Improving the Support for Investment Decisions in Financial Markets Using the System Dynamics Methodology

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1 Problem Setting

Financial markets (FiMa) are often designated as "complex systems" (Johnson et al. 2003, p. 3; Farmer and Foley 2009, p. 685). From the perspective of system theory, this view implies two aspects: Firstly, FiMa can be interpreted as *systems* having *structure* and *behavior*. Secondly, such systems have high *structural* and *behavioral complexity* (e.g. Klir 1969, pp. 50).

Investors, as parts of FiMa, seek to make reasonable investment decisions. For this purpose, it is essential to comprehend the system structure, the system behavior and interdependence between both. These necessities correspond with three questions investors are concerned with in the run-up to investment decisions: *What elements constitute the financial system?* (question$_1$). *Why do financial markets behave in a certain way?* (question$_2$). *How will security prices develop in the future?* (question$_3$) (Tab. 1, left column).

Because of the high structural and behavioral complexity of FiMa, answering these questions is difficult. In order to manage this complexity, models of FiMa are constructed. A model is a mapping of the original system, which reduces the number of the original system's attributes and exhibits a subject oriented pragmatic aspect (Stachowiak 1973, p. 131). The *model quality* is determined by its *accuracy of structure*, its *accuracy of behavior*, its *empirical validity*, and its *validity for application* (Bossel 1994, p. 36).

The questions 1 to 3 can be answered using three *generic types of models* of which each aims at different model objectives (Wildmann 2007, pp. 5): *Description models* capture the structure of the system (answer to question$_1$), *explanation models* seek to formulate hypotheses about system behavior from system structure (answer to question$_2$) and *prognosis models* try to forecast system behavior (answer to question$_3$) (Tab. 1, middle column). Based on these considerations we postulate the premise:

"The utility of (a) financial market model(s) for investment decisions is the higher, the better the model(s) can be used for description, explanation and prognosis of financial markets."

To investigate potential modeling approaches we differentiate between three types of representation: *informal* (verbal description), *semiformal* (graphical illustrations following a defined language of construction), and *formal* (mathematical functions) (Wittges 2005, pp. 18).

Following this classification, traditional models (e.g. Lux and Marchesi 2000; He and Westerhoff 2005; Shimokawa et al. 2007; survey by Hommes 2006) are formal as they consist in sets of mathematical functions. These models can be used for description and prognosis of FiMa. Yet, explanation models are often neglected. This is unfavorable as explanation models fulfil a key function by deducing behavior from structure. Hence, interpretations of behavior of financial models can be vague and speculative (LeBaron 2000, p. 693; Ehrentreich (2008), p. 4).

Table 1: System and Model Theoretic Perspective on the Problem Setting

Investigation Objectives		**Generic Model Support**	**Objective Achievement of Modelling Approaches**	
Financial market motivated	*System theoretic motivated*		*Traditional approach*	*System Dynamics*
What elements constitute the financial system?	Structure	Description model	Informal descriptions	Informal descriptions Semiformal models (Causal Loop Model, Flow Model)
Why do financial markets behave in a certain way?	Structure (with aspects of behavior)	Explanation model	not supported	Semiformal models (Causal Loop Model, Flow Model)
How will security prices develop?	Behavior	Prognosis model	Formal model	Formal model

The modelling approach we propose is the methodology of System Dynamics (SDM) (e.g. Sterman 2000). System Dynamics (SD) has proven its applicability in numerous cases (e.g. Meadows et al. 2004; Strohhecker 2005). Essential models in the SDM are the *Causal Loop Model* (CLM) and the *Flow Model* (FM) which map the structure and the behavior of the represented original system. These models can support the tasks of description, explanation, and prognosis (Tab. 1, right side). Therefore, we propose the hypothesis:

"Using the SDM increases the utility of FiMa-models and the quality of investment decisions."

To evaluate this hypothesis, we investigate the research questions a) and b):

a) Does the SDM enable to model FiMa more accurately than the traditional approach?
b) How well can we use the SD-model for the description, explanation, and prognosis of FiMa?

