An agent-based model of a Swiss real estate market

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Abstract. This study presents an agent-based model of a Swiss (financial) real estate market. Four different classes of agents are modelled, trading either one or both the SWX IAZI Investment Real Estate Performance Index or the SWX IAZI Private Real Estate Price Index. The agents apply simple rules to derive trading decisions. Moving averages are used to calculate the trend component of different time series. Depending on their class, agents rely on fundamental factors such as the Swiss rental price index, or consider alternative investment opportunities such as bonds, indicated by the Swiss Bond Index, or stocks, indicated by the MSCI World Index. Based on the agents' buy and sell decisions, the model is used to generate trading signals that can effectively be used by real-world market participants. Even though the agents' trading rules are intentionally kept simple to prevent overfitting, the quality of the generated trading signals reaches a promising level.

Keywords: agent-based modelling, agent-based computational finance, real estate market, real estate market, trading signal generation

1 Introduction

In the past, agent-based models of housing markets have repeatedly been used to help explain certain aspects of settlement patterns such as spatial or social segregation, or spatial and temporal house price patterns. Such models typically include individual agents' residential choices: rent or buy a house or move from one neighbourhood to another. Agent decisions are driven by individual factors such as income, age, family and value structure or expectations about the future, but also by global factors such as state policy and regulations, interest rates, the general economic situation or culture. An example for such a study is found in Jordan et al. (2012). Most of these studies are of interest due to their explanatory power, but are of limited applied use for investors.

Despite the existence of an extensive literature on agent-based financial markets and trading systems, no publications could be found on agent-based financial market models with a focus on real estate markets.

Another strand of studies, taking a more traditional approach, relies mainly on statistical regression and econometric models. On the micro-level, perhaps hedonic models are the most important ones in use. These models try to derive a price for an individual property by evaluating its attributes such as architecture, age and location (Sopranzetti 2010). Also studies with a focus on macroeconomic factors can be a source of information for investment decisions. However, neither econometric micro-level models such as hedonic models nor macro-level models contain an explicit representation of agent interactions and behaviour.

This study presents a multivariate, agent-based model of a Swiss (financial) real estate market. Agents act as traders/investors of an index. Unlike many other agent-based models of housing markets, no spatial representation of townships exists in the model and no houses or real estates are actually traded. Rather, the goal is to deduce trading signals from the aggregated agent behaviour. These trading signals constitute a prognosis for the development of the traded indices in the next unit of time, which can effectively be used by real-world market participants. A second purpose of the model is to support an investor's risk management by allowing to conduct scenario analyses under the variation of different time series used as input decision factors.

Although the focus is specifically on Switzerland concerning traded indices, input data used and the agents' trading strategies, the model could easily be adopted to other countries by feeding it with corresponding data. The rationale was to keep the model as simple and robust as possible and to avoid sophisticated, but implausible parameter settings, which are always in danger of overfitting a current market situation or historical training data, yet failing in case of a market regime change.

2 Model

Four different market participants are modelled as agent classes:

- *Private investors* are motivated by the premises of growing long-term returns as a result of population growth and an increasing demand for living space. Their leverage (= invested foreign capital / invested own capital) is usually rather high.
- *Institutional investors* have a mid- to long-term investment perspective and a low leverage due to a relatively high share of liquid assets. Investments in property are primarily seen as alternatives to investing in the bond or stock markets. Typical real-world examples are insurance companies, pension or real estate funds.
- *Private residentials* buy securities as an investment in their own home, which they either rent or buy. Unlike private investors, they actually live in the homes they invest in.
- *Trend followers* buy and sell securities based on purely speculative motives. They try to buy into the securities' upward trends and sell into downward trends.

All agents are initialized with the same amount of cash money, which they can invest. Different agent classes trade either one or both of the following indices[1] on a quarterly base:

- SWX IAZI Investment Real Estate Performance Index (SI Investment TR), and/or

[1] For more information visit http://www.iazicifi.ch/de/transaktionsindizes.php and http://www.six-swiss-exchange.com/indices/other/iazi_en.html (Feb. 2013).

