is determined by the financial market. These market results, allow the agent for calculating his optimal portfolio investment decision π^{opt}. Conclusively, the error induces a learning process, since it affects future investment decisions. Hence, the error feeds back on agents' future investment decisions. The learning process itself is carried out by simply adjusting weights (back propagation algorithm). Moreover, the sum of errors made by agents expresses the magnitude of financial market anomalies.

3.2. Some Preliminary Results

The neural network module has already been established from a conceptual point of view (See section 3.1). Yet the simulation works are still in progress. Nevertheless, some preliminary results can be expected. The composition of an investor's portfolio is the result of a two-stage process, i.e. the individual's appraisal of the market (micro, meso, and macro) information and the mutual influence within the subsequent interaction with each other. This process yields price forecasts. If, finally, the actual price exceeds the forecast, the agents start to adjust their weights – both the weights for positive/negative information and the weights agents take account of the forecasts of others; thus the notion of market sentiment has been incorporated into the expectation formation process. Agents decide rationally about the information they have available. Possible prediction errors will be reinforced by overcast price forecasts. As a consequence, the potential of a steadily increasing financial market bubble grows (financial market anomaly). Not before a downturn in the real economy occurs, the repercussions on the financial market will make the bubble burst. Thereby, the dynamics on the financial market depends on the investors' behaviour: which data agents choose to take into account to appraise their investment decision, to which extent agents adjust their weights to consider data generated in the real economy, and of which degree the mutual influence of investors is. The results of Sommer (1999) and Kugler/Sommer/Hanusch (1996) allow anticipating some of the results to be expected once the two modules have successfully been combined. They model a (one-share) financial market using neural networks. The economic environment, however, is simply represented by pseudo-random numbers, and does not incur information about a stylized dynamic real economy. We have extended the neural network approach two *n* firms and a variable number of investors considering varying data produced in the real economy. Hence, the interface of module I and module II is established from a formal point of view.[5] Analogously to figure 4, we expect similar price dynamics in the financial market driven by an endogenously evolving new industry.

[5] Interested readers may contact the authors to enquire about the formal neural network design.

Figure 4: The subjective market sentiment of actors (a) and the corresponding price development on the market (b).[6]