This paper is organized as follows: Firstly, we refer to the development of a FiMa-model following the SDM (Sec. 2). Then, we compare our model with traditional models regarding accuracy of behavior. Afterwards, we evaluate the model's utility during the model application (Sec. 3). Finally, we summarize our findings, identify the limitations of our concept, and give an outlook of our future research (Sec. 4).

2 Developing an SD-Model of a Financial Market

2.1 Introduction of a Theoretical Background of the Financial Market

In the following, a FiMa is understood as the conglomerate of lenders and borrowers of funds as well as their place of interaction. Traded funds embrace any kind of financial security, e.g. stocks, currencies or derivates.

FiMa-models are usually based on (I) *agent-based modeling* and (II) *behavioral finance* (Hommes 2006, pp. 1111). Agent-based modeling (e.g. Ehrentreich 2008) means to reproduce complex systems by modeling the behavior of individual agents and their interactions. Behavioral finance (e.g. Shleiver 2000) stresses that the behavior of financial agents is not rational. Instead, financial agents have been found to succumb to emotions and bounded rationality.

The *chartist-fundamentalist approach* (Hommes 2006, pp. 1116) has proven to be a successful paradigm combining (I) and (II). The approach is based on the observation that traders either use *technical* or *fundamental strategies* (e.g. Lui and Mole 1998). Technical traders are called *chartists*. Chartists try to identify trends and trade on them (e.g. Pring 2002). Fundamental traders are called *fundamentalists*. Fundamentalists expect prices to return to value sooner or later. Hence, they seek to exploit mispricing (e.g. Greenwald et al. 2001). The interactions of both trader groups produce complex system behavior that replicates real markets quite accurately (He and Westerhoff 2005, p. 1578).

2.2 Derivation of Causal Hypotheses

The CLM (Fig. 1) illustrates the basic causal objects (CO) and causal relationships (CR) of the model. All CR are coherent to the literature. Semantically similar CO are combined to a *causal frame* (CF):

