**Forecasting Financial Markets with Agent-Based Models**

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# Abstract

The building block of financial markets is the behavior of the market participants. This paper presents an agent-based model (ABM). The model allows to predict the non-linear behavior of financial markets. The predictions of the model are empirically tested in different markets. The performance of the ABM is compared with the performance of a linear and kernel regression models, information theoretic approaches and artificial neural networks. It shows and explains the superior performance of ABMs. The paper contributes a long-term experiment to the discussion of the possibility of forecasting financial markets.

***Keywords***: Financial Markets, Prediction, Agent-Based Model

***JEL classification:*** C63, G170, R20

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# Introduction

*Positioning*

*Gap*

*Purpose*

*Central argument*

*Organizing*

*Contribution*

*So what?*

Many phenomena which take place in the economy and in the financial markets are poorly understood. This manifests on the macroeconomic level in different financial crisis and on the microeconomic level in the difficulties of market predictions for asset and risk management. A better understanding of the financial markets would be of value for the financial industry and the society. An answer involving the degree of understanding gives the ability of making correct forecasts of the future behavior of the financial markets.

There are many tries to forecast financial markets with different approaches. Some approaches are more an art than a science. Most of the models have in common that they are working very well in the past and explain the history. But their forecasting power is limited. It is still an open question if it is at all possible to model financial market to make accurate forecasts.

The building blocks of financial markets are the behavior of the market participants. Market participants are changing their behavior over time for different reasons. This leads to a changing behavior of the financial markets as whole. This change of the underlying rules is a main difference to physical systems where the underlying rules are stable over time. Financial markets share this evolutionary development with other social systems. Most forecasting methods can’t adapt to the changing behavior of the agents and the markets.

Agent-based models capture the complex patterns found in real-world markets. To do so, the relatively simple behavioral structures of individual market participants – the agents – are simulated and combined to a more complex market setting. In this framework, agents decided to either buy or sell a certain financial product based on a set of fundamental and technical input parameters. Combining all agents’ decisions, a market forecast is deduced. This approach allows us to develop a dynamic, non-linear model, comprising multiple input factors. It combines explicit knowledge of the agents’ behavioral patterns with implicit knowledge in the form of time series analysis. Based on this, the behavior in bubble and crash situations can be simulated. Agent-based modeling generates virtual worlds for what-if scenario analyses and stress testing. Agent-based modelling and simulation reproduces the complex patterns found in real-world markets.

Our model consists of a set of artificial markets where actors, represented by computer agents, interact according to the rules of trading in the artificial market. The market environment enables us to first simulate inter market relations. Second, we can compare these simulations to time series of the real financial markets around the world. In this manner, we evaluate the goodness of our model – it is assumed to be a suitable model the better it captures ex post real-world market processes/ outcomes. This approach integrates the different tools and methodologies like technical, fundamental, regression analysis, artificial neural networks and so on.

The paper proceeds as follows. Section 2 presents the literature review, section 3 exposes the methodology and data, section 4: the results of different applications and in section 5, the conclusion.

# Literature review

*Background*

* *Conceptual scope*
* *Definitions*
* *Existing explanations*
* *Critique*
* *Open questions = current focus*
  1. **Financial Markets**

The discussion about the possibility of forecasting financial markets isn’t new (Ankenbrand, 1998; Samuelson, 1989). If the current price of assets incorporates all relevant information, a market is efficient. There are three levels of market efficiency: (Fama, 1970)

* All information contained in the past behavior of asset price is included in the weak form.
* All obviously publicly available information is incorporated in the current price in semi-strong form.
* All information (public and private) is incorporated in strong form.

Fama (1970, p. 383) concludes “that, with a few exceptions, the efficient markets model stands up well.” There is no evidence against the hypothesis in the weak and semi-strong form, and only limited evidence against the strong form. Twenty years later the conclusion is different. “Since there are surely positive information and trading costs, the extreme version of the market efficiency hypothesis is surely false” (Fama, 1991, p. 1575). He agrees to the definition of Jensen (1978), that prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs” (Fama, 1991, p. 1575). The implication of the Efficient Market Hypothesis is the same that it is impossible for investors to exploit information in order to earn excess returns. Fama (1991) concludes that also mutual, pension, and endowment fund cannot push research and trading beyond the point where marginal benefits equal marginal costs.

But the definition of randomness is an empirical one. Random behavior might become predictable with a better understanding of the underlying dynamics, better data sources and more computing power. Another source of randomness is complexity. But even complex systems may have collective modes of behavior that are described by simple laws. This don’t mean that is possible to forecast them because they are chaotic which is described as a sensitive dependence to initial conditions. (Farmer, 1988) (Zhang, 2013) shows recently statistically significant arbitrage possibilities which seems inconsistent. He uses agent-based models and media moods for modelling of stock markets.

Financial markets could be described as a nonlinear dynamic deterministic system with stochastic shocks and a drift component. The discrete time evolution of such a system is (Ankenbrand, 1998):

where w*(t)* is a vector with several components *wi*. The external variables or noise are subsumed in *e(t)*. The system definition with the decision to put the variables in *w(t)* or *e(t)* is arbitrary in some degree. A deterministic model with stochastic shocks is a good description of the system if there is no significant change in the market mechanism or agent behavior (Allen, 1994). The function *f* isn’t stable over time (Ankenbrand, 1998). A model with a change in the deterministic part has the potential to be more accurate than a model without adaptation (Phang, 1994). Financial markets have more in common with biological or behavioral systems and its evolution than with physical systems (Lo, 2017; Hanappi, 1994). Financial systems aren’t ergodicity (Bookstaber, 2017).

The Adaptive Market Hypothesis is an extension of Efficient Market Hypothesis. The principles of the Adaptive Market Hypothesis are (Lo, 2017, 188):

* Market participants or agents are neither rational nor irrational. They are biological entities whose features and behaviors are shaped by the force of evolution.
* They display behavioral biases and make apparently suboptimal decisions. But they can learn.
* They have the capacity of abstract thinking, specifically forward-looking what-if-analysis, predictions about the future based on past experiences, and preparation of changes in the environment.
* Financial market dynamics are the result of the agent interactions based on reasoning, learning and adaptation to the social, cultural, political, economic and natural environment.
* Survival is the force driving competition, innovation, and adaptation.

Brennan & Lo (2012) shows that rational economic behavior in which individuals maximize their own self-interest is only one possible type of behavior. Intelligent behavior increases the probability of reproductive success and has for that reason the higher chance to survive. But there is an inconsistency between the theoretical behavior of the homo economicus and the observed behavior of the homo sapiens. Hirshleifer (2001) gives a survey of such decision biases of market participants.

