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„Agent-based models in econophysics: applications to financial regulation“

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Chapter 1

Introduction

The question "What research area is Econophysics" is still asked by many economists and physicists although the term appeared more than 15 years ago as a merging of the disciplines "Economics" and "Physics" at an international conference in 1995 on statistical physics in Calcutta, India. The second chapter of the first part of this work will discuss "Econophysics" and the interests of physicists in economic issues. It will further be reviewed how physics influenced and continue to affect other sciences, especially social sciences and economics.

Particularly important contributions by physicists to other sciences are agent-based models that can be seen as an extension of the Ising model, a model of ferromagnetism in statistical mechanics. The concept of the Ising model, as one of the simplest models describing the competition between an ordering force and of imitation behavior, has been adopted by many disciplines, especially social science and economics. Their development and application, particularly in economics and finance, will be discussed in the third chapter. The first section will cover possible designs of artificial financial markets. The second chapter will discuss important models in this area developed by physicists.

In the second part, as suggested and requested by many physicists and emphasized in passionate articles in renowned journals like *Nature*[1], an agent-based model will be used to test the efficiency and dangers of possible future financial regulation. As Farmer & Foley (2009) strikingly argue for the usage of agent-based models in policy advice:

> *"The leaders of the world are flying the economy by the seat of their pants."*

Similar to a number of recent publications in this area, which will be presented in the last chapter of part one, current banking regulation will be analyzed in a toy model, inspired by the Ising model, of the financial market. In a further attempt an "ideal world" is constructed where banks completely hedge against possible losses.

Chapter 5 will present the backgrounds of financial regulation, emphasizing the difficulties of credit regulation. Chapter 6 will discuss all equations defining the agent-based model used as a baseline comparison to test regulation schemes. In chapter 7 the necessary modifications to implement regulatory measures will be developed. The final chapter presents simulation results showing that Basle-type regulation works fine in situations of low leverage levels in the financial system, but become destabilizing in scenarios with re-

[1] See e.g. Farmer & Foley (2009) and Lux & Westerhoff (2009).

alistic leverage level. Further results will indicate that even introducing the heavy requirement of complete hedging does not make the system systemically more secure.

Chapter 2

Econophysics and agent-based models

Econophysics is an interdisciplinary research area using methods from physics, in particular from statistical mechanics, in order to analyze problems in economics and finance.

Economics is the social science that is about invention, financing, production, distribution, use and disposal of goods and services.

Statistical mechanics or statistical thermodynamics, on the other hand, is a sub-discipline of physics that uses a probabilistic framework to study the thermodynamic behavior of systems composed of a large number of particles. Statistical mechanics is about relating the microscopic properties of individual atoms and molecules to the macroscopic properties of bulk materials, predominantly gases.

Methods of statistical mechanics, in particular for analyzing microscopic dynamics of a system for obtaining average properties of a macroscopic system, seem to be useful for an economic system as well. Although it does not seem realistic to formulate equations of motion for "atoms" of an economic system, concepts such as stochastic dynamics, correlation effects, self-organization, self-similarity and scaling can be applied to understand the global behavior of economic systems without detailed microscopic knowledge of the "components" of the economic system (Chakraborti, Muni Toke, Patriarca & Abergel 2011*a*, Chakraborti, Muni Toke, Patriarca & Abergel 2011*b*).

The interest of physicists in social sciences is nothing new, e.g. Daniel Bernoulli developed a theory for risk measurement (Bernoulli 1954). The beginning of interest of modern physics in economic issues can be seen with the publication of Majorana (1942)[1], who wrote a paper on the parallels of statistical physics and social sciences. With the exception of John von Neumann and Oskar Morgenstern, who helped founding the mathematical field of game theory among other things, only few works had been published in this area in the following decades until the 1990s. The name "econophysics" was attributed to H. Eugene Stanley in the 1990s, to label a large number of papers written by physicists dealing with economic problems, in particular problems associated with stock markets and financial time series. The term first appeared in an international conference in 1995 on statistical physics in Calcutta, India (Chakraborti et al. 2011*a*, Chakraborti et al. 2011*b*).

Another intersection between physics and economics as well as many other

[1] For a presentation of the English translation of Majorana's (1942) paper see Mantegna (2005).

fields including computer science, biology and chemistry is the field of complex systems. A complex system is a system consisting of individual parts that interact with one another so that as a whole it exhibits properties not apparent from the properties of the individual parts.

Agent-based models (ABMs), which can be used to study complex systems, are an extension of the famous Ising model, a model of ferromagnetism in statistical mechanics. The original Ising model, proposed by Lenz and studied by Ising (1925), assumed that the spins, which determine the magnetic moment of atoms or ions, can assume only two discrete states. The spins are arranged on a lattice or network and each spin interacts only with its nearest neighbors. The aim was to calculate phase changes in the Ising model to construct a model for phase changes. An Ising model more generally reproduces the properties of a system where individual elements change their behavior to adapt to the behavior of the other individuals in their neighborhood. Individual parts can be atoms or molecules or more broadly proteins, animals, social players or other phenomenons where imitation behavior is important (Tasca 2009). Many works in social science and economics use concepts of the Ising model and can be mapped to different versions of it[2] (Zhou & Sornette 2007, Sornette & Zhou 2006).

