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Prices, Debt and Market Structure in an Agent-Based Model of the Financial Market

Thomas Fischer and Jesper Riedler

ZEW

Zentrum für Europäische Wirtschaftsforschung GmbH

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Non-technical Summary

In this paper, we develop an agent-based model of the financial market. Agent-based modeling is a simulation-based technique that is gaining popularity in economics. In an agent-based model autonomously acting and interacting units (e.g. representing financial market participants) endogenously generate structures and system properties.

In our model, boundedly rational agents trade a financial asset. Their trading strategy thereby depends on their return forecast which is formed by either considering fundamentals or technical analysis. Agents are endowed with a balance sheet composed of a risky asset and cash on the asset side as well as equity capital and debt on the liabilities side. The risky asset is traded among agents at an endogenously set price. We assume that agents actively manage their respective balance sheet in two regards. Firstly, they choose a portfolio which optimizes the ratio between risky assets and cash conditional on their current return forecast, and secondly they aim at a fixed ratio between debt and equity (leverage ratio). Agents are constrained in their ability to acquire and dispose of debt by the credit supply of a risk managing financier and credit frictions, which hinder agents to make immediate changes to their debt levels.

We simulate our model and show that it can reproduce several empirically observable facts and relationships. Although we initially endow all agents with identical balance sheets, the size distribution of agents quickly converges to a lognormal distribution, which is typically observed for investment banks. We furthermore observe a natural tendency for inequality to increase over time. When we impose low credit frictions on the model financial market, leverage becomes procyclical, which is also typical for investment banks.

In a next step, we vary central parameters of the model exogenously in order to identify their effect on financial stability. By varying the leverage target of agents, we find that an increased target goes along with increased price volatility, more bankruptcies and higher systemic risk. It is hardly surprising that increased indebtedness of its participants makes a financial system less stable. When, on the other hand, varying the degree of credit frictions agents are confronted with, we find that lower frictions, which can be interpreted as an increased fraction of short-term credit on balance sheets, provokes complex repercussions. Specifically, lower credit frictions decrease the number of bankruptcies that typically occur within a specified time frame, but at the same time increase the probability of extreme events. Severe liquidity crises that can lead to a collapse of the entire financial system arise more frequently. Low credit frictions thus lead to a more stable model financial system most of the time, while systemic risk clearly increases. However, the introduction of a lender of last resort and an entity that gradually unwinds bankrupt agents can help to stabilize the model financial system.

Nicht-technische Zusammenfassung

In dem vorliegenden Papier entwickeln wir ein agentenbasiertes Modell für den Finanzmarkt. Die agentenbasierte Modellierung stellt eine in den Wirtschaftswissenschaften an Bedeutung gewinnende Methodik dar, in der eine Vielzahl von dezentral handelnden Einheiten (bspw. Finanzmarktakteure) mit Hilfe von Computersimulationen abgebildet und analysiert werden. Die sich aus der Interaktion heterogener Agenten herausbildenden Systemeigenschaften und Strukturen sind Untersuchungsgenstände agentenbasierter Modelle.

Die beschränkt rationalen Agenten handeln in diesem Modell ein Wertpapier aufgrund unterschiedlicher Renditeerwartungen, welche auf Basis einer Fundamentalwert- und einer Chartistenstrategie geformt werden. Die Agenten weisen eine Bilanz auf, welche aus dem riskanten Vermögensgegenstand und risikofreien liquiden Mitteln auf der Aktivseite, sowie aus Fremd- und Eigenkapital auf der Passivseite besteht. Aus dem Handelsprozess zwischen den Agenten entsteht ein endogener Preis. Agenten verwalten ihre Bilanz aktiv unter zwei Gesichtspunkten: Erstens wählen sie ein Portfolio, welches das Verhältnis zwischen riskantem Vermögensgegenstand und liquiden Mitteln abhängig von ihrer aktuellen Renditeerwartungen optimiert; zweitens visieren sie ein fixes Verhältnis zwischen Fremd- und Eigenkapital (Leverage) an. Die Fähigkeit der Agenten Fremdkapital zu beziehen oder abzustoßen ist durch das Kreditangebot eines Finanziers auf Basis eines Risikomanagementsystems sowie durch Kreditfriktionen beschränkt, welche die Agenten in der unmittelbaren Anpassung ihres Fremdkapitalniveaus behindert.

Auf Basis von Simulationen können in dem Modell verschiedene empirisch beobachtbare Fakten und Beziehungen reproduziert werden. Obwohl die Agenten zunächst mit identischen Bilanzen ausgestattet sind, konvergiert die Größenverteilung schnell zu einer lognormal-Verteilung, wie sie auch typischer Weise bei Investmentbanken beobachtet wird. Darüber hinaus können wir auch eine natürliche Tendenz zum Anstieg der Ungleichheit im Zeitverlauf feststellen. Bei Simulationsläufen des Modells mit geringen Kreditfriktionen, wird der Leverage prozyklisch, wie es auch bei Investmentbanken beobachtbar ist.

In einem weiteren Schritt variieren wir zentrale Modellparameter exogen um deren Wirkung auf die Finanzmarktstabilität zu untersuchen. Die Variation des Ziel-Leverages führt bei erhöhtem Niveau zu höherer Preisvolatilität, eine höheren Anzahl an Insolvenzen und höherem systemischen Risiko. Es ist kaum überraschend, dass eine höhere Verschuldung der Marktteilnehmer die Fragilität des Finanzsystems erhöht. Auf der anderen Seite weist das Niveau der Kreditfriktionen (ein niedrigeres Niveau kann hierbei als das Ausmaß der Kurzfristfinanzierung interpretiert werden) komplexe Rückwirkungen auf. Konkret senken geringe Kreditfriktionen die Anzahl der Insolvenzen, welche in einer vordefinierten Zeitspanne auftreten, erhöhen jedoch gleichzeitig die Möglichkeit von extremen Ereignissen. Schwerwiegende Liquiditätskrisen, welche zu einem Zusammenbruch des ganzen Finanzsystems führen können, ereignen sich mit einer höheren Frequenz. Geringe Kreditfriktionen führen somit in dem Modell zu einem Finanzsystem, welches im Normalfall stabiler ist, jedoch mit einem erhöhten systemischen Risiko einhergeht. Die Einführung eines „Lender of Last Resort“ und einer Instanz, welche insolvente Agenten graduell abwickelt, können jedoch zu einer Stabilisierung des Finanzmarkts im Modell beitragen.

Prices, Debt and Market Structure in an Agent-Based Model of the Financial Market*

Thomas Fischer
TU Darmstadt

Jesper Riedler †
ZEW Mannheim

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Abstract

We develop an agent-based model in which heterogeneous and boundedly rational agents interact by trading a risky asset at an endogenously set price. Agents are endowed with balance sheets comprising the risky asset as well as cash on the asset side and equity capital as well as debt on the liabilities side. A number of findings emerge when simulating the model: We 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, which we define 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. In particular, we observe an increasing frequency of severe liquidity crises that can lead to the collapse of the entire model financial system.

JEL classification: C63 - D53 - D84
Keywords: agent-based model - financial markets - leverage - systemic risk - credit frictions

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†Corresponding author: Jesper Riedler, Centre for European Economic Research (ZEW) Mannheim, e-mail: riedler@zew.de, phone: +49/621/1235-379.

1 Introduction

The past few years have indicated that the understanding of the dynamics in financial markets is far from satisfactory. Economists and regulators often seem to rely on intuition rather than model-guided comprehension when pondering and designing new rules for the financial system. As a result, most of the suggested financial market regulations are impeded by controversy about their efficiency and uncertainty about their impact. One reason why financial market dynamics prove so difficult to grasp and model is that they are driven by heterogeneous market participants' actions and interactions that feed back into the financial system.

Agent-based models (ABMs) constitute a promising method for advancing the understanding of the financial system's underlying dynamics.[1] We develop an ABM that includes debt in order to facilitate an analysis of the dynamics ensued by agents' capital structure. Each agent in our model is therefore endowed with a highly stylized balance sheet containing a tradable risky asset and cash on the asset side and equity capital and debt on the liabilities side. Agents trade according to their price expectations, which they form through either fundamental value considerations (fundamentalists) or technical analysis (chartists). The price of the risky asset depends on agents' transactions and therefore evolves endogenously. Leverage can generally be managed by agents but is constrained by the debt supply of an exogenous risk managing financier. We furthermore introduce a measure of credit frictions into the model, which we define as the stickiness of desired debt adjustments.[2] Simulations demonstrate how our model operates and identify some of the new possibilities of analysis provided by the model, which are unfeasible with either standard representative agent models or existing agent-based financial market models focusing predominantly on price dynamics.[3] We can report several findings. By looking at the emergent market structure of the model, we find that balance sheet size is approximately log-normally distributed and that leverage has an important influence on market structure. Higher leverage leads to greater inequality between agents. We show how credit frictions can change the relation between leverage and assets and thereby account for the differences observed for commercial and investment banks in this context: for investment banks leverage is procyclical, while no such relation can be observed for commercial banks. We furthermore study the impact of leverage and credit frictions on the stability of the model financial system. While it is hardly surprising that an increase in leverage also increases the fragility of the system, credit frictions have a more complex impact on financial stability. We observe that low credit frictions increase the stability of the financial system most of the time. Extreme events,

[1] For a discussion of the limitations of mainstream economic models see e.g. Leijonhufvud (2009); Colander et al. (2009); Kirman (2010); Stiglitz (2011). Comparisons between agent-based models and DSGE models can e.g. be found in Farmer and Geanakoplos (2009); Fagiolo and Roventini (2012).

[2] A market with high credit frictions can be interpreted as a market in which agents hold long-term debt that adjusts slowly. When credit frictions are low, on the other hand, debt has a short maturity and needs to be rolled over frequently.

[3] Analyzing the effect of bankruptcies is e.g. not feasible within a representative agent framework. The fact that the possibility of default is mostly neglected in theoretical models (cf. Goodhart and Tsomocos, 2011) is unfortunate, not least when considering the devastating effects of the Lehman Brothers default in 2008.

however, become more likely. Occasionally severe liquidity crises develop which lead to the collapse of the entire system. We introduce a lender of last resort entity and an entity that unwinds defaulting agents and show how these entities can significantly increase systemic stability. We compare the outcomes of the simulations with balance sheet data from a sample of international banks where possible and make reference to the views expressed in the relevant literature. Policy implications, especially with regard to financial stability, are given where appropriate.

The remainder of the paper is organized as follows. After reviewing the related literature in the next section, Section 3 presents the model. Section 4 then provides simulation results. Here, we start by showing some basic dynamics of an exemplary simulation in Section 4.1. We proceed, in Section 4.2, by looking at the distribution of agents' balance sheet size and the effects of leverage on market structure and stability. The role of credit frictions in our model market is analyzed in Section 4.3. Section 5 concludes.

2 Literature Review

The majority of agent-based financial market models focus on price dynamics, which emerge through the interaction of heterogeneous agents. Such models 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 fat tails and clustered volatility. Compelling reviews of the literature can e.g. be found in LeBaron (2006), Hommes (2006), Chiarella et al. (2009), Hommes and Wagener (2009), and Lux (2009). Incorporating balance sheets containing debt and equity into financial market ABMs is a sensible extension to established models and is mostly novel. A notable exception is Thurner et al. (2012). However, Thurner et al. (2012) are less interested in pure balance sheet dynamics and rather focus on the effects of leverage on returns, which they find to produce fat tails and clustered volatility. Furthermore, their setup differs from ours in many respects, including the portfolio choice of agents, the separation of investment and leverage strategies, the risk management of the financier and the role of credit frictions.