Market participants are limited in their knowledge about their environment and their computing power. Because of those limitations, we assume bounded rationality of the agents. They are using simple reasonable rules of thumb for the decision under uncertainty instead of rational optimal decision rules (Simon, 1957). Hommes (2006) gives an overview of the discussion.

The evolution of the financial markets is determined by the interaction of many dispersed agents. The action of any agent is given by the state of the market, the state of the agent and his rule set. The state of the market depends on the previous actions of the agents and the noise. The drift component is driven by the change of the individual rule set, or learning, and innovation. The assumption of traditional market theories is fixed rational agents that operate in a static and statistically predictable environment. But the interactions of the agents are characterized by limited rationality, adaptation (learning), and increasing returns. (Holland, 1988) The expectations, the imperfect knowledge of the environment, and the limited computational power lead to a subjective or bounded rationality (Simon, 1982). The adaptation not only comes from individual learning, or the improving of the rationality level. Loosing agents are disappearing from the market. Performing agents grow through the accumulation of money and imitators. In addition, new types of agents appear with new unpredictable rule sets. The structural evolution of economy and financial markets has preoccupied many economists since Adam Smith, for example Marx, Keynes, and Schumpeter. (Ankenbrand, 1998)

But there are also different recurring patterns like cycles. Claessens, Ayhan Kose and Terrones (2011) gives an analysis of financial cycles. An application shows Kostadinov and Ankenbrand (2013b) for the Swiss real estate market. Lochstoer and Tetlock (2020) explain anomaly returns with the decomposition into cash flow and discount rate news. The discount rate news predominates in market returns. Atanasov, Moller and Priestley (2020) show the prediction power of consumption for stock returns.

* 1. **Agent Based Models**

During the 2010 financial crisis Jean-Claude Trichet phrased it (Trichet, 2010): “When the crisis came, the serious limitations of existing economic and financial models immediately became apparent. [...] Macro models failed to predict the crisis and seemed incapable of explaining what was happening to the economy in a convincing manner. […] We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. [...] Agent-based modelling dispenses with the optimization assumption and allows for a more complex interactions between agents. Such approaches are worthy of our attention.”

Agent-based modelling (ABM) is a technique used to model and simulate a system’s micro-level behavior, aggregate it and then generate its macro-level behavior as an emergent, complex pattern. It thus allows us to combine a bottom-up with a top-down perspective in a coherent approach. In agent-based models, real-world actors are represented as a population of heterogeneous, interacting (software) agents. Just like market participants interact with others in the pursuit of their individual goals, agents “live” in a virtual simulation environment where they interact with other agents to pursue their individual goals. In this way, distributed and interacting assemblies of agents can lead to an emergent and potentially complex behavior of the system as a whole. This macro-level behavior is thus the result of the aggregation of simple adaptive rules followed by individual agents. Such a modelling approach naturally integrates the rational and the stable behavioral aspects (Andrikogiannopoulou, et al., 2010) of market participants. Agent-based models give insight into complex systems like markets that would be difficult to obtain with classical approaches. (D'Orazio, 2014) The experiments can be repeated with the same initial conditions. (Mueller and Pyska, 2016)

Marini, Chokani, and Abhari (2019) model the demographic aging and their influence on the social security system with an agent-based model. They use as a test case the whole population of Switzerland and analyze three immigration scenarios until the year 2035.

Haldane (2016); Haldane and Turrell (2018) and Samanidou, Zschischang, Stauffer and Lux (2007) gives an overview of ABM and its positioning in economics and finance. Bookstaber (2017), 106f summerizes the advantages of ABMs for modeling financial markets:

* Financial markets are part of the real world with different participants.
* The participants are different.
* The participants affect the environment.
* The environment affects the participants.
* The participants affect other participants.

Properties of agents in an ABM are (Woolridge & Jennings, 1995)

* Agents are autonomous without central control.
* Agents can interact with other agents.
* Agents have a perception of their environment.
* Agents act goal-directed

The list of possible characteristics of agents can be extended to more human characteristics as knowledge, belief, intention, obligations and so on. The agents model the behavior of the market participant and incorporate the insights from behavioral economics about human and institutional behavior. ABM offers a flexible framework to incorporate the individual and heterogeneous and bounded rational behavior of economic actors. (Mueller & Pyska, 2016) Lerner et al. (2015) describe the influence of emotions in the decision-making process and structure it in a model which could also be implemented in an agent-based model. A heterogeneous agent model incorporates typically two types of agents, the fundamentalists and the chartists. Fundamentalists base their decisions on economic theory. They believe that the market price will revert to the intrinsic value of an asset. They base expectations on the deviation of the market price from the fundamental value. Technical traders base their decisions on past prices. They extrapolate information from previous prices. For example, trend followers expect trends to continue in the same direction. The fundamentalists have a stabilizing effect. The chartists as trend followers have a destabilizing effect (Ellen, and Zwinkels, 2010). Heterogeneous expectations and the switching of the two types of agents could be responsible for cyclic behavior of markets and in extremis for bubbles and crash situations (Baur, et al., 2014).

Soros (2013) discuss the difference between the internal model of a market participant and the reality. This is the principle of fallibility. The market participant takes actions based on his imperfect views, for example investments. This influences the reality. That is the principle of reflexivity. These loops can lead to uncertainty. Uncertainty means the unknown of future states. Risk means on the other side the unknown of the probability of future states. (Knight, 1921) The reflexivity is another difference between social science and physics. (Soros, 2013)

Agent-based models focus on financial markets and price dynamics, which emerge through the interaction of heterogeneous agents, have been quite successful in replicating and explaining some intriguing features of the financial market, such as endogenous bubbles and crashes as well as stylized facts of return time series including volatility (Farmer, 2002, LeBaron, 2006, Hommes, 2006, Chiarella et al., 2009, Hommes and Wagener, 2009, Lux, 2009, Fischer and Riedler, 2014, Leal et. al., 2014).

Dosi, Fagiolo, Napoletano and Roventini (2012) developed an Agent-Based Keynesian Model. The model combines Keynesian mechanisms of demand generation, a Schumpeterian innovation process and a Minskian credit dynamic. It allows to mimic features of previous recessions.

The model introduced in Raberto et al. (2012) takes a macroeconomic perspective and mainly focuses on the lending channel of banks. However, the model presented in Thurner et al. (2012) focus on the effects of leverage on returns, which they find to produce fat tails and clustered volatility. Feng, Li, Podobnik, Pries and Stanley (2012) replicate with an ABM fat-tailed distributions and long-term memory of the stock market. Kukacka and Barunik (2012) model behavioral pattern like herding, overconfidence, and market sentiment with an ABM. The model can partially replicate price behavior in turbulent stock market periods.