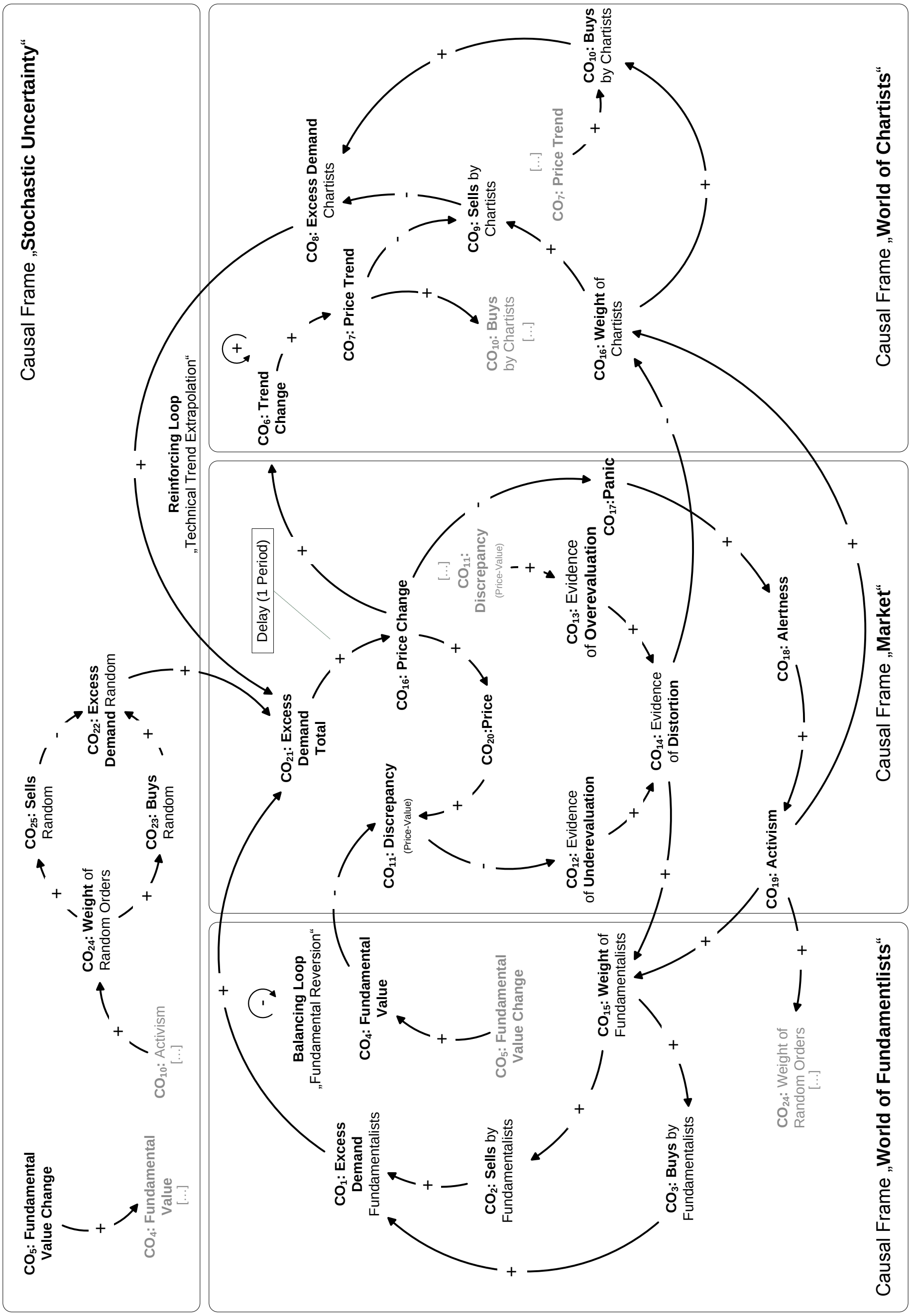

Figure 1: CLM of the financial market

- Causal frame "World of Fundamentalists": Following their strategy, fundamentalists buy more (CO_3) and sell less (CO_2), the lower the price (CO_{20}) or the higher the fundamental value (CO_4). Their excess demand (CO_1) is the net of buys and sells. The fundamental value is modeled as a random walk (CO_4, CO_5).
- Causal frame "World of Chartists": Chartists buy more (CO_{10}) and sell less (CO_9), the larger the price trend (CO_7). Their excess demand (CO_8) is the net of buys and sells. The price trend is interpreted as a moving average (CO_6, CO_7).
- Causal frame "Market":
  – *Choice of trading strategy:* As mispricing growths (CO_{11}), trend extrapolation, i.e. here technical strategy, becomes riskier because a correction becomes likely (He and Westerhoff 2005, p. 1582). Accordingly, more traders chose fundamental (CO_{15}) instead of technical strategy (CO_{16}), the more evident the distortion of prices (CO_{12}, CO_{13}, and CO_{14}).
  – *Investor inertia*: Inherently ordinary traders behave inertial showing little trading activity (Bayraktar et al. 2006, pp. 791). Yet, price decays can provoke panic (CO_{17}) among investors, which rises alertness (CO_{18}) and increases activism (CO_{19}). As a result, the weight of both trader groups (CO_{15} and CO_{16}) growths.
  – *Price adaption*: The price mechanism follows the market-maker approach (Farmer and Joshi 2002, p. 151−152). The market maker can be interpreted as a price setter and intermediary between buyers and sellers who absorbs imbalances between both (e.g. a broker). If for a given price, an excess demand exists, the market maker adapts prices. The higher the excess demand (CO_{21}), the more he will raise prices (CO_{20} and CO_{21}).
- Causal frame "stochastic uncertainty": This frame captures unsystematic effects, such as random transactions (CO_{22}, CO_{23}, CO_{24} and CO_{25}), as well as random changes of the fundamental value (CO_5).

2.3 Transformation of the Causal Model to a Flow Model

The FM (Fig. 2) illustrates the flow objects (FO)[1], which constitute the model's structure on a physical level (Sterman 2000, pp. 191). Stocks are the most important FO since they particularly determine the system state and are source of delays in the system behavior. Therefore, we concentrate on the stocks and the flows whereas auxiliaries are not described explicitly. There are four stocks in the model:[2]

- *Fundamental value* (FO_1): This stock represents the state of the fundamental world. It accumulates the occurrences in the system environment, in particular, in the real economy. It determines the average level on which prices move. Changes of

[1] The term FO designates every element of an FM: stocks, flows, and auxiliaries.