Although the study of leverage and balance sheet dynamics is mostly novel in the context of agent-based models, the issue has been addressed by prominent researchers in other contexts. Early work emphasizing the role of leverage and balance sheets can be found in the debt deflation theory of Fisher (1933) and in Minsky's financial instability hypothesis (see Minsky, 1986). In Bernanke and Gertler (1989) as well as Kiyotaki and Moore (1997) leverage acts as a financial accelerator for non-financial borrowers. The resurfacing of research on leverage and balance sheet dynamics in the aftermath of the recent financial crisis suggests its importance for understanding the workings of the financial system and the events precipitating the crisis. Adrian et al. (2010) argue that there is an important relation between financial intermediaries' balance sheet dynamics and real economic activity. The dynamics of market and funding liquidity, which reinforce each other and can lead to destabilizing effects on financial markets, are analyzed theoretically by Brunnermeier and Pedersen (2009), while Geanakoplos (2009) shows how changes to leverage can cause wild fluctuations in asset prices. More generally, the inclusion of the financial sector into new macroeconomic DSGE models (see e.g. Curdia and Woodford, 2010; Gertler and Kiyotaki, 2010) is a further indicator for the increasing importance of financial markets for economic theory. Conversely, the linkage between the real economy and the financial sector is also being addressed in recent agent-based research (see Lengnick and Wohltmann, 2013; Scheffknecht and Geiger, 2011; Westerhoff, 2011).

Our paper is also related to a large body of literature on systemic risk. Several sources of self-reinforcing dynamics have been identified that can lead to the breakdown of the entire financial system. These include classical bank runs, fire sales of assets, counterparty risk in the interbank market or synchronized behavior due to similar risk management structures (see e.g. Diamond and Dybvig, 1983; Shleifer and Vishny, 1992; Allen and Gale, 2000; Zigrand et al., 2010, respectively). Recently, considerable research has been devoted to the analysis of interbank networks with multi-agent models.[4] Interbank networks in which agents are highly interconnected allow for the pooling of liquidity risk, but at the same time open a contagion channel where idiosyncratic distress can propagate through the system (Iori et al., 2006). The general structure of the interbank network thereby influences the system's susceptibility to systemic events (cf. Georg, 2010, 2011; Lenzu and Tedeschi, 2012; Markose et al., 2012). Furthermore, the size of shocks and their locations within the interbank network are critical to their subsequent impact on the system (see Ladley, 2013; Gai et al., 2011, respectively). In general, a more concentrated system is shown to be more prone to systemic risk (Nier et al., 2007). When agents are highly leveraged and credit is short-term, a single case of bankruptcy can rapidly cascade through the interbank network, wiping out large portions of the financial system (cf. Battiston et al., 2012). The fundamental difference between research on systemic risk conducted by modeling financial networks and the approach taken in this paper lies in the underlying channel of contagion. The balance sheets of our agents are not directly linked through creditor/debtor relationships, but rather indirectly linked via overlapping portfolios. Changes in asset prices or market liquidity therefore have an impact on all agents.[5] A first attempt to incorporate both channels of contagion into one model has been made by Tasca and Battiston (2013). However, while the formal representation of their model does contain an interbank network, simulations and the subsequent analysis are conducted with a strongly simplified model. Tasca and Battiston (2013) show that the probability of a systemic event brought upon by a debt deflation dynamic depends on both market liquidity and compliance with capital requirements.

3 The Model

The model described in the following can be classified as a "few type" agent-based financial market model. While agents cannot produce entirely new trading strategies, as is possible through evolutionary learning algorithms in some "many type" models, they are given a set of predefined trading rules from which they are free to choose the rule they deem most profitable under the

[4]See Chinazzi and Fagiolo (2013) for a recent survey.

[5]This does not mean that all agents are affected equally by price movements or liquidity issues. Heterogeneous expectations lead to heterogeneous exposures in an asset.

limitations imposed on their rationality. Specifically, in our model agents can select either a strategy based on fundamentals or a chartist strategy based on technical analysis. The implied assumption that real traders choose and switch between these two strategies finds strong support in the literature (see e.g. Menkhoff and Taylor, 2007) and chartist-fundamentalist approaches figure among the most common agent-based financial market models (see e.g. Lux and Marchesi, 2000; Farmer and Joshi, 2002; Westerhoff and Dieci, 2006). In order to help the reader maintain an overview of the meaning of all variables and parameters contained in the model developed below, the reader is referred to Table 1 in Appendix A.

3.1 Model Structure

While the replication of financial market return time series stylized facts has constituted the aim of many ABMs, much less attention has been directed towards emergent behavior in the balance sheet dimension of financial markets. For this reason, we endow each agent j in our model with the following schematic balance sheet at time t:

Assets	Liabilities
$Q_{j,t}P_t$	$E_{j,t}$
$C_{j,t}$	$O_{j,t}$

The assets side of the balance sheet comprises quantity $Q_{j,t}$ of a risky asset with price P_t as well as cash $C_{j,t}$ which can be held without risk. As it will often be useful to consider logarithmic prices, we denote these in lower case (i.e. $p_t = \log(P_t)$).[6] On the liabilities side, each agent is endowed with equity capital[7] $E_{j,t}$ and outside capital (debt) $O_{j,t}$. The balance sheet total $B_{j,t}$ is given by:

$$B_{j,t} = Q_{j,t}P_t + C_{j,t} = E_{j,t} + O_{j,t} \tag{1}$$

From the beginning of period t to the beginning of period $t+1$ balance sheets evolve as sketched below:

Assets	Liabilities
$(Q_{j,t} + D_{j,t})\exp(p_t + r_{t+1})$	$E_{j,t} + \Delta E_{j,t+1}$
$C_t + \Delta C_{t+1}$	$O_{j,t} + \Delta O_{j,t}$

where $D_{j,t}$ is the demand of agent j for the asset in period t and r_{t+1} is the logarithmic return, with $r_{t+1} = p_{t+1} - p_t$.[8] The debt level $O_{j,t+1}$ in period $t+1$ consists of the debt level from the beginning of period t, i.e. $O_{j,t}$, and a change to outside capital $\Delta O_{j,t}$, which depends on the agent's strategic demand for debt and the available supply of debt. As indicated by the time index, the change in outside capital $\Delta O_{j,t}$ already takes place before the end of period t, so that agents can use the newly acquired debt for trading in period t. More

[6] We henceforth use lower-case letters for logarithmic values and upper-case letters for real values. The main rationale for using log prices p_t is to ensure that real prices P_t remain non-negative in the price formation process.

[7] We assume that agents cannot issue new equity after the initial endowment, for instance in the form of a seasoned equity offering. Equity capital therefore evolves as the difference between the balance sheet total and debt. Strategic changes to the liabilities side of the balance sheet can therefore only be incurred by changes to the debt level.

[8] The relation between logarithmic (r) and real (R) returns is defined as $r = \log(1 + R)$.

generally the time index t in the balance sheet table indicates that the value of the corresponding variable is already known (or will be decided in) period t. The time index $t+1$ indicates the emergent property of the corresponding variable, i.e. the value of the variable materializes only after agents have interacted. The timing of the model is schematized in Figure 1. Each period t in the model represents a trading day in which all agents first revise and possibly change their trading strategy (see Section 3.3), forecast the return of the following period $t+1$ (see next section), make a decision on how much debt they want to hold and ultimately trade.

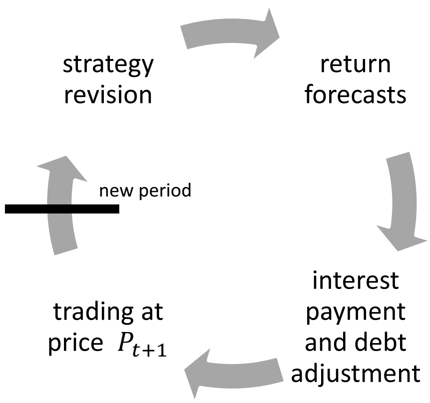


Figure 1: Timing of the model.

Equity capital grows with the returns R_{t+1} and R_C on the risky and risk free (cash) asset respectively. It decreases with interest R_i paid on debt. Both the risk-free rate and the interest rate on debt are exogenous in our model. In a frictionless market we would assume $R_C = R_i$. Equity capital (equivalent to an agent's net worth) evolves endogenously:

$$\Delta E_{j,t+1} = (Q_{j,t}P_t)R_{t+1} + C_{j,t}R_C - R_i O_{j,t+1} \tag{2}$$

We thereby assume that new assets (i.e. $D_{j,t}$) are bought and sold at price $P_{t+1} = P_t(1 + R_{t+1})$. In a model with debt bankruptcy is always possible, i.e., an agent's equity capital $E_{j,t}$ becomes smaller than or equal to zero. This possibility needs to be taken into account by introducing a resolution procedure for bankrupt agents. We force bankrupt agents to liquidize all assets they hold on their balance sheet upon bankruptcy.[9] Bankruptcies can thereby impose a fire sale externality on the market. The bankrupt agent then disappears from the market and all losses are borne by the exogenous financier.

Using the balance sheet equality from Equation (1), the change in cash amounts to

$$\Delta C_{j,t+1} = -D_{j,t}P_{t+1} + C_{j,t}R_C - R_i O_{j,t+1} + \Delta O_{j,t} \tag{3}$$

[9] Technically the demand function from Equation (7) changes to $D_{j,t} = -Q_{j,t}$ when $E_{j,t} \leq 0$, i.e., all assets of a bankrupt agent are thrown onto the market regardless of the execution price.

We model the agent's portfolio choice (i.e. the proportion $A_{j,t+1}$ of the balance sheet he wants to hold in the risky asset in the upcoming period $t+1$) in dependence of the agent's forecast of log excess return and his confidence in this forecast, which is modeled with a measure of historic forecast errors $\sigma_{j,t}^{\mathrm{FE}}$:

$$A_{j,t+1} = \frac{\mathrm{E}_{j,t}[r_{t+1}] - r_C}{\gamma \sigma_{j,t}^{\mathrm{FE}}} \tag{4}$$

Generally we denote the forecast of agent j made in period t for the variable x in period $t+1$ as $\mathrm{E}_{j,t}[x_{t+1}]$. The parameter $\gamma > 0$ can be viewed as a risk aversion parameter. The forecast error is modeled as the square root of an exponentially weighted moving average of squared differences between return expectations and return realizations:

$$\sigma_{j,t}^{\mathrm{FE}} = \sqrt{\theta^{\mathrm{FE}}(\underset{j,t-1}{\mathrm{E}}[r_t] - r_t)^2 + (1-\theta^{\mathrm{FE}})(\sigma_{j,t-1}^{\mathrm{FE}})^2}, \tag{5}$$

with $0 \leq \theta^{\mathrm{FE}} \leq 1$ being a memory parameter defining how much weight should be assigned to the most recent forecast error.