Fischer and Riedler (2014) developed an ABM of the financial market across countries where agents are endowed with balance sheets that contain equity capital as well as debt. The authors find that the empirically observable log-normal distribution of bank balance sheet size naturally emerges and that higher levels of leverage lead to a greater inequality among agents. Furthermore, greater leverage increases the frequency of bankruptcies and systemic events. Credit frictions, defined as the stickiness of debt adjustments, are able to explain a key difference in the relation between leverage and assets observed for different bank types. Lowering credit frictions leads to an increasingly procyclical behavior of leverage, which is typical for investment banks. Nevertheless, the impact of credit frictions on the fragility of the model financial system is complex. Lower frictions do increase the stability of the system most of the time, while systemic events become more probable. Moreover, Was and Lubas (2014) propose a method for creating realistic and effective models of crowd dynamics, which takes into account the Agent-based modelling combined with non-homogeneous and asynchronous Cellular Automata, dedicated for specialized engineering aims. On the basis of bibliographical research and their previous experiences. They conclude that the use of the Agent-based approach makes it possible to apply different scenarios and situational contexts, namely competitive and non-competitive evacuation or free movement of pedestrians.

Andersen and Sornette (2005) and Wiesinger, Sornette, and Satinover (2012) find a mechanism to detect windows of predictability in complex adaptive systems. The situation is successfully tested on real financial time series. The frequency of these prediction windows implies collective organization of agents and their strategies, which can condense into herd behavior.

A common critique against agent-based models is the lack of robustness. Verification and validation are for that reason important steps. (Mueller & Pyska, 2016) The disadvantage of agent-based models is being complicated with nonlinearities and stochasticity in the individual behavior and connections between the different elements. This leads to a large number of degrees of freedom. The choices made to build a given agent-based model may represent the biases of the modeler. It makes it difficult to compare the different agent-based models and gives an impression of lack of robustness in the results that are often sensitive to details. Another related problem is that of calibration and validation. Calibrating means determining the values of the parameters that enter in the definition of agent-based models, which fits best to a given set of empirical data. (Sornette, 2014) Windrum, Fagiolo, and Moneta (2007) discuss three types of calibration methods: the indirect, the Werker-Brenner, and the history-friendly calibration approach.

* 1. **Oil**

Ellen and Zwinkels (2010) develop a heterogeneous agent model for the oil market. Decisions are formed by fundamentalist or chartist. Fundamentalists trade on mean-reversion of the moving average over a period of 24 months. Chartists follow the trend in prices. Speculators then choose between these rules based on past profitability. The model outperforms both the random walk and vector autoregressive models in out-of-sample forecasting. The agent-based model of Karimi and Maleki (2018) bases on 6 different rules to make price and trend predictions of oil: weekly U.S. commercial crude oil stocks, monthly OECD commercial crude oil stocks, daily USD/EUR exchange rate, simple moving average, exponential moving average, and Bollinger bands.

* 1. **SPI**

Lillo, Moro, Vaglica and Mantegna (2008) present behavioral data of the members of the Spanish Stock Exchange. They describe trend and contrarian types of agents. The agents show also herd behavior.

* 1. **Swiss Bond Market**
  2. **Swiss Real Estate Market**

Several studies describe agent-based models of housing markets (Geanakoplos et al. 2012; Jordan et al. 2012; Gilbert et al. 2009). Most of these models were built with the intention to help explain observable patterns such as spatial and social segregation, or spatial and temporal distributions of housing prices. These models typically combine demographic factors such as age distribution or family size with economic factors such as wealth distribution, income or level of debt. Sometimes, also psychological factors are included, for example value structures or changing fashions. From all these factors, agent behavior rules are deduced. Most of these models rely on a grid-like or map-based settlement representation with individual parcels and houses. Hedonic modelling, which also focuses on single real estate objects, is yet another, more traditional approach on which many real estate market studies rely. These studies typically try to derive information from aggregated data on real estate objects in a certain region or during a certain time period.

The real estate market in Switzerland is attracting much attention at the moment. Whereas over the past few years rising prices have led to high returns for investors and very little defaults for creditors, more recently concerns about the formation of a speculative bubble followed by a corresponding correction have increased. The real estate market in Switzerland is characterized by illiquidity and high transaction costs.

The consequences of a real estate crash are dramatic for everyone involved, and it takes years to recover. The established risk management practice is to focus on the acquisition phase of new real estate objects. Effective adjustments to an already existing portfolio are only possible in a relatively stable market environment. Otherwise they can come at a very high price with the added risk of unwanted counter effects, for instance lowering market prices by selling high volumes of real estate objects. For this reason, strategic planning over a time horizon of five to ten years is essential. Doing so again requires adequate forecasting and analysis tools that offer more than simple single measure forecasts, and instead can capture the complex, dynamic dependencies between the various constituent market factors. This is where simulation models can help. Agent-based modelling generates virtual worlds for what-if scenario analysis and stress testing.

Relevant investors are the 1654 pension funds with a balance sheet of CHF 988 bn. 2017, they have invested 9.5% of their assets in directly in Swiss real estate (8.2% Wohnimobilien and 1.3% Geschäftsimmobilien) and 7.6% indirectly over funds and stocks (OAK BV, 2018).

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* 1. **Multi market models**

Ray Dalio

Joyce, M. A. S., Lasaosa, A., Stevens, I., and Tong, M. (2011). The financial market impact of quantitative easing in the United Kingdom. International Journal of Central Banking, 7(3), 113-61.

The market environment enables us to first simulate inter market relations. Second, we can compare these simulations to time series of the real financial markets around the world. In this manner, we evaluate the goodness of our model – it is assumed to be a suitable model the better it captures ex post real world market processes/ outcomes.

# Methodology

* *Summary of argument*
* *Overview of model*
* *Detailed justification*
* *Hypotheses*
  1. **Financial Markets**

The comparison of generated artificial time series like prices, volumes, etc, with real-world time series is a possible way for examining artificial markets or agent-based models. The kind of performance evaluation is determined by the expected use and the utility function. LeBaron (2006) gives a good overview. In this paper the following performance indicators are used:

* Hit rate
* Profit
* Model efficiency
* Maximum drawdown

The indicators reflect the goal of a practical usage of the models for asset management and their scientific comparability. But generally, it is difficult to measuring the performance of a non-linear system with parametric indicators. (Ankenbrand, 1998) Another possibility is to measure stylized facts for example distributions.