This is important because of the concept of *universality*, which is the empirical fact that there exist properties for a large class of systems, which are independent of microscopic details of the system. Thus, many macroscopic phenomena can be divided into a small set of universality classes, described

[2]See e.g. Callen & Shapero (1974), Montroll & Badger (1994), Orléan (1995), Johansen, Ledoit & Sornette (2000) and Kaizoji, Bornoldt & Fujiwara (2002).

only by a set of a few relevant observables.

In a more modern definition, ABMs are a class of computational models simulating actions and interactions of autonomous agents, which are employed to study their effects on the system as a whole. ABMs combine mainly elements from game theory, complex systems, multi-agent systems, evolutionary programming and cellular automata.

ABMs allow to simulate social processes starting from the implementation of the interactions or actions of many individual agents. The basic challenge is to understand how individual agents behave locally and to formulate behavioral rules. These rules in general depend on the states and interactions with the other agents in the system or they can be decided randomly. Random decisions represent behavior that is not correlated to other agents or events. With the behavioral rules in place a simulation is conducted to see how the collective system behaves as a whole.

> *"In short, ABM are scaled-down, stylized versions of highly intricate and interdependent systems wherein one can develop a better understanding of the dynamics of complex systems, such as financial markets."* (Thurner 2011).

With the growing availability of computing power, this approach gained increasing popularity since the 1990s. ABMs are currently in use in many different disciplines, most prominent in physics, material science, biology, economics, finance and social science.

Chapter 3

ABMs in finance and economics

For the better part of the 20th century, finance was dominated by a representative, rational agent approach. With the introduction of theories such as the *efficient market hypothesis* and the Black-Scholes formula for option and derivative pricing, the discipline was put on solid mathematical grounds – measure theory in particular.

But with discoveries like the no-trade theorem, excess volatility and bounded rationality, it became apparent that the representative, rational agent approach could not explain fundamental aspects of financial markets[1].

As in other disciplines since the 1990s, ABMs became a promising tool to understand behavior of financial markets.

[1]See e.g. Hommes (2006) for an extensive list of reasons.

3.1 Different designs of ABMs

A lot of different designs of ABMs of financial markets exist. When constructing ABMs researchers face a large number of design questions. According to LeBaron (2001, 2006) design questions of ABMs of financial markets consist mainly of: preferences of agents, trading and formation of prices, what securities are traded, evolution and learning in the model and the creation of useful benchmark comparison. Design preferences in accordance with LeBaron (2001, 2006) will be briefly presented below.

3.1.1 Agents preference's

The most important design question of ABMs is the representation, structure and number of the actual trading agents. There are many different approaches possible for the design of agents, varying from agents with *zero intelligence* to sophisticated agents applying *genetic algorithms*. This degree of freedom is because agents need to transform the large amount of information generated during simulation of the artificial financial market into trading decisions.

A straightforward approach is to build agents with a set of simple rules on which they form their decisions. These rules can be derived from real world behavior including trading strategies actually applied in practice. This simple approach has the advantage of an easily traceable result, but dynamic interactions between agents are only possible within these predefined strategies. Since modifications of strategies are hard to conduct during a simulation, the evolution of agents is often neglected.

Another and even simpler type of agent is called the “zero intelligence” agent. The only trading rule for such an agent is a budget constraint. These agents have proved to be quite efficient when it comes to simulate real world markets. It is interesting that despite their extremely simple design, their trading behavior can be perceived as “intelligent” or “learning”.

A third group of agents incorporates learning strategies. Artificial intelligence techniques are used to adapt the agents’ behavior and allow them to learn how to capitalize on new market inefficiencies. Artificial intelligence tools like artificial neural networks and genetic algorithms are used to determine the strategies. Interestingly, in many artificial markets, agents start with similar strategies but differences develop endogenously during the simulation. Due to constantly changing sets of rules used by each agent on such a artificial market, not only the behavior of the market but also the behavior of the agent itself can be studied. Obviously this type of agent design results in more complex computations, which requires more computing power. Another issue is, since the very nature of artificial intelligence tools itself is yet to be studied in detail, that almost nothing is known about their impact on trading behavior if applied in groups. Another criticism is that algorithms may be not smart enough and agents do not capitalize on obvious trading opportunities.

3.1.2 Trading and price formation

Methods and algorithms used by agents to conduct trading and the process of price formation play also a crucial role. Basically, four commonly used methods for price formation can be identified.

First of all, prices can be set by a market maker and adjusted based on supply and demand. In this case, the price formation process is as the following: A market maker sets a price, and agents submit requests to buy and sell at that price. Then the orders are summed, if there is an oversupply, the price is decreased and if there is an excess demand, the price is increased. Prices p at time t are often determined proportionally to the excess demand:

$$p(t+1) = p(t) + \alpha[D(p(t)) - S(p(t))] \quad , \tag{3.1}$$

with D as demand, S as supply and α as a parameter determining the sensitivity to supply and demand changes. This method is fast and easy to implement but holds the market in disequilibrium, which can be an advantage if adaptively evolving situations are part of the model. Therefore prices may stay at a level where they are far from a state that would clear the market. Furthermore, related criticism is that the method is too sensitive to the parameter α, causing either too high or too low price amplitudes.