Note that for Equation (4) we choose a similar structure as in classical myopic portfolio choice models with CRRA utility functions or models that maximize a linear combination of return mean and variance (see e.g. Campbell and Viceira, 2002). The essential difference is that here the portfolio choice variable $A_{j,t+1}$ represents the ratio of risky assets to balance sheet total rather than the ratio of risky assets to net worth. Thus, to implement the portfolio choice from Equation (4), an agent j must act so that the following relation is satisfied in the balance sheet dimension:

$$A_{j,t+1} = \frac{\mathrm{E}_{j,t}[P_{t+1}](Q_{j,t} + D_{j,t})}{\mathrm{E}_{j,t}[B_{j,t+1}]} \tag{6}$$

The proportion of an agent's balance sheet held in the risky asset is bounded by $[-1, 0] \leq A_{j,t+1} \leq 1$. The upper bound 1 arises due to an agent's budget constraint, while the lower bound can take a value between 0 and -1, depending on the constraints imposed on short selling. The closer to 0 the lower bound is set, the higher the barriers for going short. By varying the lower bound we can thus study how short-selling constraints of different intensities affect the financial market.[10]

The approach detailed in Equations (4) and (6) allows us to separate an agent's leverage strategy from his portfolio choice. In classical myopic portfolio choice models leverage is linked to investment opportunities - leverage only enters the model when large returns are expected (i.e. when $A_{j,t} > 1$). Here, on the other hand, the agent's debt choice enters the demand function, which can be obtained by rearranging Equation (6):

$$D_{j,t} = \frac{A_{j,t+1}\,\mathrm{E}_{j,t}[B_{j,t+1}]}{\mathrm{E}_{j,t}[P_{t+1}]} - Q_{j,t} \tag{7}$$

[10] While a lower bound of 0 implies that an agent can sell only as many assets as he owns (i.e. $D_{j,t} = -Q_{j,t}$), a lower bound of -1 implies that an agent cannot go short in more assets than he has means for repurchasing at any given point in time.

with

$$\begin{aligned}\underset{j,t}{\mathrm{E}}[B_{j,t+1}] &= \underset{j,t}{\mathrm{E}}[P_{t+1}](Q_{j,t} + D_{j,t}) + C_{j,t} + \underset{j,t}{\mathrm{E}}[\Delta C_{j,t+1}] \\ &= \underset{j,t}{\mathrm{E}}[P_{t+1}]Q_{j,t} + C_{j,t}(1 + R_C) - R_i \tilde{O}_{j,t+1} + \Delta\tilde{O}_{j,t} \qquad (8)\end{aligned}$$

The amount of debt $\tilde{O}_{j,t+1}$ held by the agent in the upcoming period is subject to negotiations (indicated by the tilde) between agent and financier. The amount depends on an agent's demand for debt and the financier's willingness to supply the desired debt. If neither of the negotiating parties wishes to make changes to the debt level, i.e. $\Delta\tilde{O}_{j,t} = 0$, the absolute debt volume $O_{j,t}$ will have to be rolled over at interest rate R_i. To determine the trading price we choose a process that can be described as Walrasian tâtonnement, where all agents trade at the market clearing price p_t^*, i.e. the price for which $\sum_{j=1}^{J} D_{j,t} = 0$. The demand of an agent is thereby contingent on his forecast of future returns (see Equation (7)), which is, as detailed in the next section, a function of the current price p_t. By means of numerical analysis the current price is changed until $p_t = p_t^*$ and markets clear.

3.2 Fundamental, Chartist and Debt Strategies

Agents can choose between a fundamental and a chartist strategy when forming expectations of future returns. When following a fundamental strategy, agents (i.e. $j \in \mathcal{F}$) believe that prices will revert to fundamental value. They therefore compare their perception of fundamental value $\mathrm{E}_{j,t}[f_{t+1}]$ with the current price in order to obtain a forecast of future returns:

$$\underset{j,t}{\mathrm{E}}[r_{t+1}] = \alpha^F (\underset{j,t}{\mathrm{E}}[f_{t+1}] - p_t), \qquad \forall j \in \mathcal{F} \qquad (9)$$

with $\alpha^F > 0$ being the speed at which the fundamentalist believes prices to converge to fundamental value. Fundamentalists update their perception of fundamental value by evaluating relevant fundamental news Δf_t, which can be modeled as an arbitrary stochastic process, and by identifying and correcting past valuation errors:

$$\underset{j,t}{\mathrm{E}}[f_{t+1}] = \underbrace{\underset{j,t-1}{\mathrm{E}}[f_t]}_{\text{past valuation}} + \underbrace{(\Delta f_t + \epsilon_{j,t})}_{\text{evaluation of news}} + \underbrace{\theta^F (f_t - \underset{j,t-1}{\mathrm{E}}[f_t])}_{\text{past error correction}} \qquad (10)$$

The error term $\epsilon_{j,t} \sim \mathcal{N}(0, \sigma_f^2)$ accounts for fundamentalists' imperfect information and limited cognition and implies disagreement about the true value f_t of the risky asset. In the model we assume that disagreement on fundamental value may persist for some time, but agents will eventually become aware of erroneous evaluations and correct for them. The speed of this error correction is thereby given by $0 \leq \theta^F \leq 1$.

In order to obtain a forecast of future returns, chartists ($j \in \mathcal{C}$), in a first step, extrapolate a buy or sell signal. They do so by employing moving average (MA) rules, which are among the simplest and most popular with practicing technical analysts.[11] The signal is generated by comparing a short-term MA of

[11] Brock et al. (1992) provide evidence for the MA rule's capability to predict stock returns. In an agent-based context, Chiarella et al. (2006) analyze the ensuing price dynamics when agents employ MA rules.

prices to a long-term MA of prices. Specifically, chartists identify an emerging upward trend and a buy signal ($S_{j,t} = +1$) when the short-term MA is higher than the long-term MA, and vice versa for a downward trend and a sell signal ($S_{j,t} = -1$):

$$S_{j,t} = \operatorname{sgn}\left(\frac{1}{s_{j,t}}\sum_{u=0}^{s_{j,t}-1} P_{t-u} - \frac{1}{l_{j,t}}\sum_{v=0}^{l_{j,t}-1} P_{t-v}\right), \qquad \forall j \in \mathcal{C} \tag{11}$$

The maximum number of lags $s_{j,t}$ and $l_{j,t}$ may differ from agent to agent as well as over time. Note that in order to allow for additional heterogeneity within the chartist strategy we do not specify $s_{j,t} < l_{j,t}$. A chartist j will thus follow a contrarian strategy whenever $s_{j,t} > l_{j,t}$. The forecast of future returns then depends on the direction in which the extrapolated signal is pointing, the aggressiveness of the chartist denoted by α^C and the absolute value of a random component $\rho_{j,t} \sim \mathcal{N}(0, \hat{\varsigma}_t^2)$:

$$E_{j,t}[r_{t+1}] = \alpha^C S_{j,t}\,|\rho_{j,t}| \tag{12}$$

The random component is necessary because the signal $S_{j,t}$ extrapolated by chartists does not imply a specific return expectation. We assume that while the moving average rule indicates the direction of the expected return, chartists randomly choose an absolute value of the expected return, which is scaled with the perceived price variability calculated as an exponentially weighted moving average:

$$\hat{\varsigma}_t^2 = \theta^S (r_t - r_{t-1})^2 + (1 - \theta^S)\hat{\varsigma}_{t-1}^2, \tag{13}$$

with θ^S being a memory parameter specifying how much weight is attributed to the most recent log return movement. Chartists thus adapt their return expectation to the prevailing price volatility. Chartists can therefore also be viewed as volatility traders who take strong positions in times of high volatility and vice versa.

Generally, we define the change in exposure to outside capital as

$$\Delta\tilde{O}_{j,t} = (1 - \mu^O)\left(\tilde{O}_{j,t+1} - O_{j,t}\right), \tag{14}$$

with $\tilde{O}_{j,t+1}$ being the targeted debt volume after negotiation with the financier. Since neither the agent nor the financier can force the other party to supply or demand more debt than that party is willing to supply or demand, the debt volume will be set to the lower value of the financier's supply $O_{j,t+1}^S$ and the agent's demand $O_{j,t+1}^D$:

$$\tilde{O}_{j,t+1} := \min\{O_{j,t+1}^D, O_{j,t+1}^S\} \tag{15}$$

The parameter $0 \leq \mu^O \leq 1$ in Equation (14) introduces credit friction into the debt market. When $\mu^O > 0$ the targeted changes to debt volume take place more slowly than desired by either agent or financier. When the financier delimitates the debt demand of the agent (i.e. $O_{j,t+1}^D > O_{j,t+1}^S$), the friction can be interpreted as credit maturity hindering the financier to withdraw funds at once. When, on the other hand, the financier is willing to cover the agent's full debt demand (i.e. $O_{j,t+1}^D \leq O_{j,t+1}^S$), the friction can be interpreted as the time-consuming task of raising funds from different investors. Furthermore, a very high value for μ^O could be interpreted as limited institutional space to actively manage debt levels. Customer deposits held by commercial banks e.g. constitute such a limitation: while a commercial bank can invest customer deposits to a certain extent, it cannot directly increase or decrease them at will.

The structure of our model allows for the integration of arbitrary debt demand and supply functions. A simple debt strategy for an agent could be to aim for a constant leverage ratio:[12]

$$\lambda^{\text{fix}} = \frac{O^D_{j,t+1}}{\mathrm{E}_{j,t}[E_{j,t+1}]} = \frac{O^D_{j,t+1}}{\mathrm{E}_{j,t}[B_{j,t+1}] - O^D_{j,t+1}} \tag{16}$$

Note that agents are forward-looking, i.e., their desired debt level depends on their expectation of the size of their future balance sheet. Following from the previous equation, debt demand can be derived:

$$O^D_{j,t+1} = \frac{\lambda^{\text{fix}}\,\mathrm{E}_{j,t}[B_{j,t+1}]}{1+\lambda^{\text{fix}}} \tag{17}$$

Using Equation (8) we algebraically deduce that for the period $t+1$ agent j demands:

$$O^D_{j,t+1} = \frac{\mathrm{E}_{j,t}[P_{t+1}]Q_{j,t} + C_{j,t}(1+R_C) - O_{j,t}}{R_i + \frac{1}{\lambda^{\text{fix}}}}. \tag{18}$$

We assume that financiers do not form expectations about future price movements, but rather try to assess the risk of supplying debt to individual agents. Due to the seniority of debt over equity the financier focuses on the risk that incurred losses in the subsequent periods fully deplete an agent's equity capital (i.e. the agent goes bankrupt). Specifically, the financier is willing to supply debt $O^S_{j,t+1}$ if the probability of default over the next M periods is lower than ω:

$$\Pr\left\{(E_{j,t} + O^S_{j,t+1})(1+\mathbf{R}^B_{j,t})^M \leq O^S_{j,t+1}(1+R_i)^M\right\} \leq \omega \tag{19}$$

Since the financier does not have the expertise required to assess an agent's strategy, he must solely rely on the agent's past performance (i.e debt-adjusted balance sheet growth $r^B_{j,t}$), which, for the sake of simplicity, is modeled as a log-normal random variable with $\log(1+\mathbf{R}^B_{j,t}) = \mathbf{r}^B_{j,t} \sim \mathcal{N}(\mu^B_{j,t}, z^2_{j,t})$. Mean and variance are estimated by the financier as exponentially weighted moving averages:

$$\begin{aligned} \mu^B_{j,t} &= \theta^{\text{fin}} \underbrace{(\log(B_{j,t} + R_i O_{j,t}) - \log(B_{j,t-1} + \Delta O_{j,t}))}_{r^B_{j,t}} + (1-\theta^{\text{fin}})\mu^B_{j,t-1} \\ z^2_{j,t} &= \theta^{\text{fin}}(r^B_{j,t} - r^B_{j,t-1})^2 + (1-\theta^{\text{fin}})z^2_{j,t-1} \end{aligned} \tag{20}$$

θ^{fin} thereby defines how much weight is attributed to the respective last observation. With the risk constraint in Equation (19) and with $H^{-1}(\cdot)$ being the inverse cumulative distribution function of the random variable $\mathbf{r}^B_{j,t}$, the maximum amount of debt the financier is willing to supply to agent j can be derived:

$$O^S_{j,t+1} = \frac{E_{j,t}\exp\left(MH^{-1}(\omega)\right)}{(1+R_i)^M - \exp\left(MH^{-1}(\omega)\right)}. \tag{21}$$

[12] We define leverage as the ratio of debt to equity capital (net worth): $\lambda = O/E$.

3.3 Choosing a Strategy

Agents in the model try to adapt to the prevailing situation by updating their trading strategy if it seems to be underperforming. For this purpose, each agent revises his strategy every τ_j periods. In order to avoid a synchronized change in strategy, $1 < \tau_j < n$ is a random number drawn from a discrete uniform distribution with n being the maximum number of periods before an agent revises his strategy. Formally, agent j revises his strategy at time $t \in K_j := \{t | t \bmod \tau_j = 0\}$.[13] When deciding on whether to keep or change a strategy, each agent compares a measure of the profit $\Pi_{j,t}$ his strategy has earned to a benchmark $\bar{\Pi}_t$. This comparison is modeled by a discrete choice model pioneered by Manski and McFadden (1981) and popularized in the context of agent-based models by Brock and Hommes (1998). Specifically, when agent j revises his current strategy he will stick to it with probability

$$W_{j,t}^F = \frac{\exp(\eta \Pi_{j,t})}{\exp(\eta \Pi_{j,t}) + \exp(\eta \bar{\Pi}_t)} \quad \forall t \in K_j, \tag{22}$$

whereby $\eta > 0$ can be understood as a (bounded) rationality parameter. It limits agents' abilities to identify whether their strategies are performing well or poorly in comparison to the benchmark. Low values for η imply poor identification ability and vice versa.