[2] For support on transformation of CLM to FM cf. Suchan (2009).

value are modeled as a bi-flow (FO$_2$), which represents positive or negative events in the system environment.

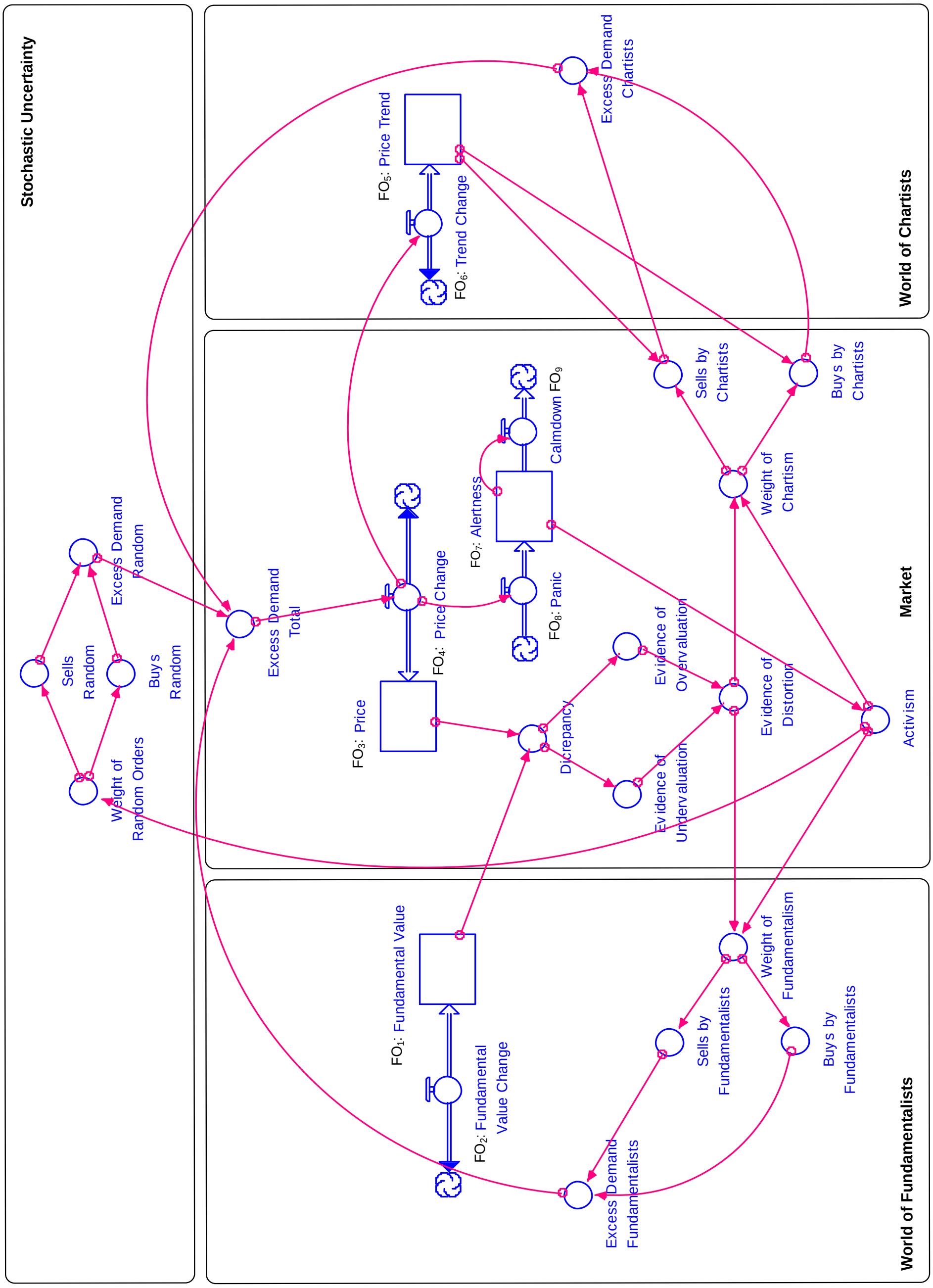

Figure 2: FM of the financial market

- *Price* (FO_3): This stock can be interpreted as the state of the market system. It represents the memory of all transactions made in the past. The level feature defers price fluctuations and reduces their size. A bi-flow (FO_4) produces positive or negative changes of prices.
- *Price Trend* (FO_5): This stock can be interpreted as the state of the technical world. It memorizes the dynamics of prices and creates persistence in price movements. More specifically, the stock causes that prices move away from value durably. Due to a bi-flow (FO_6) the trend can grow or fade.
- *Alertness* (FO_7): This stock represents the emotional state of agents. It is exemplary for investor sentiments. The fact that sentiments build up (inflow: "panic" FO_8) and settle down (outflow: "calm down" FO_9) gradually causes that transactions are motivated emotionally, even if the event that has stirred such emotions is already absent.

2.4 Validation of the Model Behavior

To answer research question a) we test the accuracy of behavior of the SD-model. Accuracy of behavior of a FiMa-model is usually evaluated by its ability to reproduce the *stylized facts* (e.g. Cont 2001) of real markets. Stylized facts are qualitative, statistical properties of real financial price dynamics. We tested the SD-model for eight of the most prominent facts. Stylized facts are tested by econometric measures. Stylized facts (1) to (5) can be illustrated in the dynamics (Fig. 3).

(1) *Excess volatility*: Prices move more than necessary in order to incorporate all fundamental news. The fact that the price (black line) is more volatile than the fundamental value (gray line) reflects this property (whole chart).
(2) *Speculative bubbles*: Prices soar above value for a significant span of time and crash afterwards (periods 155 to 255).