- SWX IAZI Private Real Estate Price Index (SI Private PR).

Both indices have existed since the early 1980ties and form some of the most important indicators to assess the current state of the Swiss real estate markets. For each index one market is modelled where agents can register market orders.

All agent classes use the indices time series to set up simple moving averages, from which they derive trend components. Additionally, all except trend follower agents also apply some of the following fundamental factors:

- Swiss Bond Index (SBI): The SBI indirectly mirrors the development of the interest rates set by the Swiss National Bank. As an alternative to investments in real estate, a rise of the SBI indicates that investing in Swiss real estate becomes less attractive and vice versa.
- Morgan Stanley Capital International (MSCI) World Index: Institutional investors, additionally to the SBI, also rely on the MSCI World Index as a comparative benchmark on an international scale. If it rises, investing in Swiss real estate becomes less attractive and vice versa.
- Swiss rental price index: The rental price index is a statistical index measure collected by the Swiss Federal Statistical Office. A rising index indicates an increased attractiveness of investing in real estate.

Whereas the IAZI indices are published at the last day of a quarter, the SBI, MSCI and the rental price index are published on a sub-quarterly base and are practically available at the quarter's end. All time series run from the first quarter of 1987 to the third quarter of 2012, resulting in roughly100 quarters or trading rounds.

Table 1 gives an overview of which agents trade on which markets.

Markets/traded indices	**SI Investment TR**	**SI Private PR**
Private Investor	X	X
Institutional Investor	X	
Private Residential		X
Trend Follower	X	X

Table 1. Agent classes and markets/traded securities

Table 2 shows the decision input factors used by each agent class.

Time series used as decision input	SI Investment TR	SI Private PR	Swiss Rental Price Index	Swiss Bond Index	MSCI World Index
Private Investor	X	X	X	X	
Institutional Investor	X		X	X	X
Private Residential		X	X	X	
Trend Follower	X	X			

Table 2. Decision input factors per agent class

Agents in a certain class usually have different trading strategies combining their decisional input factors in different ways. A very simple implemented trading strategy is to count the time series' trend directions the agent observes, and to buy more securities if at least half of the trends indicate an increasing attractiveness of investments in real estate. A slightly more sophisticated strategy additionally assigns weights to the different time series' trends.

Each round, first, the new moving average values are calculated. Second, agents evaluate those moving averages they base their decisions on and then register buy or sell market orders. Third, all markets are cleared. In the current model, agents do not have a price target but take the market price as given, so no matching between buy and sell orders is performed. Instead, agents trade securities with a "virtual" market maker with infinite resources. Fourth, statistical output measures are calculated. Last, trading signals are generated based on the total market trading volume:

$$s_t = \begin{cases} 1, \; if\ |v_t| > c \; AND \; v_t > 0 \\ -1, \; if\ |v_t| > c \; AND \; v_t < 0, \\ 0, \; otherwise \end{cases} \qquad \text{with } v_t = (m_t^b - m_t^s)p_t \tag{1}$$

where s_t is the trading signal (1=BUY, -1=SELL, 0=NO_ACTIVITY) at time t, c a signal threshold, v_t the traded volume, m_t^b and m_t^s the total number of bought resp. sold units and p_t the price per unit. Depending on the trading strategy, some traders consider trading only on a change of the signal (e.g. from 0 to -1), whereas others trade at a higher frequency using every single signal. Adjusting the signal threshold c to the right value has some importance. A low threshold leads to a high number of buy and sell signals, but it also increases the noise level. Conversely, a high threshold increases the signal quality, but also decreases the frequency of buy and sell signals. An attempt to further predict the size of price changes is not taken.