The hit rate h indicates how many times an up or down price movement has been correctly predicted by the model. It takes on values between 1 and 0.

where

*x* is the time series

*y* is the predicted time series

*n* is the number of data sets

*h = 1* implies a 100% correct prediction of the directional changes. *h = 0* implies 0% prediction of directional changes. Therefore, *h > 0.5* offers a better result than tossing a coin what is easy to obtain in a trending market. (Refenes, 1995, 69)

While the hit rate accounts for the number of correctly predicted price movements, it does not contain any information about the relative size of these movements and the resulting potential gains and losses. One single drawdown can nullify a whole series of precedent gains. Therefore, we also consider the model profit *p* and efficiency *f* or the distance from the ideal net profit (Refenes 1995, 71):

and efficiency *f* or the distance from the ideal profit (Refenes 1995, 71):

where *x* is the time series and *y* are the predicted time series.

The maximum drawdown measures the risk. It is the largest cumulated profit drawdown, measured from the previous cumulated profit high, before a new cumulated profit high occurs (Pardo, 1992, p. 35).

Most of the models offers a good convergence what means a high accuracy of model fitness in-sample. But the generalization capability is much worse what means the accuracy of model fitness out-of-sample. (Ankenbrand, 1998) Economic problems are often under sampled with non-stationary datasets.

The biggest challenge in the design of forecasting models is to avoid the overfitting. The following possibilities exist:

* Use of a priori knowledge
* Keep the model simple and small
* Split of the dataset in a training, validation and out of sample dataset
* Cross validation
* Use optimization and machine learning carefully.
* Be humble.

There are different possibilities to generate a priori or explicit knowledge. The first one is the use knowledge from academia or practice about the financial markets to design the market or agents. Second you can compute an extensive feasibility analysis as proposed in Ankenbrand (1998). The size of a model is determined by the degrees of freedom. A rule of thumb is that the dataset should be ten times the degrees of freedom. (Refenes, 1995) To be humble means only try to model the deterministic part and not the stochastic part of the market behavior.

* 1. **Agent Based Models**

An agent-based models could be referred as an artificial market. The procedure is more analytical than computational (LeBaron, 2006). Based on a set of input parameters, agents take a decision to either buy or sell such an asset. From the combination of all agents’ buy and sell decisions, a market forecast is deduced.

The model has a forecasting and optimizer part. The forecasting process is iterated, and consists of the following steps:

* Decision and order placement of the agents
* Calculation of the price
* Clearing and settlement of the orders
* Learning / adaptation of the parameters

The optimizer…

The design of the agents bases on a conceptual model of individual investors. The model has the following structure based on Lovric (2011):

* Assets
  + EURUSD
  + YENUSD
  + EURCHF
  + Bond USD
  + Bond EUR
  + Bond YEN
  + Bond CHF
  + S&P 500
  + DAX
  + Nikkei 225
  + SPI
  + Gold
  + Oil
  + Cash
    - USD
    - EUR
    - YEN
    - CHF
* Utility function
  + No Goal
  + Profit
  + Risk
    - Volatility
    - Maximum drawdown
  + Sharpe ratio
* Decision frequency
  + Daily
  + Weekly
  + Monthly
  + Quarterly
* Strategies (e, f)
  + Trend (1)
  + Contrarian (2)
  + Fundamentalist Trend (3)
  + Fundamentalist Contrarian (4)
  + Moving Average Trend (5)
  + Moving Average Contrarian (6)
  + Exponential Moving Average Trend (7)
  + Exponential Moving Average Contrarian (8)
* Interfaces
  + Input variables (g, h)
    - EURUSD
    - YENUSD
    - EURCHF
    - Bond USD
    - Bond EUR
    - Bond YEN
    - Bond CHF
    - S&P 500
    - DAX
    - Nikkei 225
    - SPI
    - Gold
    - Oil
  + Preprocessing
  + Interaction with other agents
  + Orders (Trading ratio, b, d)
* Learning
* Demografics
  + Private
    - Location
    - Gender
    - Age
    - Income
  + Institutions
    - Location
    - Type

The variables can be constant, or they can be dynamic and change the value over time. They can be related and influence each other. In the following the individual variables and the underlying theories are described.

The agent’s utility function defines the goals and risk attitude. The goals can be classical like the maximation of profit, or social preferences, like sustainability, status seeking or survival. The risk attitude differs in risk aversion, neutrality and seeking. Demographic factors for example, like gender or age, or investment horizon influence the risk attitude and utility function. (Lovric, 2011)

The time preference is captured with the discount factor, the investment horizon and the frequency. The agents have a pool of strategies to reach their goals. The agents are simple reactive agents in the present model who use past time series as input to their trading decision (LeBaron, 2006). To make trading decisions, the agents in the model rely on a set of both technical and fundamental factors based on past movements of different time series (Hommes, 2006). They decide to either buy or sell an asset, or to take no action at all.

The interfaces describe the way in which the agents with the environment. They use information from various sources for their strategies. Typically, the information are other time series. But they an also be corporates news, twitter feeds or others. The input variables can be used raw or preprocessed. The agents can interact with other agents and, for example, learn from the most successful agents and mimic their strategies. (Lovric, 2011) Or they do not have any information about the behavior of the other agents in the model except for the (past) price movements of different assets (LeBaron, 2006). The order interface allows the agent to place orders.

Learning means evaluating and updating strategies based on the past performance or exchange/combine strategies with other market participants (Lovric, 2011)

Demografics contain a collection of different characteristics depending on whether it is a private market participant or a company.

Technical traders study market data to gain insight into price movements of an asset. To do so, they search for recurring patterns of price movements. In our artificial population, technical trading agents are univariate traders. Many technical analysts believe in a trend behavior of financial markets and use moving averages or momentum analyses to detect such trends. Hence, they tend to buy assets when they are expensive and sell them when they are cheap. We include a trend follower who buy (sell) an asset if its price in the last trading cycle exceeds (falls below) the price in the previous period.

Where *x* is the time series, *m* the cash account, *n* the deposit, *r* the trading ratio and *o* the buy respectively sell order.

The second type are the contrarian traders which do the opposite: They buy assets which are out of favour and therefore run against the crowd. They buy (sell) an asset if its price in the last trading cycle is lower (higher) than in the previous one.

The third type of agents are the fundamentalists, who act value oriented in comparing the value of the traded asset with the value of another asset. In our model setting, they buy a particular asset if its value development is higher than the one of a compared asset.

where *q* is the input time series

The design of the agents can be based on explicit knowledge like describe before, or on implicit knowledge from self-learning agents. A comprehensive survey of multiagent reinforcement learning give Busoniu, Babuska and De Schutter (2008).