(3) *Volatility clustering*: Tranquil and turbulent periods alternate with each other: Compare periods 290 to 320 and periods 320 to 450.
(4) *Uncorrelated returns*: The walk of prices appears to be chaotic (whole chart).
(5) *Gain/loss asymmetry*: The number of extreme falls in prices is significantly larger than the number of equally strong increases: Whereas during the upward trend from periods 320 to 450 price changes are relatively small, changes are large during the following fall from periods 450 to 475.
(6) *Heavy tails*: The variance of the distribution of returns is due to large deviations to a higher degree than predicted by the normal distribution: An excess kurtosis of 1.4 of the distribution of periodical returns proves this feature.
(7) *Aggregational Gaussianity*: As one increases the time scale over which returns are calculated, their distribution approximates the normal shape: For example for a time scale of thirty periods, the excess kurtosis has reduced to 0.67.

(8) *Volume/volatility correlation*: Strong movements of prices are accompanied by high trading volume: Indeed, with 0.45 the correlation is significantly positive.

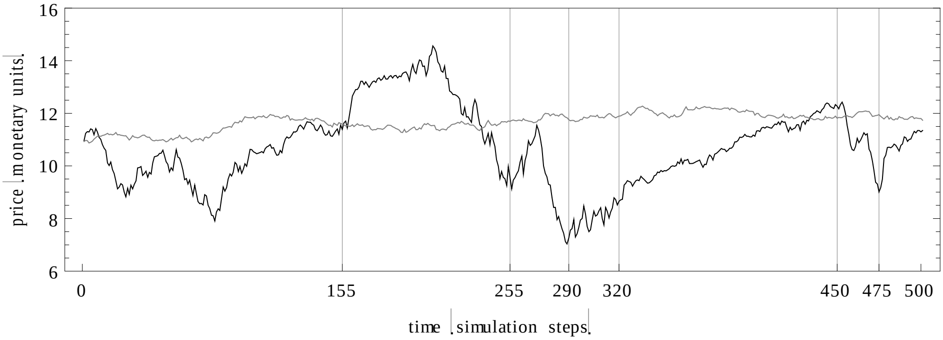

Figure 3: System behavior of a financial market (here: typical simulation run)[3]

The survey by Chen et al (2008) can be used to compare the accuracy of behavior of the SD-model with traditional ones. The authors study fifty formal models of FiMa and summarize the stylized facts reproduced by each. Some of the models simulate two or more groups of agents (like ours); more complex ones simulate every agent autonomously. The most accurate model (Shimokawa et al. 2007) was tested positively for only seven facts, whereas we tested eight facts. We assume one reason for the high accuracy of behavior of the SD-model to be its complex structure that accounts for a relatively high number of real world relationships. In contrast, traditional models focus on a smaller number of real world relationships. A cause might be that the structure of a formal model looses transparency if the number of formal equations is high.