The profitability measure is computed as an exponentially weighted average of the most recent growth in an agent's equity capital and past equity growth:

$$\Pi_{j,t} = \begin{cases} \bar{\Pi}_t & \text{if the strategy in } t \text{ does not equal the strategy in } t-1 \\ \theta^{\Pi}(\log(E_{j,t}) - \log(E_{j,t-1})) + (1-\theta^{\Pi})\Pi_{j,t-1} & \text{else} \end{cases} \tag{23}$$

with $0 \leq \theta^{\Pi} \leq 1$ being a memory parameter assigning how much weight is attributed to the most recent equity growth. Note from Equation (23) that the profitability measure for agent j is set to the benchmark when he changes his strategy. Thereby $\bar{\Pi}_t$ is simply the average of all agents' profitability measures, i.e.:

$$\bar{\Pi}_t = \frac{1}{J} \sum_{j=1}^{J} \Pi_{j,t} \tag{24}$$

We assume that although agents cannot directly observe the benchmark profitability, they have a notion of whether their own strategy is performing better or worse than the average strategy. The fact that this notion is not perfect is reflected by the rationality parameter η in Equation (22).

Upon opting for a chartist strategy, an agent must choose the specifications for the moving average rule, i.e. he must determine the maximum lags in Equation (11). In period $t \in K_j$ agent $j \in \mathcal{C}$ draws $s_{j,t}$ and $l_{j,t}$ randomly from a triangular distribution with the respective lower limits s^{low} and l^{low}, the respective upper limits s^{up} and l^{up} and the respective modes $c_{j,t}^s$ and $c_{j,t}^l$, with $s^{\text{low}} \leq c_{j,t}^s \leq s^{\text{up}}$ and $l^{\text{low}} \leq c_{j,t}^l \leq l^{\text{up}}$. The purpose of employing a triangular distribution with a variable mode is to ensure that chartists gravitate to the specifications of successful moving average rules. Specifically the modes are

[13] The modulo operator ensures that each agent only trades in a period t which is a multiple of his trading frequency τ_j.

chosen so that the expected value of the triangular distribution[14] equals the expected value for the lag parameters $\hat{s}_{j,t}$ and $\hat{l}_{j,t}$ computed from a probability mass function where the respective lags for each chartist is weighted by its relative profitability:

$$\hat{s}_{j,t} = \sum_{j\in\mathcal{C}} \left(s_{j,t} \frac{\exp(\eta\Pi_{j,t})}{\sum_{j\in\mathcal{C}} \exp(\eta\Pi_{j,t})} \right) \tag{25}$$

$$\hat{l}_{j,t} = \sum_{j\in\mathcal{C}} \left(l_{j,t} \frac{\exp(\eta\Pi_{j,t})}{\sum_{j\in\mathcal{C}} \exp(\eta\Pi_{j,t})} \right) \tag{26}$$

Note that the choice of memory parameter is also dependent on the rationality η of agents.

4 Simulations

In order to simulate the model described in the previous section, we first have to define parameter values and initial conditions. Quite a few parameters including rationality and memory relate to behavioral aspects of market participants and are therefore not directly observable. Since we mainly aim at deriving qualitative results and the calibration of complex agent-based models poses a considerable challenge (cf. Winker et al. (2007)), we refrain from trying to estimate the behavioral parameters for our model. The choices for parameter values are therefore often without deeper economic meaning. In the exemplary simulation presented in the following subsection, we introduce some of the dynamics the model features with the parameters and initial conditions documented in Tables 1 and 2. For the simulations in Sections 4.2 and 4.3, we change selected parameters in order to analyze their qualitative (ceteris paribus) effect on the model economy. As our model incorporates random terms at several instances[15], each simulation result is unique. In fact, simulation outcomes display strong path dependence. In order to ensure that the patterns emerging in our simulations are not caused by coincidence, we run numerous simulations for each parameter value. The exact number of runs depends on the specific analysis and ranges between 40 and 10,000 runs.

4.1 Exemplary Simulation

We define the process of fundamental value evolution as a noise process with a trend and mean reversion, which lets us emulate upswings and downswings.[16]

[14] Given the lower and upper limits, the relation between the mode c and the expected value μ of a triangular distribution amounts to $c = 3\mu - (x^{\text{up}} + x^{\text{low}})$ (Evans et al., 2000).

[15] Specifically, this includes noise ϵ_t in the expectation process of the fundamental traders. The exact values for the moving average lags are randomly drawn for each agent from a specific distribution. The same holds true for the value $\rho_{j,t}$ determining the absolute value of chartists' return expectations. Last but not least, the frequency τ_j with which agents revise their strategy is assigned randomly at the beginning of each simulation.

[16] Formally, this is modeled by an Ornstein-Uhlenbeck process where the daily return of the fundamental value $r_{f,t}$ evolves according to the following stochastic differential equation with a Wiener process W_t: $dr_{f,t} = \theta(\mu - r_{f,t})dt + \sigma_f dW_t$. The daily expected return is arbitrarily set to $\mu = \frac{0.05}{250}$ (i.e. 5 percent growth per trading year), volatility to $\sigma_f^2 = 0.01$, and mean reversion speed to $\theta = 0.1$. The model is initialized by setting $p_0 = f_0 = 0$.

Category	Symbol	Description	Value
General Simulation Parameters	N	Number of agents	500
	T	Simulation periods	$1,000d \equiv 4a$
Portfolio Composition	γ	Risk aversion	4
	θ^{FE}	Memory for forecast error	0.1
Fundamental Trading	$\epsilon_{j,t}$	Error term in trading	$\epsilon \sim \mathcal{N}(0, \sigma_f^2)$
	θ^F	Error correction term	0.03
	α^F	Aggressiveness of fundamental traders	1
Chartist trading	α^C	Aggressiveness of chartists	5
	θ^S	Memory for price variance estimator	0.1
Leverage	λ^{fix}	Target leverage	25
	μ^O	Credit friction	0
Financier	ω	Maximum accepted default probability	0.1%
	M	Maturity (in days)	10
	θ^{fin}	Memory of the financier for the forecast process	0.1
Switching mechanism	η	Rationality	100
	θ^{Π}	Memory for strategy comparison	0.1
	τ_j	Frequency of strategy change	Drawn from uniform distribution with the limits 1 and 250
Fundamental Price Process	$E(r_{f,t})$	Daily expected return	$\frac{0.05}{250}$
	σ_f^2	Price volatility	0.01
	θ	Mean reversion speed	0.1

Table 1: Benchmark simulation parameters.

The initial endowment of all $N = 500$ agents is the same: the balance sheet total of each agent amounts to $B_{j,0} = 2/N$ and each agent holds the amount of risky assets that leads to an optimal portfolio when expecting the return to be equal to the trend of the fundamental value process.[17] Agents target a leverage ratio of $\lambda = 25$, which means that agents are endowed with equity that is around 4 percent of total assets. This is not unusual for large banks or investment banks (cf. Adrian and Shin, 2010). At $t = 0$, the passive side of the balance sheet is constructed in order to satisfy a leverage of $\lambda = 25$. The constraints imposed by the credit supply of the financier, however, cause the agents' leverage to drop substantially in the first period. We make the simplifying assumption that $R_i = R_C = 0$ and thereby completely abstract from the effect of interest rates in this paper. Initially, chartists and fundamentalists each account for 50 percent of traders. The specific frequency τ_j with which each agent revises his strategy is initially drawn from a uniform distribution with the limits of 1 and 250, which means that agents revise their strategy at least once every trading year (one

[17]Note that when agents initially expect the price to increase by the daily trend, they greatly underestimate the average absolute daily variation of fundamental value. This means that agents will typically expect much higher returns than initially (i.e. when $t = 0$) and, correspondingly, have a much higher demand for assets in the subsequent periods ($t > 0$). When taking into account that the total number of assets in the market is fixed, it becomes evident that we have (deliberately) initialized the model with excess liquidity. This is necessary in order to avoid systematic shortages of liquidity (which would distort prices) when the fundamental value increases or agents default. Agents, in turn, internally manage the upward price pressure entailed by excess liquidity by going short. A short sale effectively increases the number of assets available for trading.

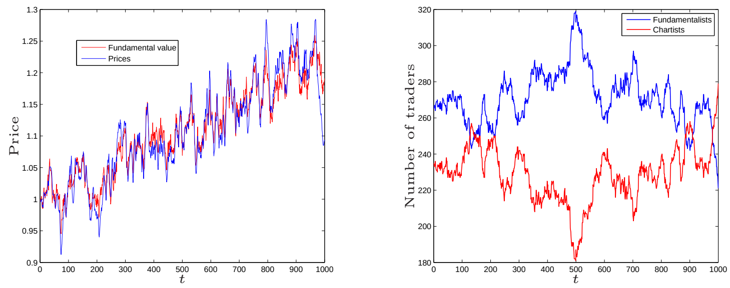
Category	Symbol	Description	Value
Financier	$\mu^B_{j,0}$	Initial estimator for adjusted balance sheet growth	$E(r_{f,t}) = \frac{0.05}{250}$
	$z^2_{j,0}$	Initial estimator for volatility of adjusted balance sheet growth	$(\sigma^{FE}_{j,0})^2 = 0.05$
Portfolio composition	$(\sigma^{FE}_{j,0})^2$	Initial forecast error for all agents	$0.05\ (\triangleq 5 \cdot \sigma^2_f \triangleq 5 \cdot Var(\Delta f))$
Chartist trading	$\hat{\varsigma}^2_{j,0}$	Price volatility estimator of chartists	$0.01 \triangleq \sigma^2_f$
	$s_{j,0}/l_{j,0}$	Length of short and long moving average	Drawn from uniform distribution with the limits of 1 and 200
Balance Sheet	$B_{j,0}$	Balance sheet sum	$\frac{2}{1{,}000}$
	$A_{j,0}$	Proportion of risky assets	$\frac{E(r_f)}{\gamma(\sigma^{FE}_{j,0})^2} = 0.1\%$

Table 2: Benchmark simulation initial conditions.

simulation period represents one trading day) and at the most every trading day. For the chartist strategy the boundaries of the moving average lags $l_{j,t}$ and $s_{j,t}$, which are initially drawn from a uniform distribution, are set to 1 and 200, which are common values in business practice (see e.g. Lo et al., 2000). In the benchmark simulation, we set the credit friction parameter to its minimum, i.e. $\mu^O = 0$, allowing agents and financiers to make immediate changes to the amount of debt they hold on their balance sheet or provide as credit.

Figure 2(a) shows the price dynamics of an exemplary simulation run. It can be observed that the price diverges from the fundamental value on a regular basis. The changes in market composition depicted in Figure 2(b) thereby have a substantial effect on the efficiency of the asset price. This is documented in the first regression of Table 3. When linearly regressing the absolute logarithmic difference between price and fundamental value against the market share of chartists trading in the model ($\frac{\#\text{ of chartists}}{\#\text{ of solvent agents}}$), we find a significant positive relation. On the other hand, it does not seem to matter much, whether the chartists in the model predominantly follow a momentum ($l_{j,t} > s_{j,t}$) or contrarian ($l_{j,t} < s_{j,t}$) strategy. The results of the second regression of Table 3 indicate a slightly higher potential for price inefficiency when a large proportion of chartist traders follow a momentum strategy ($\frac{\#\text{ of momentum traders}}{\#\text{ of chartists}}$). However, this only explains a very small part of the variation in the price deviation from fundamental value. The reason for this lies in the heterogeneous use of the moving average rule. Two chartists following a momentum strategy with a different lag structure (i.e. different choices for $l_{j,t}$ and $s_{j,t}$) can receive a different trading signal $S_{j,t}$. The degree to which the trading signals generated by the moving average rules are equivalent can again explain a substantial part of the variation in price inefficiency, as indicated by the third regression documented in Table 3. The proxy for the homogeneity of trading signals ($\frac{|\sum_{j\in\mathcal{C}} S_{j,t}|}{\sum_{j\in\mathcal{C}} |S_{j,t}|}$) ranges between zero and one. When all chartists receive the same signal the proxy equals one; when buying and selling signals are evenly distributed among chartists, the proxy equals to zero.