The second method addresses the issues from the method above. It is a method where markets "clear" periodically, either through a numeric algorithm or analytically with some reasonable simplifications. This is quite the opposite of the first method in terms of advantages and disadvantages. Prices are clearing the market, but this is often not a representative nor satisfactory situation for the permanent trading activity in financial markets.

The other two mechanisms are somewhere in between these extremes. The most realistic way is to let the agents build up order books for buying and selling stocks. The drawback of this method is that both, the agents' strategies as well as the market architecture must be built using the same constraints.

The final price formation method is to match agents randomly and let them trade only if it benefits both of them. This method can be used to model decentralized markets such as the foreign exchange trading.

3.1.3 Securities and assets

The traded assets are another import design question of ABMs. Most researchers are focusing mainly on price formation and agent behavior and neglect other properties of the market. Therefore, often only a few simple types of tradable securities are used with prices connected to a fundamental value, calibrated to actual values from real world data. Often fundamentals of assets like dividends are revealed each period to the agents, which is seldom the case for investors in the real world.

Limited by computational power and the need for tractability of ABMs, they seldom feature more than two assets, for example a risky and a risk-free asset, which is clearly far from real world conditions. Therefore certain aspects of real markets such as diversification or derivative trading cannot be studied in this way.

3.1.4 Evolution and learning

Evolution and learning is important in many artificial markets because judging strategies beforehand is impossible since their performance depends on the behavior of others. A striking example for a rational strategy with a negative outcome is to hold on to a short position on a rising bubble.

Evolution and learning can appear in numerous ways in ABMs. Many artificial markets use tools from artificial intelligence to model learning. A common tool to model evolution and learning is to apply genetic algorithms. These algorithms are often used as an optimization technique for different problem solving situations.

In almost every evolutionary method there is a population for problem solving solutions. For each solution there is a rule or fitness value that allows a ranking of the solutions in a population. During a simulation, the solutions with the lowest ranks will be removed. An important design parameter is the proportion of the population to be removed. If the setting is too high, the population converges too quickly to a suboptimal solution and if the setting is to low, simulations converge too slowly.

In artificial financial markets, typical fitness values are either wealth or "utility". In the case of wealth, modeling evolution is less important because agents with more wealth automatically impact prices more strongly.

Often trading strategies or rules are evolved and evaluated overtime. Evaluation can be based on forecasts or directly on demand from trading strategies. Forecast-based models first evaluate predictions and convert them in a second step in demand using preferences. In the second case, strategies are evolved based on their impact on utility.

3.1.5 Benchmarks and calibration

The last design question is calibration and finding of useful benchmark comparisons. A benchmark case, so that the behavior of the market is well defined, is important for the plausibility of the artificial market. The parameters for market dynamics such as those leading the market to equilibrium must be defined and their sensitivity must be well understood. They should be comparable to estimated parameters derived from actual markets. When price series of computational markets are compared to those of real markets, the relevance of each parameter must be shown to increase the plausibility of the artificial market.

3.2 Types of artificial financial markets

As discussed above, there is a large number of possible designs for ABMs of financial markets. These artificial financial markets can be characterized in many ways. A common distinction is by the number of different strategies that are used by agents. ABMs that analyze only a small number of trading strategies in detail are called few-type models. ABMs where many different trading strategies are tested, or where agents could dynamically adopt their strategies are called many-type models.

Another way of distinguishing ABMs is to focus on the aim of the model. LeBaron (2006) identified a number of different classes of models with different aims. He distinguished ABMs that analyze specific trading strategies from ABMs that create a dynamic trading environment for the agents and analysis which strategies evolve. Another class of ABMs aims to reproduce known empirical results from financial market time series, so-called "stylized facts", including fat tails or clustered volatility of asset returns. A few ABMs have even gone further in attempting to actually fit parameters of financial data in a direct estimation process, which is a complex procedure in terms of computing power.

Important artificial financial markets have been reviewed by LeBaron (2006) and Hommes (2006) and will be in part presented in the remainder of the chapter. With LeBaron (2006) focusing more on many-type models and the mentioned aims of the models, Hommes (2006) concentrates more on few-type models and the effects of heterogeneous strategies of agents.

3.2.1 Few-type models

Few-type models analyze only a small number of trading strategies in detail. Literature is quite extensive on small scale ABMs, but Hommes (2006) provides an overview of important artificial financial markets in this area. Below I will present two important examples from the overview, starting with an early example with chartists and fundamentalists, followed by example work on behavioral finance.

Chartists and fundamentalists

Many few-type ABMs contain two different types of agents, chartist and fundamentalists. Chartist or technical analysts do not use market fundamentals for their trading strategy. Instead they buy and sell according to observed patterns in the time series of historical prices. They try to extrapolate trends and patters as their trading strategy. An example for a trading strategy of a technical analyst is the moving average trading rule, where traders buy an asset when a short run moving average crosses a long run moving average from below and sell when crossing from above.