LeBaron (2006) distinguish four market mechanism for markets:

* In a temporary market equilibrium, the price is determined so that the total demand is equal to the total offer. This is computationally costly, because the demand and offer for every agent must be calculated for different hypothetical prices.
* The price impact function calculates the price based on demand and supply of each particular asset under consideration. They evolve according to:

Where *x* is the respective index and *y* is the predicted or artificial time series. *d* is the demand and s the supply of each asset. The elasticity of the price is depending on . Market makers execute the difference of buy and sell orders of the other agents for their own account. They always clear the market and therefore guarantee its liquidity.

* In the order book pricing mechanic, the buy and sell orders, which are matching, determine the price.
* In the matching mechanism, the agents (randomly) trade, if the needs (orders) fit. This mechanism is appropriate for trading without formal and centralized trading facilities.

The simulation is ‘round-based’. In each round/quarter, agents re-evaluate the current situation based on their sources of information and decide whether to buy or sell an asset. They then place their trade orders in an order book. Agents can only use market orders for simplification purpose. No limit or conditional orders are supported by the model environment. From all buy and sell orders, a price forecast is computed. This forecast constitutes the model’s collective guess.

The last step of the trading cycle is the clearing and the settlement of the orders. The assets and the cash are added or removed to or from the account of the agents based on the realized price. Moreover, the new value of the cash and asset portfolio is calculated for every agent.

Next, a new cycle begins with the placement of the orders of the agents based on their trading rules. All orders that are placed are also executed once every trading cycle because there exists a market maker for every market, who has the obligation to execute the difference of buy and sell orders on his own account at the price *xt* (LeBaron, 2006). The buy and sell orders of the different agents don’t match usually. The excess demand or supply is managed over the inventory of the market maker, who adapts the price based on the net excess. This leads to another foundation of the pricing equation (Hommes, 2006).

Agents trading successfully for some time accumulate more wealth than others. As time goes by, they start trading higher volumes. Consequently, their influence on the virtual market or forecast increases. This allows modeling the drift component (changes) of the market resulting from innovation, regulation, etc. (Kostadinov and Ankenbrand, 2013a). This implicit selection drives the agent population towards a dynamic fitness maximization (LeBaron, 2006; Kostadinov and Ankenbrand, 2013a).

The market data are used to verify the assumptions and the design of the agent-based model. The similarities of the agent-based model and the real market are measured by comparing the price time series of the artificial and the real market. Introducing ad hoc parameters, one could get a more realistic and reliable model. The parameters are obtained from past time series observation which the agents can use for their trading decisions. This allows to integrate different partial theories especially coming from the micro or agent level or the macro level of the markets and to test this hypothesis about the structure and the development of a market. (Ferber, 1994).

Besides producing predictions for the next cycle, the model can be used for long term scenario analysis and stress testing. The values of the input indicators depend on scenarios. The price calculation of the multistep forecast is calculated as:

Dynamic trading ratio (depending on success)

Alpha Hypothesis

* Shorter time means less risk
* Averaging
* Volatilitäts Clustering
* Risk Parity
* Position also from strength of trading signal depending
* Threshold Values for trading

Utility function Kahnemann/Tversky (Lo, 2017, 58)

Probability Matcher instead of Buy and Hold (Lo, 2017, 193f) for Risk Mgmt

Shannon’s Demon

* 1. **Oil**

* 1. **SPI**

The Swiss Performance Index (SPI) is the broad index of the Swiss stock market. It includes approximately 230 equity issues. The included stocks must be primary listed in Switzerland and must have a free-float equal to or greater than 20 percent. The calculation method is the capital-weighted Laypeyres formula based on the freefloat. The full market capitalization was CHF 1’553 billion and free float adjusted CHF 1’353 billion (as of 29.12.2017). (SWX, 2018)

Owners of the SPI stocks are private households, institutional investors like pension funds, insurance companies and banks, and cooperation/government. Household and institutional investors can hold the equities direct or indirect. For that reason, relevant investors are investment advisors and fund managers which hold the equities behave of their clients. Based on different datasources (Bloomberg, 2018; OAK BV, 2018; SNB, 2018) the following simplified ownership structure is used:

* Private Housholds 10% direct 25% indirect
* Institutional Investors 10% direct 25% indirect
* Cooperations/Government 30% direct

The performance of the followings models are compared:

* A neural network model (Ankenbrand, 1995a; Ankenbrand, 1995b)
* A linear regression model (Ankenbrand, 1998, 65ff)
* A neural network model (Ankenbrand, 1998, 67)
* Kernel Regression (unpublished)
* David Maturaarbeit

The specification of the neural network model is (Ankenbrand, 1995a)

*x(t+1) – x(t) = f(du(t), ich(t) – ich(t-1), s(t) – s(t-1))*

where

*x* is the SPI

*du* is the DEMUSD exchange rate

*ich* is the Bond CH yield

*s* is the S&P 500.

The specification of the linear regression model is (Ankenbrand, 1998, 65)

*x(t+1) – x(t) = 0.0008(d(t) – d(t-1)) – 0.7(ich(t) – ich(t-1)) – 0.4(ius(t) – ius(t-1)) – 0.1(ij(t) – ij(t-1))*

where

*x* is the SPI

*ich* is the Bond CH yield

*ius* is the Bond US yield

*ij* is the Bond J yield

*d* is the DAX.

The in-sample data are from January 1987 to December 1996 on a monthly basis.

Base on Ankenbrand (1998) the following investors are in addition to trend follower tested: DAX, Bond US, Bond YEN, Bond CHF, EURUSD and S&P 500. The highest improvement is the S&P 500 delivering.

Feng, Gigilio and Xiu (2020) test 150 factors on their influence on stock prices.

* 1. **Swiss Bond Market**
  2. **Swiss Real Estate Market**

The agents are grouped in three different classes representing real-world investors: Institutional investors, private residents or self-users and trend followers or speculators. Depending on their class, agents invest in either the SWX IAZI Investment Real Estate Price Index (SI Investment PR; IAZI, 2014a), and/or SWX IAZI Private Real Estate Price Index (SI Private PR; IAZI, 2014b). To make trading decisions, they rely on a set of both technical and fundamental factors based on the movements of different time series[[1]](#footnote-1). Their decision includes whether to buy or sell the index or alternatively to take no action. Table 1 gives an overview on all agent classes, the index they trade and the time series they use as input decision factors.