This allows an answer for research question a): The SD model does enable to model FiMa more accurately than other concepts, since the semiformal model permits to handle a higher structural complexity.

3 Support of Investment Decisions

3.1 Description of Financial Market Structure

Support for investment decision can be given by insights about the system. For this purpose, it is an essential precondition to know the system structure. To this regard, the SD-model can be used as a *description model* (Tab. 1, right column). The theoretical framework (Sec. 2.1) has outlined the main structural hypothesis of the system. Later, these hypotheses have been specified (Sec. 2.2). The advantage of

[3] Simulation with *Mathematica 6.0*. In case of interest for model equations, please contact the authors.

the SD-model is that all CO and CR are illustrated explicitly in the CLM (Fig. 1). By offering a semiformal representation, the CLM increases the number of insights of the system structure (Shepard 1967, pp. 156).

3.2 Explanation and Prognosis of the Financial Market Behavior

In order to assess the model's potential for explanation and prognosis, we consider two scenarios: a speculative rally and a market crash (Fig. 4). The model should be able to explain the behavior of prices and yield evidence about the price dynamics in the future – an important criterion for improving investment decisions.

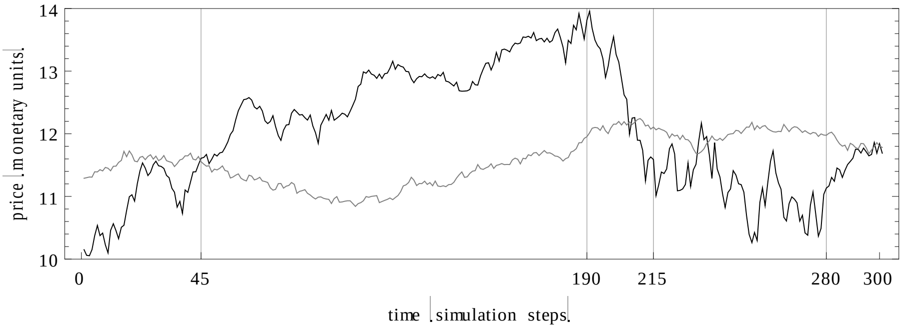

Figure 4: System behavior of a financial market (here: speculative rally and crash)

Scenario 1: A speculative rally

Within the periods 45 to 190, a speculative rally builds up. Speculative rallies emerge because technical trading induces positive feedback into the dynamics of prices (Fig. 5). The loop is reinforcing: If chartists identify an upward trend, they react by buying more and selling less. As a result, their excess demand increases and prices tend to rise. The positive change of prices manifests the upward trend and the loop repeats. If not countered by other forces, a speculative rally begins.

Useful insights for financial prognosis and investment decisions are: Firstly, speculative rallies are not necessarily driven by fundamental developments, because the positive feedback runs independently of the fundamental value (insight$_1$). Secondly, the positive feedback demonstrates that price dynamics show certain momentum that is stored in the stock, price trend. It follows that assuming rallies to continue, at least in the short-term, is rational. Hence, the SD-model suggests that betting on trends to continue is a profitable short-term strategy (insight$_2$).

Within the periods 190 to 215, the market crashes. The reason is negative feedback by fundamental traders (Fig. 6). The loop works balancing: If prices overshoot value, fundamentalists react by selling more and buying less. As a result, their excess demand decreases and prices tend to fall. If prices are still above value, the loop repeats.