Fundamentalists center their trading strategy and expectation on future price developments upon market fundamentals and economic data like earnings, dividends, economic growth and unemployment rates. They invest in an asset if it is undervalued compared to a perceived fundamental value and sell if it is overvalued (Farmer & Joshi 2002, Farmer 2002).

Rational versus noise traders

Another group of few-type ABMs depends on two types of heterogeneous agents called rational and noise traders. These types of ABMs are inspired by behavioral finance. Noise or ordinary traders, which were introduced by Shiller (1984), base their trading decisions either on false information or on non-fundamental considerations. They are perceived as selling and buying nearly at random. Rational traders, also called "smart money", are investors who have completely rational expectations about future asset returns. They use sophisticated techniques to formulate their trading strategies. Compared to chartist and fundamentalists discussed earlier, which are both not fully rational, rational traders take the presence of other traders into account, regardless of their strategies. Examples for rational trades are hedge funds or large financial institutions engaged in arbitrage.

3.2.2 Many-type models

In contrast to the mentioned few-type models that have only a few different agents, in most cases only two, many-type models feature many different agents with different trading strategies. The specific trading rules of few-type models are replaced by a larger set of strategies or by a dynamic trading environment where agents are evolving. These models start with a random set of starting strategies for the agents and try to determine which strategies will fail and which will survive. LeBaron (2006) provides an overview of important many-type models, of which two important examples will be presented below.

Larger sets of strategies

The first subset of may-type models deals with situations where the economic environment is well-understood and where regularly is a simple homogeneous rational expectations equilibrium, which can be used for benchmark comparison.

An example for a model of this type was introduced by Lettau (1997). He constructs a simple artificial financial market with learning agents and two assets, one risky and one risk-free, using a genetic algorithm to find the optimal portfolio strategy. The agents must decide which part of their wealth they are investing in the risky asset. The price of the risky asset is set exogenously and it pays a random dividend that is normal distributed. The risk-free asset pays zero interest. To keep the artificial market simple, there is no feedback from agents' demands on the returns of the risky asset and consumption of assets is neglected. Each period the portfolio of the agents is composed by the application of a genetic algorithm. With the optimal solution for the portfolio problem known, the main focus of the model is to determine if and when agents achieve this optimal portfolio solution.

Emergence of trading strategies

The next type of artificial market models try not to test specific strategies but provide an dynamic trading environment where it can be observed which trading strategies will appear through evolution. These types of models are called artificial complex adaptive systems. They start with a random pool of initial strategies and it can be seen which are capable of self-reinforcing to survive and which will fail and vanish. They also study dynamics of market efficiency and watch if markets move into a state where inefficiencies occur and if strategies appear to exploit these inefficiencies. The goal of these models is to study markets which are not classically efficient but are moving to informational efficiency.

A prominent example for this type of ABM is the Santa Fe Artificial Stock

Market[2] (SFASM). The SFASM was developed by the Santa Fe Institute and is one of the early examples of artificial complex adaptive systems. The SFASM has existed since 1989 in several different designs[3]. A stock exchange is simulated with a large number of traders dealing with each other. Different traders use different strategies, and the SFASM allows to modify these strategies during simulations. It then forms an evolutionary ecology, where less well-adapted strategies do not survive without eliminating the more successful ones. Most of the SFASMs features are replaceable and can be modified to perform different experiments. The framework can be used to study problems of finance in particular questions like a transaction tax, agents who have access to different information sources or test various market-making mechanisms. Additionally it allows to use different classes of utility functions, apply a number of alternative random processes and use different mechanisms for evolutionary selection of agents (Arthur, Holland, LeBaron, Palmer & Tayler 1997).

3.2.3 Reproducing of empirical results

Another set of artificial financial markets concentrates on the replication of so called empirical stylized facts. Stylized facts emerging from the statistical analysis of returns in different types of financial markets are discussed in numerous papers[4]. ABMs have the advantage that they generate sizable

[2]See e.g. LeBaron, Arthur & Palmer (1998) or LeBaron (2005) for a detailed description.

[3]See Palmer, Arthur, Holland, LeBaron & Tayler (1994) for a description of an earlier form.

[4]See e.g. Cont (2001).

trading volume consistent with empirical observations and therefore allow for reviewing and replicating stylized facts. In the literature there are innumerable works that use ABMs to reproduce stylized facts[5]. Many of these models that are motivated by stylized facts like asset prices indicate a near unit root behavior, asset returns are not predictable and show virtually no autocorrelation, the return distributions develop fat tails and show long range volatility clustering (Hommes 2006).

In all cases the model specifics are always less important than the reproduction of empirical facts from financial market time series.

Probably the most popular empirical feature to reproduce with ABMs is clustered volatility first observed by Mandelbrot (1963) in time series of financial asset returns. While stock returns themselves are relatively uncorrelated, the volatility of returns is auto correlated. A prominent example for ABMs successfully explaining stylized facts was introduced and successively developed further[6] by Lux (1995). In particular, clustered volatility was reproduced through interaction of fundamentalist and chartist. Recently Thurner, Farmer & Geanakoplos (2009) showed that even under the assumption of reasonably rational value-investors, clustered volatility and fat tails occur when feedback effects of leverage are included.