Table 1: Agent classes, traded indices and input decision factors

|  |  |  |  |
| --- | --- | --- | --- |
| *Agent class* | **Institutional Investors** | **Private residents/ self-users** | **Trend followers/ speculators** |
| *Characteristics* | * Insurance companies, pension and real estate funds * A mid- to long-term investment perspective * Low leverage * Investment in property as an alternative to bonds or stocks * Perform technical and fundamental analysis | * Potential land- and house owners who buy real estate for their own, private use * A long-term perspective | * Trade real estate for speculative reasons * Always follow the markets’ trends * Short-term investment perspective * Rely on technical analysis |
| *Market/ traded index* | * SI Investment PR | * SI Private PR | * SI Investment PR * SI Private PR |
| *Decision inputs* | * SI Investment PR * Swiss rental price index * Swiss Bond Index * MSCI World Index * Swiss population | * SI Private PR * Swiss rental price index * Swiss Bond Index | * SI Investment PR only or SI Private PR only |

Source: Kostadinov and Ankenbrand (2013a)

Instead of using long term interest rates (Swiss Bond Index) it would be interesting to test short term interest rates as an independent varianle (Sutton et al., 2017).

Immobilien Zyklus The Secret….

* 1. **Crypto Currencies**
  2. **Multi market models**

The performance of the followings models are compared:

* Static ABM model (Ankenbrand, 1997; Ankenbrand, 1998, 91ff)
* Dynamic ABM model (Ankenbrand, 1998, 91ff)
* Complex ABM model (Ankenbrand, 1998, 91ff; Ankenbrand, 1999)
* AVACO Global Macro (unpublished)
* An Information theoretic approach weekly data YENUSD (Ankenbrand, 1999)

Ankenbrand, T. & Klan, P. (1999). Application of information in financial markets prediction. Barcelona: FMA European Conference.

# Results

* *Logic of research design*
* *Description of measurement and/or observation procedures*
* *Validity and reliability tests*
* *Analytical procedures*
* *Description of the data – context, units of analysis, site, sample, appropriateness*
* *Descriptive*
* *Statistical or qualitative patterns*
* *Inferences and implications*
  1. **Oil**

The training data set contains daily datapoints from January 1982 to December 2010. The validation set contains … datapoints from January 2011 to July 2020. Missing data points (except weekends and holidays over all time series) are filled in with the last valid data point.

* 1. **SPI**

Results, but to verify in AVACO SPI V0.xlsm

Lansing and Tubbs (2018) describe a multiplicative combination of sentiment and momentum to predict the return on the Standard & Poor’s 500 stock index over the next month. SPI has to be tested.

* 1. **Swiss Bond Market**

Based on Ankenbrand (1998) the following agents are in addition to the buy and hold tested: Bond CH, 3 M CHF, Bond US, DAX, Spread CH, Spread USD. The actual model is buy and hold agent and a trend follower.

The volume of the Swiss Bond market is CHF 500 Mio.. Investors are

* Banks
* Insurance companies
* Pension companies
* Fonds
* Retail

Swiss Bonds has often a safe haven function in uncertain times (Nitschka, 2014).

## **Swiss Real Estate Market**

We ran the ABM model over a time period from December 1986 to September 2014, resulting in 110 trading rounds. Table 2 gives an overview of the results:[[2]](#footnote-2)

Table 2: Simulation results: Model quality measures

|  |  |  |
| --- | --- | --- |
|  | **SI Investment PR** | **SI Private PR** |
| **Observed upward price changes** | 59 | 66 |
| **Observed downward price changes** | 51 | 44 |
| **Generated BUY signals** | 63 | 74 |
| **Generated SELL signals** | 47 | 36 |
| **Hits** | 84 | 85 |
| **Misses** | 26 | 26 |
| **Hit rate** | 0.75 (75%) | 0.75 (75%) |
| **Model efficiency** | 0.54 (54%) | 0.54 (54%) |

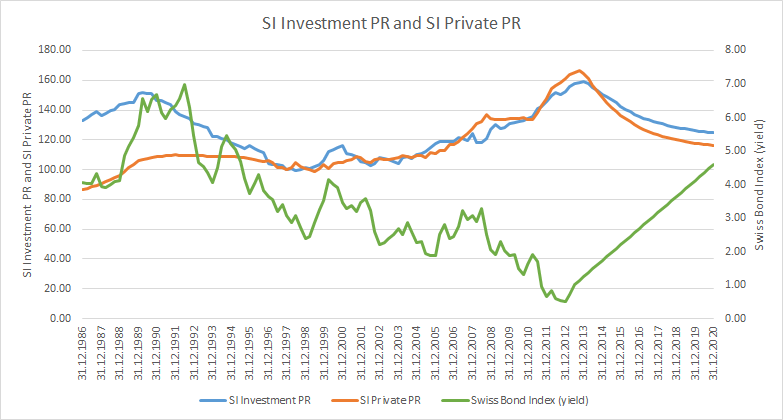
Investment Real Estate Price Index (SI Investment PR), and Private Real Estate Price Index (SI Private PR)

For both observed indices, the SI Investment PR and the SI Private PR, the hit rate has a value of 0.75. This means that in 3 out of 4 quarters the trend prediction of the Swiss real estate market was correct. Although the hit rate gives an overall impression of the number of correctly predicted price movements, it does not say anything about the relative size of these movements and the resulting potential gains and losses. As is well known, a single big drawdown can nullify a whole series of precedent gains. The current model efficiency is 0.54 for the SI Investment PR and 0.54 for the SI Private PR. The economic meaning is the relation between the realized and the possible profit and is 54%. The presented ABM therefore indicates a high degree of reliability.

A criticism of agent-based models is that there are too many degrees of freedom (LeBaron, 2006). The parameter space can be reduced through a stringent economic foundation and an evolutionary control of the development of the parameters.

Besides producing trend predictions for the next quarter, the model can be used for long-term scenario analysis and stress testing. In the following example, the effects of a long-term rise in interest rates on the SI Investment PR and SI Private PR are analyzed. The simulation is run up to the last quarter end (Q3 2014) relying on historical data. The interest rates are continuously increased as an example scenario. From this point on, the output time series (SI Investment PR and SI Private PR) is generated by the model. Figure 3 shows the outcome of the simulation runs for both target indices and also the yield of the Swiss Bond Index as the varied input measure during the period from December 1986 to September 2014.

Figure 3: Scenario analysis results



For both indices, a long-term increase of the interest rates leads to a clearly observable and significant decrease of both indices.

In a situation lacking both positive as well as negative market forces, the simulated market is nevertheless inclined towards a negative correction. The reason is that the majority of agents have already invested in real estate, and their potential to adding further assets to their existing investment portfolio is limited due to monetary limitations. The maximum affordable purchase of an average Swiss household at the end of 2014 was CHF 734’000. At the same time the price for an average property was CHF 800’000. The broad population isn’t any more able to buy a property with the solid financing (Keating and Hasenmaile, 2015).