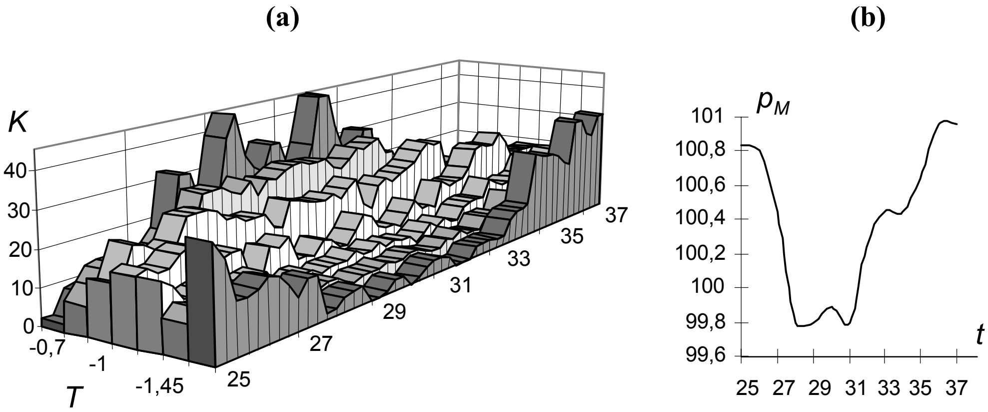


Diagram 4 (a) illustrates the distribution of the individuals market sentiment considered in period 25 to 37. *T* expresses market sentiment and is determined by the deviation of the actual share price from the individual's forecast.[7] The closer *T* is to the expected highest price, the more optimistic the individual becomes. Henceforth, the scale in diagram 4 (a) reads: the higher (lower) *T* the more (less) optimistic the agents are. The height of each column signifies the number of agents sharing the same market sentiment. Conclusively, the dynamic of the share price is the result of the investors' interdependent decision-making process: first, the investor analyzes the data, taking into account also the actual share price of the previous period, and second, via interaction derives his investment bid. Finally, the actual share price is determined in the market. Thus, overdrawn expectations (owing to erroneous price forecasts) of future share prices propagate through the system and reinforce a positive/negative market sentiment. Diagram 4 (b) shows the corresponding price dynamics. A high share price at the beginning spurs the expectations of falling prices (negative market sentiment). The subsequent investment decisions make the share price go down and progressively increases a negative market sentiment. In return, this reinforcement effect induces that future price forecasts become more pessimistic than the actual share price turns out to be. Hence, optimism returns into the market and lets the share price increase. The scope of this sentiment fluctuation – the turnaround of the share price development – depends on the learning process. To put it in other words, it depends on the sensitivity to changes in the (micro, meso, macro) market data and the mutual influence of interacting agents.

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[6] Compare Sommer (p. 134, 1999).

[7] The positive/negative input information is kept constant is this scenario, i.e. there is no change in the dynamics of the real economy.

After a comprehensive numeric study of the two connected modules, the following outcome should be expected. Figure 5 depicts the alleged results of the model: since we only model a one-way influence of the real economy on the financial market, the curves about entries, exits and total firms is a given result of module I. In other words, these curves will not change because a feedback effect from the financial market on the real economy is neglected for simplicity. The only curve that we focus on in the simulation runs is the market capitalization curve. This curve should be embedded in the real economy context as shown below. In an industry with a high rate of knowledge diffusion we observe a rather turbulent development on the industry life cycle.[8] Rapid knowledge diffusion vehemently increases the potential of firm formation.[9] We observe five phases of an industry life cycle.[10] In an infant industry stage (phase 0)[11], stock markets have not yet perceived the new industry. With the upswing of the emerging market, not only imitators in the real economy but also more and more investors get interested in the new market (phase I, euphoric phase I). There are first-movers in the real economy as well as early investors in the financial markets. Successively, the growth rate of the new sector in the economy is increasing. In this third phase (euphoric phase II) the euphoria in the real economy as well as on the financial market keeps on, although first negative information particularly in the form of exits, which start to augment. Investors still have a favourable investment attitude and pay high share prices.[12] The dynamics in the real economy evolve faster than investors manage to learn. This drives financial market anomalies and increases the bubble. In the consolidating phase (phase III) a shake-out occurs, which severely reduces the number of firms in the industry. Market capitalization plummets; reinforcing[13] pessimism prevails among investors until a turn-around indicates a recovery of the financial market in phase IV.[14]

[8] Compare also figure 1.

[9] For more details see Grebel (2004) and Grebel/Pyka/Hanusch (2003).

[10] A lower rate of knowledge diffusion may reduce the number of phases observed. Compare figure 1.

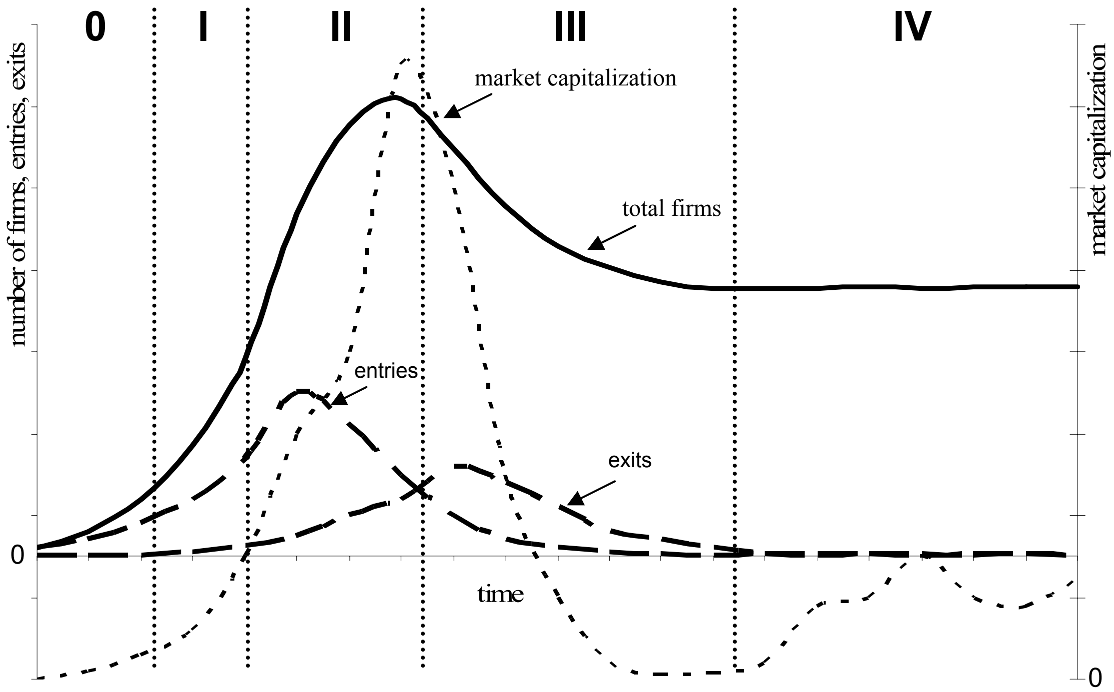
[11] The numbering of phases is in accordance with Perez (2003).