[5]See e.g. Arthur et al. (1997), LeBaron et al. (1998), Farmer & Joshi (2002), Farmer (2002), Kirman & Teyssière (2002) and Giardina & Bouchaud (2003).

[6]For follow up research see (Lux 1998, Lux & Marchesi 1999, Lux & Marchesi 2000).

Chapter 4

ABMs for economic policy advice

Recent experience of the financial crisis in the first decade of the 21st century prompted a broad discussion of financial regulation. Until now, economic policy makers had basically two different types of models at their disposal. The first type involves statistical models that utilize past empirical data in order to make forecasts. These models make useful predictions as long as there are only minor changes, but fail if there occur overall systematic or systemic changes. The other type involves models with assumptions such as the efficient market hypothesis or the general equilibrium theory, which also assumes a perfect world with little or no change and are therefore incapable of understanding and even less predicting a crisis (Farmer & Foley 2009, Thurner 2011). Furthermore, these models generally do not take feedback loops, synchronization or network effects into account. Therefore economic policy makers usually base their decision-making process on experience, common sense, or as Farmer & Foley (2009) put it,

> *"The leaders of the world are flying the economy by the seat of their pants."*

With ABMs gaining increasing popularity over the last two decades, they are about to become an accepted tool for the analysis of economic problems. Many advocated during the recent financial crisis and in the aftermath that they should play an important role in deciding future economic policy[1]. Thurner (2011) advised the OECD that,

> *"The recent crisis has made it clear that there is poor understanding of systemic risk. The regulation scheme Basle II, which cost millions to be established worldwide, has spectacularly failed."*

ABMs have been successfully used in economic modeling for two decades and are able to reproduce empirical features of financial markets, which is not possible or only with difficulties through traditional approaches. Furthermore, ABMs are among the most encouraging methods to understand systemic risk in financial markets and they seem to be the best thing at hand for testing economic policies prior to their implementation, provided they are done in a quantifiable, fully reproducible and falsifiable way.

[1] See e.g. Bouchaud (2008), Farmer & Foley (2009), Lux & Westerhoff (2009) and Thurner (2011).

4.1 Recent examples of ABMs for policy advice

In the remainder of the chapter I briefly present a current selection of approaches to use ABMs for policy advice. These models represent a broad spectrum of economic policy issues, from specific topics like a transaction tax to broader questions like fiscal policy as a whole, which require simulating an entire economy.

4.1.1 *"Regulatory Medicine Against Financial Market Instability: What Helps And What Hurts?"*

Based on the model of Thurner et al. (2009), Kerbl (2010) studied the effects of regulatory measures such as a ban of short selling, a mandatory risk limit and the introduction of a transaction tax on trading. He used the model from Thurner et al. (2009) as the representation of the financial market in its unregulated form and tested regulatory measures on it. His findings showed that only a mandatory risk limit has positive impact from every point of view, while a short selling ban reduces volatility but shows increased risk of tail events. A transaction tax on trading can reduce the likelihood of crashes but increases volatility. Additionally he showed that the interplay of regulatory measures is not negligible and can have unforeseen side effects.

4.1.2 *"Who Does a Currency Transaction Tax Harm More: Short-Term Speculators or Long-Term Investors?"*

Demary (2008) focused also on a currently broadly discussed transaction tax. He analyzed whether a transaction tax would affect long- or short-term investors more. His approach used an ABM with more complex trading strategies of agents. As a result he found that, in line with the expectations of those advocating of a transaction tax, trading strategies involving short-term speculation would be reduced in favor of long-term investment. Interestingly he also found that such a tax is capable of reducing volatility but increases the likelihood of tail events, quite the opposite of Kerbl's (2010) findings.

4.1.3 *"The Use of Agent-Based Financial Market Models to Test the Effectiveness of Regulatory Policies."*

Westerhoff (2008) followed a similar approach to Kerbl's (2010) and Demary's (2008). He also tried to explore if ABMs offer new insights in the success and failure of regulatory measures, such as central bank interventions, trading halts and a transaction tax as well. He used a relatively simple and transparent framework for his analysis, with agents using fundamental and technical indicators for their strategies as discussed above. Contrary to Kerbl (2010), Westerhoff's (2008) work indicated that all of these regulatory measures in general have a potentially stabilizing effect on financial markets and they seem to reduce volatility of prices as well as limit distortions.

4.1.4 *"Monetary and Fiscal Policy Analysis with an Agent-Based Macroeconomic Model."*

Another approach was followed by Haber (2008). He introduced a macroeconomic ABM of a national economy simulating both the private and public sector. Each individual actor like households, companies and government agencies are separate agents with their own behavior and expectations. He set the focus on monetary and fiscal policy and showed that different models of expectation formation can affect the outcome of these policies evaluated in that context. He further indicated that the results of policy evaluation could depend on the chosen baseline.