A shortcoming of the model is the apparent smoothing of the price, resulting in first-order autocorrelation of returns. This inconsistency with real return time series can be overcome by introducing arbitrageur-agents trading on this regularity.[18] However, because the analysis of return time series and their stylized facts is not a focus of our model, we refrain from further extending the model, which would increase model complexity. For a brief overview of our model's ability to reproduce the stylized facts of return time series please refer to Appendix B.



(a) Prices and fundamental value (b) Market Composition

Figure 2: Dynamics in an exemplary simulation.

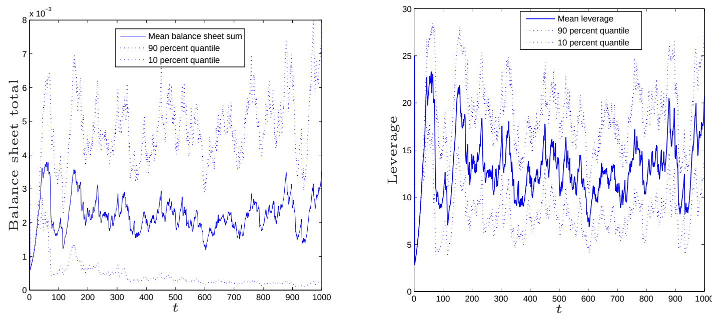
independent variable	**Coef.**	**Std. Error**	R^2
chartist market share	0.1753***	0.012	0.1758
constant	-0.0654***	0.0055	
share of momentum traders	0.0336***	0.0064	0.0272
constant	-0.0018	0.0032	
trading signal equivalence	0.0201***	0.0012	0.2136
constant	0.0062***	0.0006	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$

Table 3: Regressing price inefficiency ($|p_t - f_t|$) against the chartist market share; against the proportion of chartists following a momentum strategy; against the degree of trading signal equivalence for the exemplary simulation.

Figure 3 shows the dynamics of the mean balance sheet total as well as mean leverage. Although all agents are initially equal, the initial homogeneity changes quickly as simulation time progresses. As the plotted quantiles illustrate, substantial differences between agents develop. The nature of how these differences evolve in terms of balance sheet size will be addressed in the upcoming section. The apparent co-movement of mean leverage and mean balance sheet total is also noteworthy and will be addressed in Section 4.3.

[18]The model presented by LeBaron (2010) has e.g. included such agents.



(a) Balance sheet total (b) Leverage

Figure 3: Mean and quantiles of agents' balance sheet total and leverage for the exemplary simulation.

4.2 Distribution and Leverage

Distributions of e.g. wealth, income or output constitute an emergent property of an economy and can reveal valuable information about its state.

As stated, we initially assume that all agents are of equal size and thereby homogeneous. In the simulation, however, the distribution converges to a stable log-normal distribution. This result is presented in Figure 4, showing that the Jarque-Bera statistic (testing for the normality of logarithmic balance sheet size) converges to a value lower than the critical value given a 5 percent significance level.[19] The most convincing argument for the emergence of a log-normal distri-

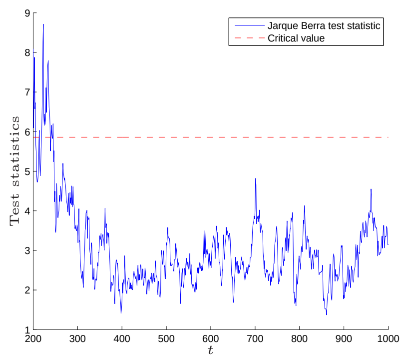
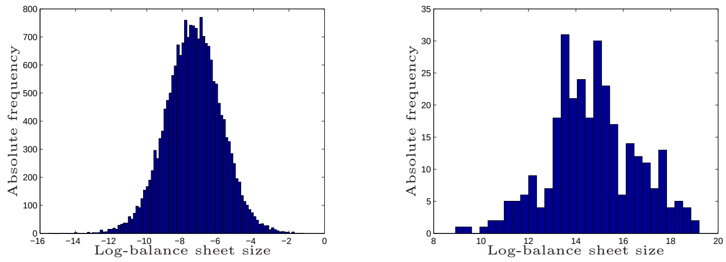


Figure 4: Jarque-Bera test statistics for the log-balance sheet size distribution (median results after 40 simulation runs).

bution for balance sheet size in our model is given by *Gibrat's law*, which states that convergence to log-normality occurs when balance sheet growth is nor-

[19]Note that we suppressed the first 200 periods due to the fact that we initially assume all agents to be equal, which leads to very high test statistics. Furthermore, we take the median of the simulation results to control for outliers.

mally distributed and independent from size.[20] Figure 5(a) shows the emerging distribution for the 40 simulations.[21] For comparison, Figure 5(b) depicts the distribution of an international sample of investment banks.[22] The distributions qualitatively resemble each other, as is also confirmed by the Jarque-Bera test for log-normality. The test statistics are provided in Table 5 in the appendix.[23]



(a) Histogram of 40 simulation runs at $t = 1,000$

(b) Histogram of investment banks in 2009

Figure 5: Histogram for simulations and empirical data.

When looking at the average evolution of balance sheets throughout simulations (see Figure 6), we observe no particular trend in mean balance sheet size, whereas the variance displays an increasing trend. Furthermore, the size dispersion of balance sheets, which we measure with the coefficient of variation (i.e. σ/μ),[24] steadily increases, which is indicative of an endogenous increase of inequality with progressing simulation time. Effectively, our model suggests that the financial system naturally generates a large number of small institutions and a small number of very large institutions. There is thus a natural tendency for the system to produce institutions that are *too big to fail*.

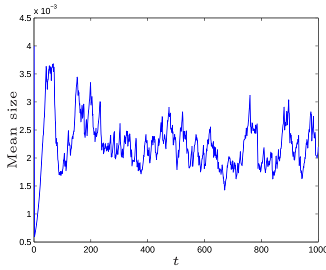
[20] If we assume $x_t - x_{t-1} = g_t x_{t-1}$ for small values for growth rate g_t, the function converges to $\log x_t = \log x_0 + g_1 + g_2 + \cdots + g_t$, implying a log-normal distribution (Sutton, 1997).

[21] The multitude of simulation runs ensures that the log-normal feature is general model property rather than an idiosyncratic single simulation result.

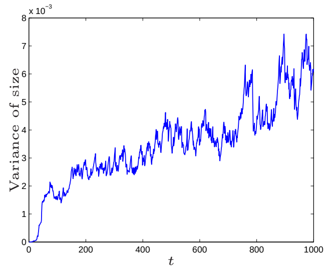
[22] Here we use annual balance sheet data of international investment banks from the Bankscope database.

[23] As presented in Janicki and Prescott (2006) this result does not hold for commercial banks, which can rather be described by a Pareto distribution. A theoretical rationale can be found in their business model and in a product differentiation argument: regional banks provide credit to regional small and medium-sized enterprises. The non-log-normal distribution of non-financial firms (cf. Axtell, 2001) is therefore also reflected in the distribution of commercial banks (Ennis, 2001).

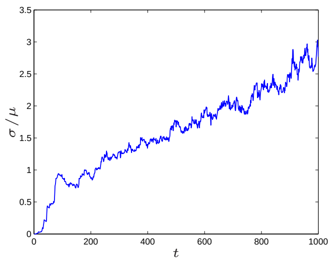
[24] The coefficient of variation provides an inequality measure insensitive to changes in the mean (Cowell, 2000).



(a) Balance sheet size



(b) Balance sheet variation



(c) Balance sheet inequality

Figure 6: Endogenous average evolution of balance sheets (median results after 40 simulation runs).

Leverage seems to play an interesting role in the evolution of balance sheet distribution. In order to analyze this role, we replace the debt supply function of the risk-managing financier with unlimited debt supply, while agents keep aiming for a constant leverage λ. By varying the target leverage for all agents from $\lambda = 0$-15, we can now control for the overall leverage in the model economy. Note that we only provide simulations up to a leverage target of $\lambda = 15$ rather than the more realistic target value of $\lambda = 25$ in the benchmark simulation. In the framework without the stabilizing financier, the model market becomes highly fragile for large values of λ, with frequent breakdowns of the entire financial system.

As shown in Figure 7, our model displays a positive and convex relation between leverage and size dispersion. The quintessence of Figure 7 is that leverage seems to foster the natural evolution towards greater inequality described above. This conclusion may be of importance for policy makers. In this context, the introduction of a maximum leverage ratio, which is part of the Basel III regulatory framework, may not only help to stabilize the financial system in a more traditional sense (lower leverage decreases the probability of default), but could also decrease the speed with which inequality increases. Lower size dispersion arguably generates less institutions that classify as *too big to fail*.[25]

[25] At first glance, the data seems to support the emergent positive relation between leverage and inequality in our model. At least when looking at data of international investment banks from the end of the dot-com crisis in the year 2002 until 2009, such a relation can be observed (we present simple regression results in the Appendix in Table 6). Yet, we feel that a more thorough empirical validation is not only beyond the scope of this paper but also beyond the scope of our dataset.

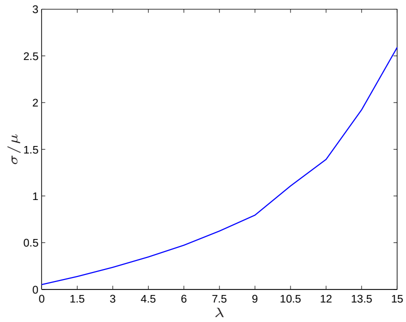
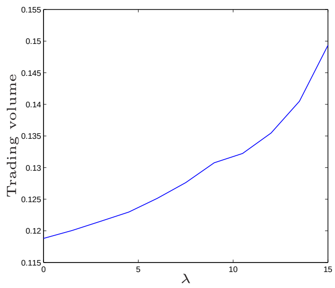


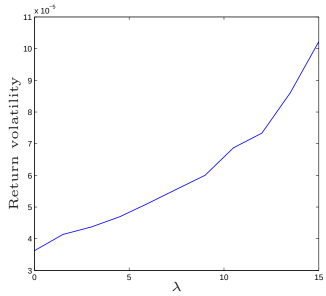
Figure 7: Size inequality for variation of target leverage λ in simulations (median results after 40 simulation runs).

Although there exists some empirical evidence suggesting that banks, the agents in our model, target a constant leverage (cf. Gropp and Heider, 2010), an unlimited supply of debt is certainly not a realistic assumption. When looking at the effects of leverage on our model financial market, it should be kept in mind that a constrained debt supply may lead to less clear or even different results. Nevertheless, we briefly want to show some interesting patterns emerging in simulations in the context of varying leverage targets. As most of these patterns are empirically untested, further research is needed before meaningful conclusions can be drawn.

Figure 8(a) shows an emerging positive relation between leverage and trading volume. Here leverage acts as a multiplier to trades: A higher leverage target causes agents to acquire or dispose of larger sums of nominal debt in order to meet their target as the value of the risky asset on their balance sheet rises or falls, respectively. Since debt is obtained and repaid in cash, any change in agents' nominal debt also changes the composition of agents' balance sheets. The rebalancing of portfolios generates trading volume, which therefore increases as the leverage target is raised.



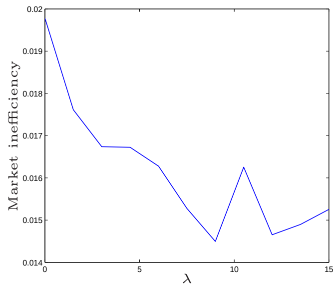
(a) Total trading volume



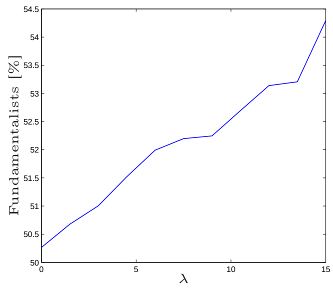
(b) Return volatility

Figure 8: Trading volume and price volatility for variation of target leverage ratio λ (median results after 40 simulation runs).