[12] Remember that investors learn about the dynamics of the real economy represented by the neural network. The learning process (adjusting weights which information is weighted with) is a time-consuming process.

[13] The reinforcement effect is a feature that comes out of the neural network approach. See section 3.1.

[14] The declining phase of the industry life cycle has been neglected.

Figure 5: Conceptual expectations about the integrated model.



This outcome would match empirical facts of the "New Economy" period.[15] The latter we consider the phenomenon of a high rate of knowledge diffusion in the economy.

The modular construction of our model allows two investigate several scenarios.[16] Each module can be altered. The real economy module renders a different evolution of the industry life cycle assuming a low rate of knowledge diffusion.[17] This would also induce a different evolution of the financial market. Aside from that, we can solely look at the financial market and consider sophisticated and naive traders. Once the feedback effects on the real economy have been accomplished in our modelling venture, we are able to exert different partial analyses not neglecting the overall context.

4. Conclusions and Further Research

The basic building blocks of our modelling attempt are two modules, a real economy module that reflects the Schumpeterian dynamics of an endogenously evolving industry and a neural network module that describes investment behaviour. Both models are micro-based and discuss the behaviour of boundedly rational agents that act under strong uncertainty.

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[15] Compare for example Klandt (2003).

[16] The modular modelling procedure is also exerted within the real economy module. Compare Grebel (2004).

[17] Compare figure 1.

In the real economy module, agents strive to found a firm: they absorb new technological knowledge, evaluate their own endowments and capabilities, assess the support of their social network and consider the current economic environment. Newly founded firms take part in market competition and thus drive the dynamics of the industry life cycle.

The neural network (financial market) module illustrates the adaptation (learning) process of boundedly rational agents that make a portfolio decision – under strong uncertainty – considering facts about (micro, meso, macro) market data and taking into account opinions and the share price expected by others. The module as indicated above is constraint to a one firm one share financial market with a constant number of investors and exogenously given set of information.

For a start, we simply connect the two models in the following way: the economic data produced in the real economy module serves as input information for the neural network module; the latter has been extended for adjustment reasons. For time being, repercussions from the financial market onto the real economy will be neglected.

Owing to the endogenous evolution of the industry, firms are heterogeneous in their endowments. This heterogeneity determines their competitiveness and consequently involves entries and exits in the economy; therefore, the number of firms varies over time. Accordingly, for connecting purposes, the number of shares in the financial market has to be variable, too; henceforth we expand the neural network to a *n* firms *n* shares market. Aside from that, the number of investors may increase as the economic prospects improve over time.

It is not only speculative investment behaviour that causes financial market anomalies. At the beginning of a new innovative industry, entrepreneurial behaviour is based on a high degree of uncertainty. Accurate predictions of a new technology's economic potential (i.e. profit opportunities) are impossible. New firms have to struggle with strong uncertainty, entrepreneurial decisions may seem promising, but may turn out wrong in the long run. Insolvency may put an end to a highly praised business venture. Such misinterpretations drive the market turbulence of a new industry. Conclusively, this influences investment behaviour and therefore leads to a turbulent stock market dynamics, too. Doing this, we implement the Schumpeterian dynamics of the real economy side into financial markets and expect to show the emergence of financial market anomalies.

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