Part II

Applications to financial regulation

Chapter 5

Introduction

In the second part an ABM is now used as a toy model of the financial market to test the efficiency and dangers of credit regulation schemes. The ABM used as a baseline, representing the unregulated market, was first introduced by Thurner et al. (2009) and will be extended to incorporate credit regulation schemes. Current banking regulation in the shape of Basle II compliant credit risk mitigation techniques will be implemented and in a further attempt an "ideal world" is constructed where banks completely hedge against possible losses.

In the remainder of chapter 5 I will present the backgrounds of financial regulation, emphasizing the practical difficulties of credit regulation. Chapter 6 presents the baseline model in accordance with Thurner et al. (2009) and explains all equations defining the ABM used as a baseline comparison to test regulation schemes. In chapter 7 the necessary modifications to implement regulatory measures will be developed. The final chapter presents simulation results showing that Basle-type regulation works fine in situations of low leverage levels in the financial system, however they become destabilizing in scenarios with realistic leverage level. Further results indicating that even introducing the heavy requirement of complete hedging does not make the system systemically more secure.

Regulatory bodies for the financial sector are mainly concerned with protecting the creditors of banks, the reduction of systemic risk (resulting from conditions where the failure of a single entity could cause major or multiple bank failures) and the proper conduct of banking business. To achieve their objectives regulators require banks to fulfill minimum standards, most important minimum capital requirements – the amount of money banks need to put aside, and restrict banks from having too large exposures to a single counterparty.

To comply with regulations, banks in the credit business need to establish provisions or commit equity to cover for losses of interest and principal. There are always some borrowers that default on their obligations, but the actually experienced losses vary depending on the number and severity of default events. The average level of credit losses a bank expects to experience is referred to as expected losses. Banks view these losses as a cost component of the credit business and include them in pricing of credit exposures. Losses above the average level are referred to as unexpected losses. These losses occur only occasionally and interest rates, including risk premium, charged on individual credit exposures do normally not fully cover them. Therefore the overall pricing of credit exposure should reflect the possibility of peak losses and banks need to hold capital to cover them. Because of high capital costs, banks have a big incentive to minimize the capital to cover for credit exposures. Therefore they use a number of legal means to reduce both the expected and unexpected losses.

Internationally, the Bank for International Settlements Basel Committee on Banking Supervision provides a framework – the Basel Accords for minimal capital requirements of banks. The latest version of the accords (Bank for International Settlements 2006), commonly known as *Basle II*, incorporates detailed requirements for recognized credit risk mitigation techniques used to reduce the capital banks need to hold.

An important credit risk mitigation technique is collateralized transactions where credit exposure is hedged either fully or in part by collateral deposited by a counterparty. Often collateral is not fixed in value but changes overtime. When taking collateral, banks must calculate their adjusted exposure to counterparties according to the rules of their regulatory body to take full account of the effects of that collateral. A recognized approach within the Basle II framework is to apply *haircuts* or margins on the collateral.

Haircuts are percentages that are subtracted from the value of an asset that is being used as collateral. The size of the haircut should reflect the possible future fluctuations in the value of the asset. According to the Basle II framework, banks are required to adjust both the amount of the exposure to the counterparty and the value of the collateral received from the counterparty. This ensures volatility adjusted amounts for both exposure and collateral.

In the following we are discussing and implementing two approaches to limit the exposure of banks to their counterparties. In the first one, banks adjust the margin requirement according to internal estimated haircuts determined by the volatility of the underlying asset, effectively limiting the maximum leverage investors can use. In the second approach, banks further reduce the exposure by buying derivatives to secure the collateral they hold.

To calculate interest rates on loans, banks use a benchmark interest rate and add a *risk premium*. Because loans are fully collateralized, banks apply only a minimal fixed spread around a benchmark interest rate. Benchmark rates are, for example Fed Funds Effective (Overnight Rate) or EONIA (Euro Overnight Index Average).

Chapter 6

The baseline model

The baseline model, representing the unregulated market, is an ABM with four different types agents and a standard market clearing mechanism.

Two of the agents are informed investors, e.g. hedge funds and uninformed ones, e.g. noise traders. The informed investors are value-investors who simply put *buy low and sell high.* Therefore they use a strategy that reacts on mispricing by taking a long position (buying a positive quantity of assets) when the price is below a perceived fundamental value V. The noise traders buy and sell nearly at random, with a small preference that makes the price weakly mean-revert around V. Both traders, in the baseline model, have only a choice between owning a single asset, such as a stock or a commodity (without dividends and consumption) or holding cash.

The third type of agents are banks. Informed investors can increase the size of there positions by borrowing from a bank using the asset as collateral. Banks limit lending so that the value of the loan is always less than the current price of the assets held as collateral. This limit is called minimum margin requirement. In case the asset value decreases, so that minimum margin requirement is no longer sustained, banks issue *margin calls* and informed investors must sell assets to maintain minimum margin requirements. If large price jumps occur and informed investors cannot repay the loan, by selling their complete portfolio, they default. This kind of transaction is called margin trading and has the effect of amplifying any profit or loss from trading. In the baseline model interest rates are fixed to zero and banks set a fixed minimum margin requirement in relation to the size of the informed investor.