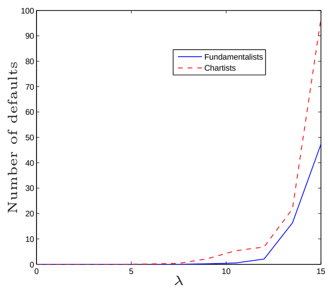
Increased trading activity translates into a higher return volatility as can be observed in Figure 8(b). It comes as somewhat of a surprise, however, that increased volatility entails higher price efficiency (Figure 9(a)), meaning that prices are more closely connected to their underlying fundamentals.[26] The reason for this counterintuitive link is depicted in Figure 9(b): higher leverage leads to a greater average proportion of fundamental traders in the model market. Higher leverage means that agents operate with less relative equity capital, which is quickly depleted in downturns. In order to survive, it becomes increasingly important for agents to anticipate price movements. Here fundamentalists are at an advantage. Figure 9(c) shows the number of bankruptcies for both fundamentalists and chartists. The number of defaulting chartists[27] is always higher than the number of defaulting fundamentalists. The losses incurred by chartists have a stronger impact with increasing leverage. Leverage, in our model, may thus help to stabilize the market. This emergent behavior of the model is reminiscent of the classical argument for the existence of efficient markets. Friedman (1953) already argued that in the long run, speculative trading is not profitable and will therefore eventually disappear.



(a) Market inefficiency



(b) Proportion of fundamentalists



(c) Number of defaults for fundamental and chartist traders

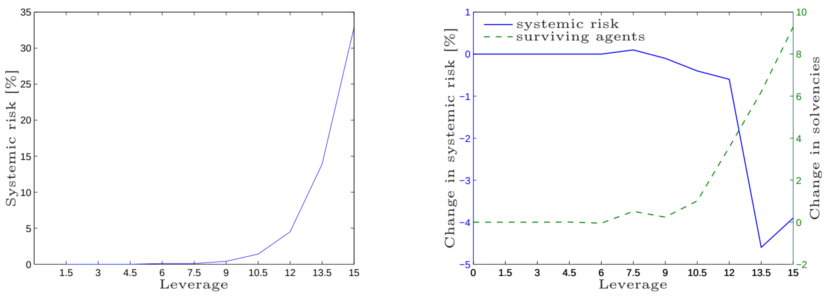
Figure 9: Market efficiency, composition, and stability for variation of target leverage ratio λ (median results after 40 simulation runs).

[26] As proposed in Westerhoff (2008), we measure inefficiency as the median absolute difference between log-fundamental value and price: $MI = median(|f_t - p_t|)$. In a first-order approximation, this can be interpreted as the percentage point deviation from fundamental value.

[27] More precisely, those agents who form expectations using technical analysis prior to defaulting.

On the other hand, the observed efficiency gain is deceptive. As illustrated in Figure 10(a), leverage strongly increases the probability of systemic events. For the purpose of our analysis we define a systemic event as one where all agents default within the 1,000 trading periods (4 trading years) we simulate. Part of the increase in systemic risk is due to a positive feedback process triggered when a big agent defaults or when many agents default simultaneously. Defaulting agents liquidize their assets in a fire sale, which can affect prices and lead to contagion. A large drop in prices evaporates the equity of agents and leads to further defaults. Trend-following chartists may evoke further price declines in the following periods. A loss spiral could ensue, causing the system to fail.

In order to measure the effect of such loss spirals on the fragility of the model financial system, we introduce a resolution entity (RE) into the model, which takes on all assets of distressed agents in order to sell them gradually (over 20 trading days) rather than in a fire sale. In order to filter out the defaults caused by fire sales within the price determination process, we first determine the order in which the agents default and then transfer only the assets of the first defaulter to the resolution entity. The price determination process is then repeated. Optimally, the transfer of assets of the first defaulter to the resolution entity prevents the default of further agents. If this is not the case, we again determine the order of defaults, and in addition to the assets of the first defaulter, the assets of the next defaulter are transferred to the resolution entity. This procedure is repeated until no further agents default. All fire sale dynamics due to defaults can thus be filtered out.[28]



(a) Systemic risk

(b) Impact of the RE

Figure 10: Systemic risk and the impact of the resolution entity (RE) in dependence of the leverage target (based on 1,000 simulation runs).

We find that the resolution entity can reduce the probability of fire sale-induced systemic failure, as shown by the solid blue line in Figure 10(b). For high leverage targets the RE can reduce the probability of systemic events by 4 percentage points and more. In addition to reducing systemic events, the number of agents surviving a simulation run is increased when the resolution

[28]To obtain the order in which agents default we calculate the price $P^*_{j,t+1}$ (default price) at which the equity of agent j is equal to zero: $E_{j,t+1} = B_{j,t+1} - O_{j,t} = B_{j,t} + (P^*_{j,t+1} - P_t)Q_{j,t} - O_{j,t} = 0$. The order of defaults is revealed by ordering ascendingly all agents defaulting in the same period according to the difference between their specific default price $P^*_{j,t+1} = \frac{O_{j,t} - B_{j,t} + P_t Q_{j,t}}{Q_{j,t}}$ and the current price P_t. The first defaulter is e.g. the agent whose default price is closest to the current price.

entity is introduced into the model (see the dashed green line in Figure 10(b)). However, in consideration of the eminent fragility of the model financial market when leverage targets are high (see Figures 9(c) and 10(a)), the resolution entity fails to significantly stabilize the system. Most bankruptcies and systemic events observed are not due to fire sale dynamics, but rather thinly capitalized agents unable to absorb adverse price shocks. This makes clear that while it is sensible to implement mechanisms able to constrain the impact of self-reinforcing dynamics such as fire sales, financial fragility is mainly a result of fragile (inadequately capitalized) financial institutions.

4.3 Credit Frictions

Agents and financiers in our model actively manage their demand or supply of debt. The immediacy with which desired changes to debt can occur is constrained by the credit friction parameter μ^O in Equation (14). High credit frictions (i.e. high values for μ^O) imply slow changes to debt and vice versa. Frictions arise from the maturity structure of debt or from institutional characteristics of different bank types, which both restrict deliberate and immediate changes to the capital structure of agents. Credit frictions thus have the potential to affect the behavior of the financial system as a whole. To analyze the effects of credit frictions we first show how they affect the relation between leverage and balance sheet size. Following the method of Adrian and Shin (2010), we scatter-plot the logarithmic changes of leverage against the logarithmic changes of balance sheet size.[29] Setting $\mu^O = 1$ (complete credit frictions) means that agents and financiers have passive leverage strategies. The nominal debt agents are endowed with at the beginning of a simulation remains on their balance sheets while changes to the value of agents' assets lead to a negative relation between leverage and total assets. Consider a simple example: In period t, the total balance sheet sum amounts to $B_t = 100$ and debt equals $O_t = 90$, which implies a leverage of $\lambda_t = \frac{O}{B-O} = \frac{90}{100-90} = 9$. If in the subsequent period $t+1$ the value of the assets on the balance sheet declines so that $B_{t+1} = 99$, then $\lambda_{t+1} = \frac{90}{99-90} = 10$.[30] This negative correlation, as plotted in Figure 11, can typically be observed for household data (see Adrian and Shin, 2010). It seems, however, very unlikely that (professional) financial market participants would follow a completely passive leverage strategy. If we allow for slight leverage adjustment, the correlation between leverage and balance sheet size changes. A high value for μ^O implies that adjustments to agents' debt levels are constrained and take time. Commercial banks e.g. face such constraints, as customer deposits, which they cannot raise or reduce at will, figure prominently on the liabilities side of their balance sheets. Figure 12(a) shows the leverage-balance-sheet correlation for $\mu^O = 0.99$ while Figure 12(b) shows the correlation for commercial banks in EU27.[31] The two graphs lack a clear positive or negative relation. The transformation of the leverage-balance-sheet correlation stemming from a marginal reduction of credit frictions from $\mu^O = 1$ to $\mu^O = 0.99$ can be explained by the substantial cumulative effects of even very high credit frictions.

[29] More precisely, logarithmic changes of balance sheet size are changes in logarithmic balance sheet size after 50 periods, i.e. $\log(B_{j,t}) - \log(B_{j,t-50})$. The same applies for leverage.

[30] Formally, when the nominal value of debt does not change over time the following statement holds: $\frac{\partial\lambda/\lambda}{\partial B/B} = -\frac{B}{B-O} < 0$.

[31] We use quarterly data between 1996 and 2009 from the Bankscope database.

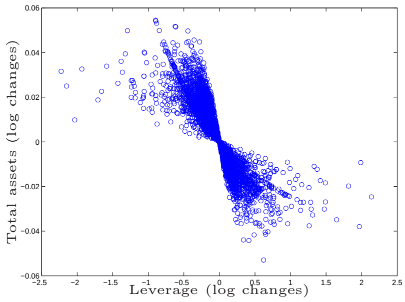
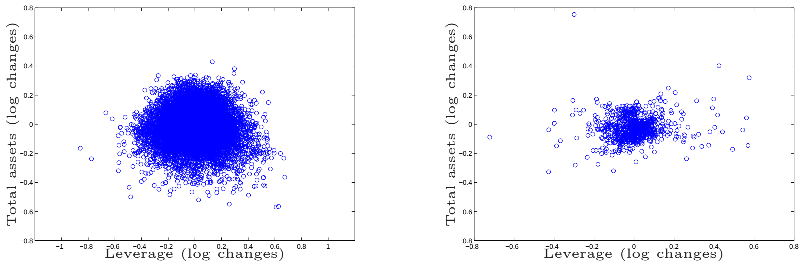


Figure 11: The correlation between balance sheet total and leverage for the passive agent (based on 40 simulation runs).

While agents' debt levels do not change at all under complete credit frictions, in an environment where $\mu^O = 0.99$, approximately 92 percent of the desired debt adjustment can be achieved within a trading year (250 trading days).[32]



(a) Model data with $\mu^O = 0.99$

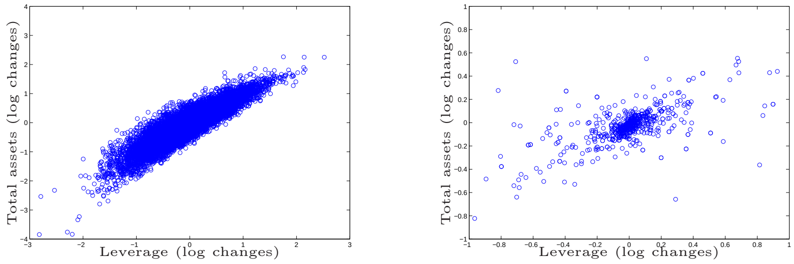
(b) Data from commercial banks

Figure 12: The correlation between balance sheet total and leverage with high credit frictions (based on 40 simulation runs).

Conversely, Adrian and Shin (2010) show that the relation between leverage and balance sheet growth is positive, i.e. leverage is procyclical, for investment banks (see Figure 13(b)). Figure 13(a) exemplarily shows that our model produces a clearly positive correlation for μ^O a value of 0. In these cases there are little constraints on the adjustment of leverage. Investment banks tend to have very short-term debt (e.g. Repos) on their balance sheets, which allows them or their financiers to quickly adjust the leverage to values they deem appropriate. This characteristic is reflected in the low values for μ^O. The procyclical nature of leverage entering the model with low credit frictions can be explained by the debt supply function of the financier: a persistent positive development of an agent's balance sheet suggests to the financier that the agent is well-informed, thus he perceives a lower risk level and is willing to supply more debt. On the other hand, when losses reduce the size of balance sheets, the financier will be

[32] This result can be obtained by iterating the following formula for 250 periods: $\text{debt}_{t+1} = \text{debt}_t + (1 - 0.99)(\text{debt}_{\text{desired}} - \text{debt}_t)$.

more concerned about the safety of credit supplied to agents and will consequentially reduce his supply of debt.