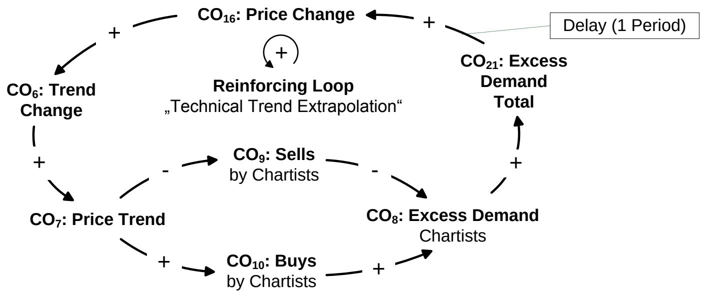

Figure 5: CLM of the reinforcing loop technical trend extrapolation

Scenario 2: A market crash

If prices have realigned, fundamentalists have no incentive to trade anymore, and the feedback settles down. Taken together, the loop generates a force that pulls the system state (CO_{20}) towards a target level (CO_4). The force is the stronger, the more prices deviate from value. As a result, every rally will end sometime, at least in the long-term, and prices will revert to the value (insight$_3$).

Besides, the breakdown is faster than the rally before (insight$_4$). Furthermore, prices do not only fall back to the value but undershoot it (insight$_5$). This occurs because chartists trade on the negative trend and, thereby, induce momentum. Hence, the negative feedback by fundamentalists is reinforced by the positive feedback by chartists. In the wake of the breakdown, price volatility tends to be high (periods 215 to 280) (insight$_6$). The reason is high trading activity: The price fall has provoked panic among investors that has raised their alertness and activity. For traders' alertness is a stock variable showing persistence, trading activity is still excessive when its cause, the crash of prices, has already gone by (Fig. 2 and 3).

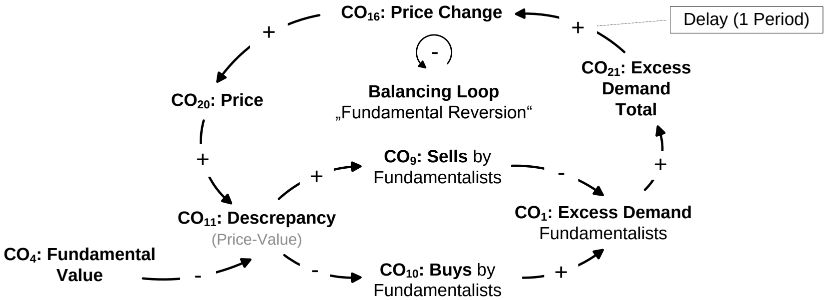

Figure 6: CLM of the balancing loop fundamental reversion

Useful insights for financial prognosis and investment decisions are: Firstly, betting on a fundamental reversion is a profitable long-term strategy (cf. insight$_3$). Secondly, the end of a downturn is probably a good opportunity for investments, since securities tend to be underpriced (cf. insight$_5$). Thirdly, even though being promising, buying after a crash is risky, because the market must be expected to behave highly volatile (cf. insight$_6$). Thus, short-term losses should be accepted.

These analyses lead to a positive answer for research question b): *The semiformal models, CLM and FM, support the goals explanation and prognosis:* The CLM facilitates to identify feedback loops, and the FM illustrates the stocks in the system that are responsible for persistence. Taken together, both models can be used to explain price dynamics based on the market's structure. These insights can also be used for prognosis and, hence, to improve the quality of investment decisions.

4 Conclusion

The present paper investigated if the SDM can support investment decisions. With respect to research question a) the SD-model replicated more stylized facts than traditional models. With respect to b), the semiformal models (CLM and FM) provided support for the description of the system structure and the system behavior. Aspects for explanation and prognosis of price behavior could be gained by simulation runs interpreted by CLM- and FM-analyses. Therefore, we conclude the hypothesis to be temporarily confirmed: *The SDM enhances the utility of FiMa-models and improves the quality of investment decisions.*

Nevertheless, we emphasize limitations: We validated the model quality only for accuracy of behavior. However, according to Sec. 1, three other criteria determine model quality, too. In the future, we will check the empirical validity by a backtesting. Regarding validity of application, we plan to collect evidence by experiments with one SD-group and one control group. Finally, we will conduct a case study to explore the applicability of the SDM for financial investment support.

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