In addition to these three types of agents there is a representative investor who finances an informed investor according to the performance. The amount they invest or withdraw from an informed investor depends on recent historical performance compared to a fixed benchmark return r^{b}. Therefore, successful informed investors attract additional capital beyond what they earned through trading, and similarly, unsuccessful informed investors lose additional capital.

6.1 Supply and demand

At each time step t, the asset prices $p(t)$ are set by equating the sum over the demand of the informed investors $D_h(t)$ and the noise traders $D_{\mathrm{nt}}(t)$, to

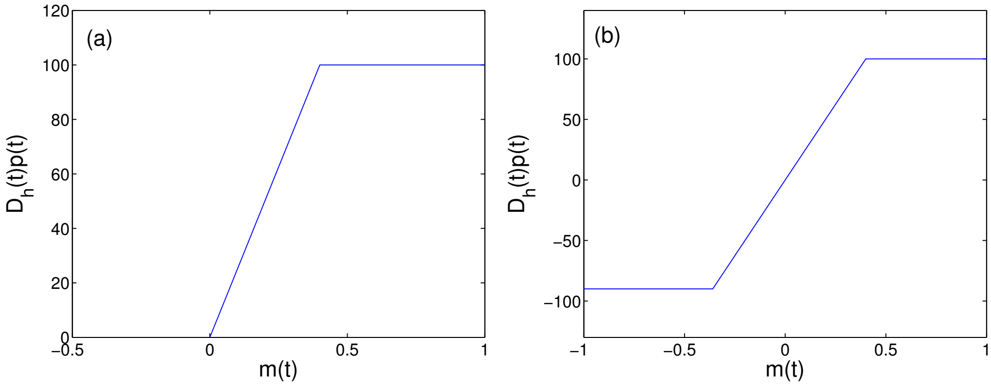

Figure 6.1: Demand function $D_h(t)p(t)$ of an informed investor as a function of the mispricing signal $m(t) = V - p(t)$. (a) The informed investor does nothing if the asset is overpriced and starts buying more and more assets as the price decreases, until the maximum leverage limit at $m = m^{crit}$ is hit. Beyond this the demand remains flat. (b) With short selling allowed, the informed investor additionally shortens the asset if it is overpriced.

the fixed total supply of the asset N

$$D_{\rm nt}(t) + \sum_h D_h(t) = N \quad . \tag{6.1}$$

The first type of agents in the model are the informed investors (hedge funds h). At every time step the informed investors must decide how much of their wealth $W_h(t)$ they are going to invest. The wealth of an informed investor is the sum of its cash $M_h(t)$, and the current value of the asset $D_h(t)p(t)$,

$$W_h(t) = W_h(t) = D_h(t)p(t) + M_h(t) \quad . \tag{6.2}$$

When the informed investor is borrowing cash, $M_h(t)$ is negative and represents a loan from a bank.

The informed investors in the model are *value investors* who base their demand $D_h(t)$ on a mispricing signal, $m(t) = V - p(t)$. The perceived fundamental value V is fixed at a constant value, which is the same for all informed investors and the noise traders. As Figure 6.1 shows, each informed investor (hedge funds h) calculates its demand $D_h(t)$, based on the perceived mispricing. As the mispricing increases, the value of the portfolio $D_h(t)p(t)$ an informed investor wants to hold increases linearly. However, the demand is bounded when the informed investor reaches the maximum leverage level. Here, informed investors only differ in their aggression parameter β_h, which quantifies how strong they respond to mispricing signals, $m(t)$. With $W_h(t) \geq 0$, the informed investor's demand $D_h(t) = D_h(t, p(t))$ can be written as

$$D_h(t) = \begin{cases} 0 & \text{if } m(t) < 0 \\ \lambda_{\max} W_h(t)/p(t) & \text{if } m(t) > m_{\text{crit}} \\ \beta_h m(t) W_h(t)/p(t) & \text{otherwise} \quad , \end{cases} \tag{6.3}$$

and with short selling allowed[1],

$$D_h(t) = \begin{cases} (1 - \lambda_{\max}) W_h(t)/p(t) & \text{if } m(t) \leq m_{\text{crit}}^{\text{short}} \\ \lambda_{\max} W_h(t)/p(t) & \text{if } m(t) > m_{\text{crit}}^{\text{long}} \\ \beta_h m(t) W_h(t)/p(t) & \text{otherwise} \quad . \end{cases} \tag{6.4}$$

With a short selling ban in place and the asset being overpriced ($p(t) > V$) the informed investor holds no assets. In the second case the asset is heavily

[1]See (Kerbl 2010): p. 6 for informed investor's demand with short selling allowed.

underpriced causing the informed investor to use the maximum allowed leverage, $\lambda_h(t) = \lambda_{\max}$. This happens when $m(t) \geq m_h^{\text{crit}} = \lambda_{\max}/\beta_h$. Otherwise the asset is underpriced but the mispricing is not too large. The informed investor takes a position proportional to the mispricing $m(t)$, the informed investor's wealth $W_h(t)$, and its aggression parameter β_h, which differs between informed investors.

With short selling allowed and in case the asset is overpriced, the informed investor takes also a position proportional to the mispricing $m(t)$, the informed investor's wealth $W_h(t)$, and the aggression parameter β_h. The demand is again cut of by maximum allowed leverage.