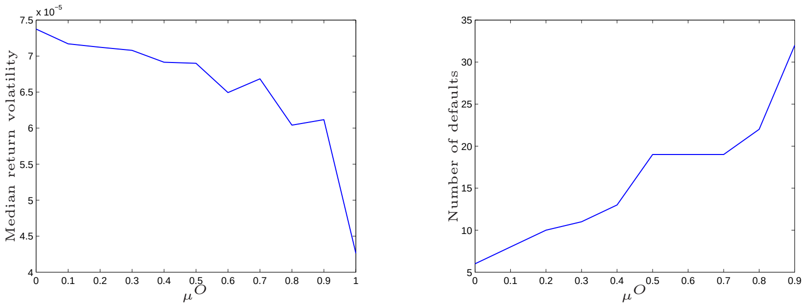
(a) Model data with $\mu^O = 0$

(b) Data from investment banks

Figure 13: The correlation between balance sheet total and leverage with low credit frictions (based on 40 simulation runs).

The procyclicality of leverage induced by low credit frictions and the financier's risk management affects the price behavior of the risky asset. Figure 14(a) shows a negative relation between credit frictions and average return volatility. An increase in friction reduces the procyclicality of leverage and yields a lower average volatility. Our model suggests that return volatility could be reduced through an increase of credit frictions, e.g. by curtailing the short-term debt supply to agents. Short-term borrowing has often been cited as a key contributor to financial instability and its curtailment has been called for on various occasions (cf. Diamond and Rajan, 2001). However, as Figure 14(b) indicates, such regulation could turn out to be counterproductive. Since outliers distort the mean number of defaults when credit frictions are low, we plot the ninety percent quantile of the number of defaults for 1,000 simulation runs, i.e. in only 10 percent of the simulation runs does the number of defaults equal or exceed the plotted value. The case of complete credit frictions is omitted for clarity. Here, in 10 percent of the simulations the number of defaults exceeds or is equal to 296. There is a clear, positive relation between credit frictions and the number of defaults. Thus, the active management of debt levels, which can best be accomplished in an environment with few credit frictions (i.e. an environment with short-term credit), appears to be essential for the stability of our model financial market. However, this observation proves to be highly deceptive. Figure 15 shows that increasing credit frictions leads to a decrease in systemic risk. The diametrical development of defaulting agents and systemic risk is striking: While Figure 14(b) tells us that less than 6 agents default in 90 percent of completed simulation runs[33] when credit frictions are low, a systemic event occurs on average approximately every tenth simulation run (i.e. once every 40 trading years). In the case of complete credit frictions, on the other hand, there is not a single completed simulation run with less than 200 defaults (see 16(a)), whereas a systemic event occurs only once in 1,000 simulation runs (i.e. once every 4,000 trading years).

[33]In a completed simulation run, at least one agent must survive 1,000 trading periods, i.e. 4 trading years.



(a) Volatility (b) Defaulting agents (90% quantile)

Figure 14: Volatility and defaults in dependence of credit frictions (based on 40 and 1,000 simulation runs respectively).

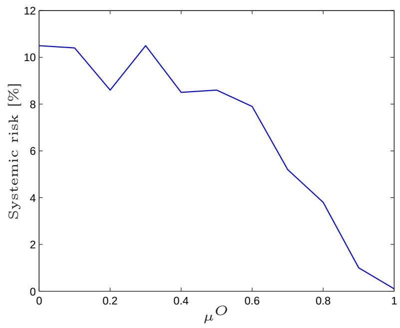
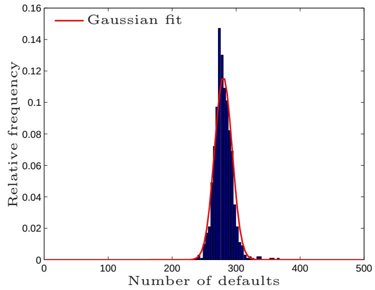


Figure 15: Systemic risk in dependence of credit frictions (based on 1,000 simulation runs).

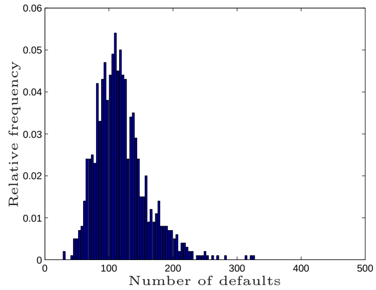
As documented in Figure 16, credit frictions fundamentally change the underlying probability distribution of the number of defaulting agents per simulation run. While complete credit frictions ($\mu^O = 1$) lead to an almost Gaussian distribution of defaulting agents, decreasing credit frictions shifts the distribution to the left (towards fewer defaults) and lengthens the right tail of the distribution. In other words, decreasing credit frictions stabilizes the model financial market most of the time, while extreme events with a large number of bankruptcies and systemic events become more probable. For simulations with low credit frictions and over a limited range of bankruptcy events the probability density of defaults per run resembles a power law. Figure 17 plots the relative frequency of defaults (ranging between 0 and 100 defaults) for simulations with $\mu^O = \{0.9, 0.5, 0\}$ on a log-log graph.[34] Power laws are sometimes considered the statistical fingerprint of complex systems (cf. Sornette, 2007).

The shape of the probability distributions of defaulting agents per simulation run for low credit frictions implies that it is impossible to infer the general stability of the model financial system from observing short or medium-term

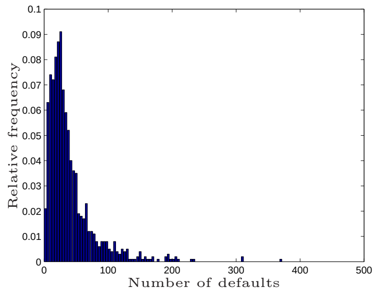
[34] In a log-log graph a power law becomes a linear relationship. Because a high number of defaults per simulation run is a rare event, simulations were repeated 10,000 times for Figure 17.



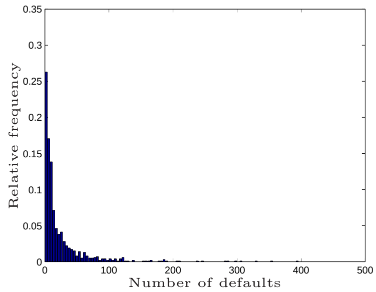
(a) $\mu^O = 1$



(b) $\mu^O = 0.99$



(c) $\mu^O = 0.98$



(d) $\mu^O = 0.97$

Figure 16: Probability distributions of the number of defaulting agents per simulation run (based on 1,000 simulation runs).

market behavior. Figuratively speaking, when credit frictions are low agents can interact within a financial market that seems perfectly stable for 39 years until the entire system breaks down in year 40. On the other hand, when credit frictions are high, bankruptcies in the financial system may be commonplace, but it turns out to be very unlikely for any hypothetical generation of agents to ever witness a collapse of the entire system.[35] This counterintuitive trade-off between the fragility of individual agents and the fragility of the whole system can be explained as follows: Decreasing credit frictions increases the swiftness with which the financier can withdraw credit from agents that begin to invest imprudently. The balance sheets of those agents thus become less leveraged, which diminishes their risk of bankruptcy. At the same time, decreasing credit frictions increases the potential for self-reinforcing dynamics and the risk of a systemic event: Imprudent agents may run into liquidity problems when the financier decides not to renew their credit lines. They must sell assets to repay debt. When credit dries up quickly and/or affected agents are big, fire sales can depress prices, causing further agents to suffer losses. This will be of concern to the financier, who may further restrict his credit supply. Along with more fire sales, trend-following chartists will amplify the negative price movement, leading

[35] In his book "The Black Swan", Nassim Nicholas Taleb refers to this problem of induction as "the turkey problem": A turkey being treated nicely and fed regularly may infer with increasing confidence that humans mean it no harm. A few days before Thanksgiving, however, the turkey's confidence is shattered. This metaphor illustrates the inherent danger of relying on past experience to reach general conclusions about the stability of financial markets.

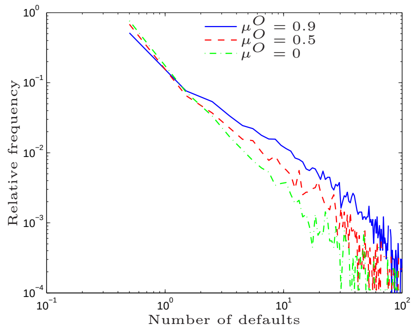
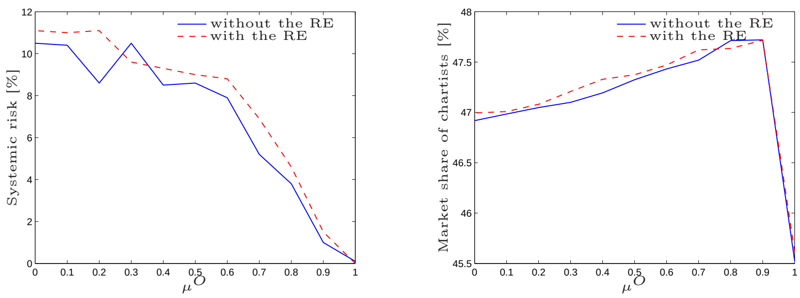


Figure 17: Probability distribution of the number of defaults per simulation run ranging from 0 to 100 defaults (based on 10,000 simulation runs).

to a loss spiral and possibly to a systemic event. When credit frictions are high, agents are unlikely to run into severe liquidity problems because nominal debt changes slowly. A liquidity crisis, as described above, thus becomes less probable and systemic risk is reduced.

The resolution entity employed in the previous section to gradually sell off assets of distressed agents cannot stop the system from being fragile when liquidity issues are the root of fragility (see Fig. 18(a)). Oddly, the resolution entity even slightly increases systemic risk. A probable explanation for this is that the gradual, but evenly distributed, selling of assets by the resolution entity creates a small trend that can be exploited by chartists. A slightly increased profitability of the trend-extrapolation strategy goes along with a marginally higher concentration of chartists in the market (see Fig. 18(b)). Chartists amplify liquidity induced loss spirals causing the market to crash more often.



(a) Systemic risk

(b) Chartist market share

Figure 18: Impact of the resolution entity (RE) on systemic risk and the market share of chartists in dependence of credit frictions (based on 1,000 simulation runs).

In order to disrupt the liquidity-induced loss spiral, a lender of last resort is needed. We implement a very simple entity that acts as a lender of last resort. The entity intervenes when liquidity for an agent dries up. Whenever the financier cuts the debt supply of an agent by more than 20 percent[36] of that agent's total debt-supply, the lender of last resort steps in to provide liquidity. When the entity provides liquidity to an agent, negative debt adjustments are restricted. Technically, the credit friction parameter μ^O is increased to 0.99 for the agent in question. For the sake of simplicity, however, agents under the control of the entity are allowed to continue with their trading business as usual. The lender of last resort entity cedes control of an agent's debt only when the external financier is again willing to supply more debt than the agent demands.[37] Figure 19 shows that the lender of last resort entity can suppress the liquidity-induced loss spiral and substantially reduce systemic risk when credit frictions are low. Unlike the case where only the resolution entity is active, the joint implementation of the lender of last resort and the resolution entity further increases systemic stability because chartists can no longer amplify liquidity-induced loss spirals when a lender of last resort is present. Furthermore, when the lender of last resort provides liquidity to distressed agents, but lets them, as in our case, continue with their trading business as usual, those agents become very susceptible to bankruptcy. The resolution entity then ensures that fire sales due to defaults are taken care of and thereby stabilizes the system. With both entities active systemic risk can be reduced from above 10 percent to below 4 percent for low credit frictions. In other words, the average frequency of a systemic event can be extended from once every 40 trading years to once every 100 trading years.