If however negative market impulses prevail, a significant negative correction is to be expected according to our simulation results. Therefore, according to the model a further long-term rise in the Swiss real estate markets is to be expected only in a regime of prolonged, strong and positive market forces. Our conclusion goes in the same line with Toivonen and Viitanen (2015), which consider that when market actors are aware of the forces appearing in their action environment, they are able to notice any new phenomena emerging and quickly adapt their actions and even steer the development to the desired direction.

Unlike the other countries shown in figure 2, in Switzerland real estate prices continued to rise also in the years 2007 to 2014. Given the finding that in real estate cycles the downturn phase mirrors the preceding upturn phase, and assuming that the cycle’s tipping point was reached today, then both indices can be projected into the future. These projections actually correspond well with the simulation results provided by our agent-based model of the Swiss real estate market in figure 3. As we have argued above, prices will either continue to rise or otherwise they will fall, but a prolonged sideways movement is not very probable.

If however negative market impulses prevail, a significant negative correction is to be expected according to our simulation results. Therefore, according to the model a further long-term rise in the Swiss real estate markets is to be expected only in a regime of prolonged, strong and positive market forces. The scenario analyses indicate that the Swiss real estate market is in a rather weak condition. In the absence of positive market forces, the market has a tendency towards a negative correction, which becomes more poignant in the presence of negative market forces such as rising interest rates. In the simulated scenarios, increasing interest rates can lead to a strong negative correction of the real estate markets.

The AVACO model fits very well to the development of the Swiss real estate market since 1986. It can be used for forecasting in asset management and for scenario analysis in risk management. Scenario analyses conducted by AVACO indicate that the Swiss real estate market is in a rather weak condition. In the absence of positive market forces, the market has a tendency towards a negative correction, which becomes more poignant in the presence of negative market forces such as rising interest rates. In the simulated scenarios, increasing interest rates can lead to a sharp correction of the real estate indices.

## **Crypto Currencies**

* 1. **Multi market models**

The model covers an international set of currency, bond, equity and commodity markets for the time between January 1982 and September 2014 on a monthly basis.

We include the following markets:

• Currency markets: EUR/USD, YEN/USD, EUR/CHF

• Bond markets: United States, Euro Area, Japan, Switzerland

• Equity markets: S&P 500, DAX, Nikkei 225, SPI

• Commodity markets: Gold and oil

This market environment covers the main financial regions and instruments with a Swiss bias. Only one good is traded in each market. This is realistic and easily understandable for the currencies exchange markets. However, the bond and stock markets are simplified because there is only one asset traded in each market, whereas in reality different stocks and bonds are traded in one single market. While this assumption is simple, it is also realistic because it amounts to a situation similar to trading an index (future).

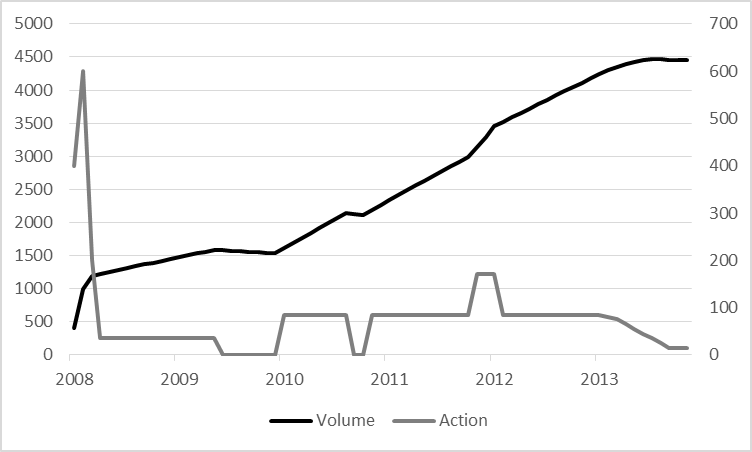
To make trading decisions, the agents in our model rely on a set of both technical and fundamental factors based on past movements of different time series. They decide to either buy or sell an asset, or to take no action at all. We model two types of agents: Fundamentalist and technical traders. Table 1 provides an overview of all agent classes, their characteristics, the market they trade in and the time series they use as input decision factors.

|  |  |  |
| --- | --- | --- |
| ***Table I.* Agent Classes** | | |
| Market | Technical | Fundamentalist |
| EURUSD | Trend follower with lag 1  Trend follower with lag 3 | Input Oil  Input YENUSD |
| YENUSD | Trend follower with lag 1  Trend follower with lag 3 |  |
| EURCHF | Trend follower with lag 1 | Input S&P 500  Input Oil |
| Bond USD | Trend follower with lag 1  Contrarian with lag 1 | Input EURUSD  Input EURCHF |
| Bond EUR | Trend follower with lag 1  Trend follower with lag 3 | Input EURUSD  Input YENUSD  Input S&P 500 |
| Bond YEN | Trend follower with lag 12  Contrarian with lag 6 | Input S&P 500  Input Nikkei 225 |
| Bond CHF | Trend follower with lag 1  Contrarian with lag 1 | Input EURUSD |
| S&P 500 | Trend follower with lag 1  Trend follower with lag 6  Trend follower with lag 12 | -Input Bond USD  Input Gold |
| DAX | Trend follower with lag 1  Trend follower with lag 12 | Input Oil |
| Nikkei 225 | Trend follower with lag 1  Trend follower with lag 6 | Input EURCHF  Input Oil |
| SPI | Trend follower with lag 1  Trend follower with lag 6  Trend follower with lag 12 | Input EURCHF |
| Gold | Trend follower with lag 6  Trend follower with lag 12 |  |
| Oil | Trend follower with lag 3  Trend follower with lag 6 | Input EURUSD  Input Gold |
| This table give an overview of the used agents. The trend follower decide on the time series itself with a certain time lag. The fundamentalist compares the value to the traded time series with the value of the input time series. | | |

There are different agents for every market with different trading profiles, trading rules and home currencies. The agents are simple reactive agents in the present model who use past prices as input to their trading decision before executing their output, which is an order they place in the order book in every trading cycle. They do not have any information about the behavior of the other agents in the model except for the (past) price movements of different assets.

The Fed’s QE actions are implemented by including an additional central bank agent buying assets. The Figure 1 shows the timeline of its QE actions and the total outstanding volume of the Fed transactions.

Fed Quantitative Easing



***Figure 1.* Fed Quantitative Easing Actions**

This figure shows Fed Quantitative Easing monthly actions and the total volume of the actions between 2008 and 2014.

Based on this timeline the Fed agent is buying the different asset classes.