In the current model version, no individual agent learning or fitness-based selection mechanism on a population level is implemented. However, a wealth effect is in place. Successful agents accumulate more wealth over time. This enables them to trade higher volumes, and therefore their influence on the trading signal generation increases over time.

3 Results

This study is mainly interested in the quality of the generated trading signals, and not so much in the performance of particular agents or agent groups. A measure to assess the quality of the generated trading signals is the hit rate:

$$h = \frac{n_{hit}}{n_{hit}+n_{miss}+n_{no\_activity}}, \tag{2}$$

where h is the hit rate, n_{hit}, n_{miss} and n_{no_action} the numbers of generated hits, misses and no_activity signals. A hit is defined as a correctly predicted price change, and a miss as an incorrectly predicted price change. If h equals 1 then 100% of the generated buy/sell signals correctly indicate the observed price change. A value of 0.5 implies that the signals are completely random and all hits and misses exactly compensate each other.

Calculating the model efficiency can complement the hit rate (Refenes 1995, 71):

$$r_d = \frac{\sum_{i=1}^{n} s_t(p_{t+1}-p_t)}{\sum_{i=1}^{n} |p_{t+1}-p_t|}, \tag{3}$$

where the model efficiency r_d is a distance measure between the achieved and the ideal net profit, and all other variables are as described above. An ideal value of $r_d = 1$ implies that the model captures 100% of all possible gains through price changes. A high number of NO_ACTIVITY signals as well as a high number of misses will result in a low model efficiency r_d. Table 3 gives an overview of the achieved results.

	Iazi Investment TR	Iazi Private PR
Observed upward price changes	71	55
Observed downward price changes	28	44
Generated BUY signals	77	71
Generated SELL signals	20	25
Generated NO_ACTIVITY signals	2	3
Hits n_{hit}	65	65
Misses n_{miss}	34	34
Hit rate h	0.64	0.64
Model efficiency r_d	0.45	0.58

Table 3. Simulation results

The results in table 3 represent one of the best parameter choices optimizing between markets, hit rate and model efficiency at the same time.

4 Discussion and outlook

Even though the model was designed and implemented based on the principles of simplicity and robustness, and therefore intentionally has been only modestly optimized or fine-tuned, it generates trading signals of a relatively high quality. The agents combine both fundamental and technical factors for their trading strategies. It would be not too difficult to achieve a still better fit for the chosen historical data, for example by increasing the level of sophistication of the agents' trading strategies, but this would inherently carry the danger of overfitting. An important feature of the model is that it does not require any prior training phase.

The model's main benefit is to act as a simulation tool for market participants to analyse different scenarios of time series development. It could also serve as one basis to set up an investment product. Of course, to be of real use, such an agent-based model must always be embedded in the context of an investment or portfolio strategy, and a corresponding risk management system must be in place.

As stated earlier, the current model version does not yet include adaptation on the population level. Trading strategies are still (statically) hand-coded per agent, thus the population size is currently rather small. For a future model version, the author's plan is to use genetic programming or grammatical evolution to breed a perpetually dynamically adapting population of agents, with each agent having its own individual trading strategy.

Another goal is to adapt the model to other (financial) markets.

5 References

Jordan R, Birkin M., Evans A. (2012): Agent-Based Modelling of Residential Mobility, Housing Choice and Regeneration. In: Heppenstal, A.J., Crooks, A.T., See, L.M., Batty, M. (editors, 2012), Agent-Based Models of Geographical Systems. Dordrecht: Springer Science + Business Media. DOI 10.1007/978-90-481-8927-4_25.

Refenes A.-P. (1995): Neural Networks in the Capital Markets. New York: John Wiley & Sons

Sopranzetti B. J. (2010): Hedonic Regression Analysis in Real Estate Markets: A Primer. In: Lee C.-F., Lee A.C., Lee J. (editors, 2010): Handbook of Quantitative Finance and Risk Management. New York: Springer Science + Business Media. p 1201-1207. DOI: 10.1007/978-0-387-77117-5_78