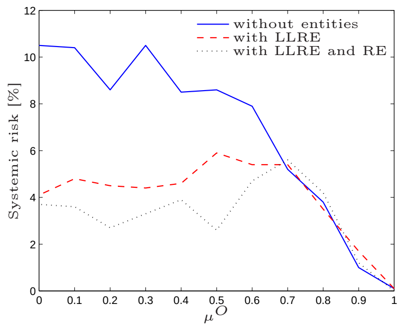


Figure 19: Impact of the lender of last resort entity (LLRE) and the resolution entity (RE) on systemic risk (based on 1,000 simulation runs).

5 Conclusion

In this paper we develop an agent-based model of the financial market where agents are endowed with balance sheets that contain equity capital as well as debt. By conducting simulations we are able to analyze several aspects of the financial system that are mostly inaccessible with conventional economic models. Several results are reported: We show that the distribution of agents'

[36] This value is set arbitrarily.

[37] The lender of last resort entity is inactive for the first 100 periods of the simulation in order to not disturb any initial adjustments from variables' initialization-values to endogenously desired values.

balance sheet size evolves endogenously to an approximately log-normal distribution. Such a market structure is typically observed in real banking markets. Leverage has a decisive impact on the market structure. We observe a positive and convex relation between leverage and size-inequality among agents. This suggests that a highly leveraged financial sector is more inclined to produce institutions that qualify as *too-big-to-fail*. Not surprisingly, high leverage in our model increases both the average number of bankruptcies within 1,000 trading periods and systemic risk. We find that to a certain extent bankruptcies trigger systemic events as fire sales of assets by defaulting agents can lead to a self-reinforcing loss-spiral. However, an external resolution entity that prevents fire sales by winding up defaulting agents is able to reduce bankruptcies as well as systemic risk to some extent. Our model demonstrates that the correlation between leverage dynamics and balance sheet dynamics is strongly influenced by credit frictions, the stickiness of desired debt adjustments. Complete credit frictions lead to a negative relation between leverage and balance sheet changes, while high credit frictions lead to no specific relation at all, which is typically observed for commercial banks. Investment banks, on the other hand, characteristically exhibit a positive correlation between leverage and balance sheet changes, which emerges in our model when credit frictions are low. Furthermore, the financial stability of our model financial system is intricately tied to credit frictions. While high credit frictions increase the number of bankruptcies they decrease the system's susceptibility to systemic events. We observe that, when credit frictions are low, systemic events are often the result of a severe liquidity crisis. The introduction of a lender of last resort entity can suppress the self-reinforcing liquidity-induced loss spirals and thereby significantly reduce systemic risk.

The investigations conducted in this paper represent only a small subset of feasible investigations. The impact of short selling constraints, the propagation of external shocks, investigations of trading volume, rationality and disagreement are all issues that could be assessed with the model framework presented in this paper. However, the potential usefulness of the model is constrained most notably by a lacking calibration and empirical validation. While a more thorough validation of the model's qualitative predictions would clarify where the model can reveal valuable insights, a calibration of the model would make it more attractive for policy considerations.

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Appendix

A Explanation of Symbols Used

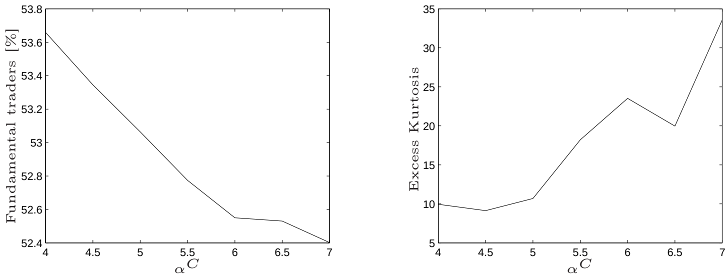
Category	Symbol	Description
Simulation Parameters	N	Number of agents
	T	Simulation periods
Balance sheet	$P_t \equiv \exp(p_t)$	Market price
	$Q_{j,t}$	Quantity of assets
	$D_{j,t} = \Delta Q_{j,t}$	Asset demand
	$C_{j,t}$	Cash (risk-free asset)
	$O_{j,t}$	Outside capital (debt)
	$E_{j,t}$	Net worth (equity)
	$B_{j,t}$	Total balance sheet sum
	$A_{j,t}$	Proportion of risky assets
	$\lambda = O_{j,t}/E_{j,t}$	Leverage ratio
Interest rates	$R_t = (P_t/P_{t-1}) - 1$	Return on risky assets
	R_C	Interest on risk-free asset (cash)
	R_i	Interest on debt
Portfolio Composition	γ	Risk aversion
	θ^{FE}	Memory for forecast error
	$\sigma^{\mathrm{FE}}_{j,t}$	Forecast error for all agents
Fundamentalist trading	$\epsilon_{j,t}$	Error term in trading
	θ_F	Error correction term
	α_F	Aggressiveness of fundamental traders
Chartist trading	α^C	Aggressiveness of chartists
	θ^S	Memory for price variance estimator
	$\varsigma^2_{j,t}$	Price volatility estimator of chartists
	$s_{j,t}$ ($l_{j,t}$)	Length of short (long) moving average
Leverage	λ_{fix}	Target leverage
	μ^O	Credit friction
Financier	ω	Maximum accepted default probability
	M	Maturity (in days)
	θ^{fin}	Memory of the financier for the forecast process
	$\mu^B_{j,t}$	Estimator for adjusted balance sheet growth
	$z^2_{j,t}$	Estimator for volatility of adjusted balance sheet growth
Switching mechanism	η	Rationality
	θ^{Π}	Memory for strategy comparison
	τ_j	Frequency of strategy change
Fundamental value	$\mathrm{E}(r_{f,t})$	Daily expected return
	σ^2_f	Price volatility
	θ	Mean reversion speed

Table 4: Model variables and parameters.

B Stylized Facts

To a certain extent, the model presented in this paper is able to reproduce the stylized facts of financial market return time series. These include fat tails (excess kurtosis) and slowly decaying autocorrelation of absolute returns (implying clustered volatility), while the first-order autocorrelation of returns remains insignificant (Cont, 2001). We find that particularly the parameter controlling for chartist aggressiveness α^C (see Equation (12)) plays an important role in generating these stylized facts. For the sake of brevity, we will restrict ourselves to the discussion of that parameter. However, results for the other parameters are also available upon request.

When increasing the aggressiveness α^C of chartists, the buy or sell signals received from applying a moving average rule are translated into greater demand or supply of the risky asset. This increases the price impact of the chartist strategy. The increasing reflection of chartists' expectations in the price of the asset leads to a higher market share of chartists. This is the case because, unlike fundamentalists, chartists ride the asset price bubbles they create. The more pronounced these bubbles are, the more profitable the chartist strategy results to be. Figure 20(a) documents the drop in market share of fundamentalist traders as chartists become more aggressive. More pronounced bubbles, however, go along with more severe crashes. The probability of large price movements increases, which is reflected by growing excess kurtosis in Figure 20(b). Our model can thus produce fat tails that are in accordance with the empirical literature (Cont, 2001) as well as other agent-based financial market models (cf. e.g. LeBaron et al., 1999; He and Li, 2007; Lux, 2009).



(a) (b)

Figure 20: Market composition and kurtosis for variations of chartist aggressiveness α^C (mean results based on 1,000 simulation runs).

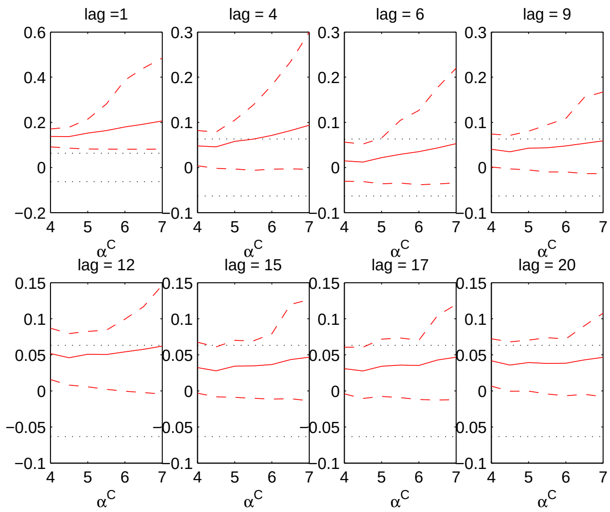


Figure 21: Autocorrelation of absolute returns within the first 20 lags for variation of α^C, mean (solid) and 10% and 90% quantile (dashed lines) (based on 1,000 simulation runs).

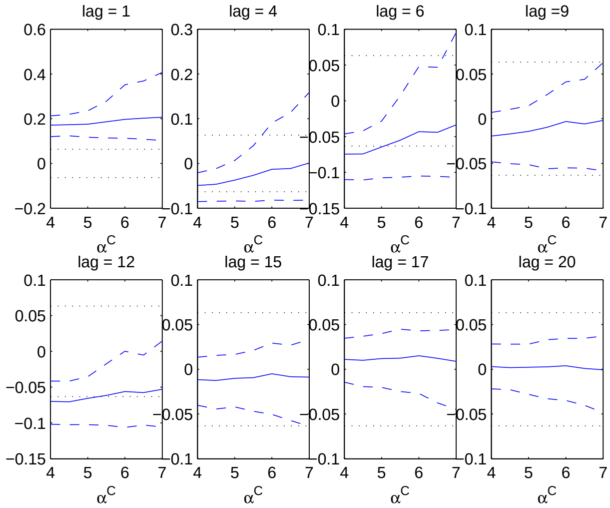


Figure 22: Autocorrelation of raw returns within the first 20 lags for variation of α^C, mean (solid) and 10% and 90% quantile (dashed lines) (based on 1,000 simulation runs).

The autocorrelation structure of returns in our model is also influenced by chartist aggressiveness α^C. Higher aggressiveness of chartists increases the autocorrelation of absolute returns and, with the exception of the first lag, brings the autocorrelation of raw returns closer to zero. Figures 21 and 22 show the autocorrelations in dependence of α^C for various lags of absolute and raw returns respectively. In a real financial market, the observed significant first-order autocorrelation of raw returns, which implies a general underreaction to news, would be traded away by arbitrageurs trading at high frequency. Such traders are not present in our setup.[38]

The reason why higher values of α^C lead to an increase in volatility clustering is because chartist trading in our model entails a noise component. Equation (12) shows that while the direction (signal $S_{j,t}$) of a chartist's return expectation is extracted from technical analysis, its amplitude ($\rho_{j,t}$) is random. Increasing α^C practically increases the variance of the noise component. Noise will therefore be increasingly reflected in the price of the risky asset. However, the impact of noise-trading on the price is also dependent on the number of chartists trading at a given time. Since, as see in Figure 2(b), the market composition varies rather slowly, volatility clustering prevails. In the context of agent-based financial market models He and Li (2007) have already noted that noise-trading not only strengthens the slow decaying of absolute return autocorrelation, but

[38] LeBaron (2010) has e.g. implemented an agent type trading on first-order autocorrelation in his model of a financial market. Because the analysis of return time series is not a focus of our model, we refrain from introducing further agent types, which would surely increase the complexity of the model.

also transforms the autocorrelation function of raw returns from one indicating market underreaction into one in accordance with the unit-root assumption.

C Results of Econometric Tests

Year	Jarque-Bera test statistics	Critical value
1996	5.06	11.53
1997	9.99	11.16
1998	4.74	10.90
1999	5.66	10.85
2000	5.84	10.86
2001	4.45	10.85
2002	2.44	10.99
2003	2.85	11.05
2004	2.34	11.10
2005	0.74	11.17
2006	0.27	11.20
2007	0.03	11.27
2008	0.79	11.42
2009	0.14	11.35

Table 5: Jarque-Bera test statistics computed for the log-balance sheet size of OECD investment banks (Bankscope data).

independent variable	Coef.	Std. Error	R^2
mean leverage	0.0057242*	0.0016657	0.6631
constant	2.415804***	0.0817424	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 6: Regressing the coefficient of variation (σ/μ) against the mean leverage of international investment banks from 2002 until 2009 (annual data).