The results outlined in Table 2 clearly show that our “basic” model captures well the global market developments during the sample period considered.

|  |  |  |
| --- | --- | --- |
| ***Table 2. Performance Results of the original agent-based Model*** | | |
| Market | Hit Rate | Model Efficiency | |
| EURUSD | 55.8% | 18.7% | |
| YENUSD | 56.5% | 18.8.% | |
| EURCHF | 51.4% | 6.9% | |
| Bond USD | 65.0% | 32.6% | |
| Bond EUR | 63.4% | 36.0% | |
| Bond YEN | 62.1% | 33.0% | |
| Bond CHF | 62.9% | 35.9% | |
| S&P 500 | 59.1% | 22.6% | |
| DAX | 58.1% | 22.3% | |
| Nikkei 225 | 48.8% | 13.4% | |
| SPI | 61.9% | 28.1% | |
| Gold | 52.2% | 16.9% | |
| Oil | 52.9% | 15.7% | |
| This table reports empirical results for monthly data. The sample period runs from January 1982 to September 2014. | | |

Building up on this, Table 3 shows the results of the ABM that includes the Fed and their respective QE actions. It can clearly be seen that their actions improve the overall model results. The Fed’s QE has an impact on the markets for currencies and stocks. Surprisingly, it does not affect the bond markets. Our model therefore shows that QE measures undertaken in the United States have produced asset bubbles in the stock markets.

|  |  |  |
| --- | --- | --- |
| ***Table 3 Performance Results of agent-based Model with the Fed as agent*** | | |
| Market | Hit Rate | Model Efficiency | |
| EURUSD | 56.8% | 28.4% | |
| YENUSD | 57.8% | 20.6% | |
| EURCHF | 51.4% | 6.9% | |
| Bond USD | 65.0% | 32.6% | |
| Bond EUR | 63.4% | 36.0% | |
| Bond YEN | 62.1% | 33.0% | |
| Bond CHF | 62.9% | 35.9% | |
| S&P 500 | 60.1% | 26.4% | |
| DAX | 59.8% | 29.2% | |
| Nikkei 225 | 51.4% | 18.0% | |
| SPI | 62.4% | 30.8% | |
| Gold | 52.2% | 16.9% | |
| Oil | 52.9% | 15.7% | |
| This table reports empirical results for monthly data. The sample period runs from January 1982 to September 2014. | | |

In order to predict possible effects of QE in the Euro Area as announced on October 2, 2014, by the ECB into our modelling framework:

The program starts in October 2014.

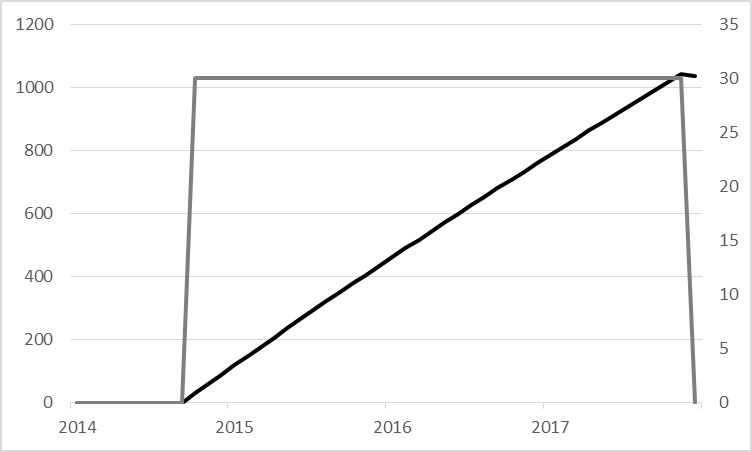
It will last at least two years.

It will have a sizeable impact on the ECB’s balance sheet.

Based on these assumptions, we develop the following scenario.

Figure 2 shows a timeline for constant QE actions of a total outstanding volume of up to EUR 1 billion.

ECB Quantitative Easing

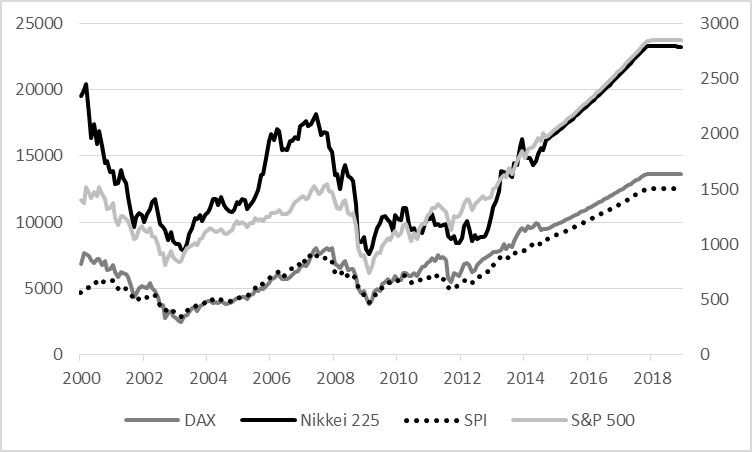


***Figure 2.* ECB Quantitative Easing Actions**

This figure shows ECB Quantitative Easing monthly actions and the total volume of the actions between 2014 and 2017.

Figure 3 shows the long term simulated stock market time series on this timeline.

Stock price indices



***Figure 3.* ECB Quantitative Easing Actions**

This figure shows the simulation of Stock price indices from October 2014 to December 2018. All indices are based on monthly data for the sample period from January 1982 to September 2014.

This paper employs a multivariate agent-based model of a broad set of international financial markets to model the effect of quantitative easing (QE) actions undertaken by the Fed. Moreover, we use its results to simulate the impact of QE measures by the ECB on market movements as announced by the ECB in early October 2014. Based on relatively simple assumptions about our agents’ behavior, the model is capable of mirroring well key events in international financial markets. It therefore allows the long term simulation of different markets, their interaction, contagion of shocks and behaviour in times of crises. Most importantly, back testing of our model’s predictions with past data clearly shows that including QE in its framework improves it. Moreover, we can then use it to predict an international stock market rally induced by the ECB’s unconventional monetary policy.

# Conclusion

* *Summary and interpretation of results*
* *Main contribution to the core audience*
* *Contributions to peripheral audience*
* *Limitations – boundaries*
* *Future research*

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1. Data sources: Swiss rental price index provided by Bundesamt für Statistik (2014), Swiss Bond Index published by Neue Zürcher Zeitung, MSCI World Index by MSCI (2014). [↑](#footnote-ref-1)
2. By coincidence both the hit rate and the model efficiency happen to have the same values for both indices. This can of course not be generalized. [↑](#footnote-ref-2)