Leverage λ_h is the ratio between the informed investor's portfolio value and its wealth,

$$\lambda_h(t) = \frac{D_h(t)p(t)}{W_h(t)} = \frac{D_h(t)p(t)}{D_h(t)p(t) + M_h(t)} \quad . \tag{6.5}$$

The informed investor is required by the bank it borrows from to keep $\lambda_h(t) \leq \lambda_{\max}$. In case there is no change in the demand of an informed investor between two time steps, leverage would be $\bar{\lambda}_h(t) = D_h(t-1)p(t)/W_h(t)$. If $\bar{\lambda}_h(t) > \lambda_{\max}$, the informed investor, in the model, must sell assets in order to bring leverage $\lambda_h(t)$ below the maximum allowed. This is known as meeting a *margin call.*

The cause of a margin call can be either the price falls from $p(t-1)$ to $p(t)$, causing $W_h(t)$ to fall by a larger percentage than the asset price (because of leverage), or because the wealth falls from $W_h(t-1)$ to $W_h(t)$ due to withdrawals (redemptions) from investors, as will be discussed below.

If $W_h(t) < 0$, i.e. the value of the loan is larger then the value of the portfolio, the informed investor defaults and goes out of business. The informed investor must sell all its assets, therefore $D_h(t) = 0$, and returns the revenue to pay off as much of the loan as possible. The remaining loss is borne by the bank. For simplicity, it is assumed that the losses do not affect banks and they continue to lend to other informed investors as before. After T_{reintro} time steps the defaulting informed investor reemerges again as a new informed investor, as described below.

The *noise traders'* demand is defined in terms of the cash value, $\xi_{\text{nt}}(t)$, they want to spend on the asset, which evolves according to the random process

$$\log \xi_{\text{nt}}(t) = \rho \log \xi_{\text{nt}}(t-1) + \sigma \chi(t) + (1-\rho) \log(VN) \quad , \tag{6.6}$$

where χ is independently normally distributed with mean zero and standard deviation of one. The noise traders' demand is consequently

$$D_{\text{nt}}(t) = \frac{\xi_{\text{nt}}(t)}{p(t)} \quad . \tag{6.7}$$

With $\rho < 1$, the cash value $\xi_{\text{nt}}(t)$ follows a random walk with a mean reversion. In the limit as $\rho \to 1$ the log-returns $r(t) \equiv \log p(t+1) - \log p(t)$ are normally distributed. If there would be no informed investors or the demand of all informed investors would be zero, the asset price is set such that $D_{\text{nt}}(t) = N$. Therefore without the presence of informed investors the log-returns are nearly normally distributed, with tails that are slightly truncated (and hence even thinner than normal) due to the mean reversion.

6.2 Wealth dynamics of informed investors

During simulations, each informed investor starts with the same wealth $W_h(0) = W_0$. Each time step, the informed investor h calculates its wealth $W_h(t) = W_h(t, p(t))$ as described below.

The informed investors' wealth increases or decreases according to the profits or losses from trading. In addition the cash of informed investors changes due to deposits or withdrawals by investors, as described below.

A pool of investors, who are treated as a single representative investor, deposit or withdraw cash from each informed investor such as a hedge fund or mutual fund, based on a moving average of its recent performance. This process is well documented[2]. This guarantees an approximate steady state behavior with well-defined first moment in the long-term statistical averages of the wealth of the informed investors, i.e. it allows the wealth to vary within boundaries, but prevents it to grow without bound.

In case an informed investor's wealth decreases below a critical threshold, W_{crit}, the informed investor decides to go out of business. By using a positive survival threshold to remove informed investors the creation of "zombie investors", which persist for many time steps with nearly no wealth and no relevance for the market, is avoided. After a number of time steps, T_{reintro}, the informed investor is replaced by a new one with initial wealth W_0 and the same parameter β_h.

[2]See e.g. Busse (2001), Chevalier & Ellison (1997), Del Guercio & Tka (2002), Remolona, Kleiman & Gruenstein (1997) and Sirri & Tufano (1998).

Let

$$r_h(t) = \frac{D_h(t-1)[p(t)-p(t-1)]}{W_h(t-1)} \tag{6.8}$$

be the rate of return by informed investor h on investments at time t. The investors make their decisions to invest in an informed investor based on $r_h^{\text{perf}}(t)$, an exponential moving average of the rate of return, given by

$$r_h^{\text{perf}}(t) = (1-a)\, r_h^{\text{perf}}(t-1) + a\, r_h(t) \quad . \tag{6.9}$$

The flow of capital in or out of the informed investor, $F_h(t)$, is given by

$$F_h(t) = \max\left[-1, b\left(r_h^{\text{perf}}(t) - r^{\text{b}}\right)\right] \max\left[0, \tilde{M}_h(t)\right] \quad , \tag{6.10}$$

where

$$\tilde{M}_h(t) = D(t-1)p(t) + M(t-1) \tag{6.11}$$

is the amount of cash an informed investor would have if selling all assets at the current price, b is a parameter controlling the fraction of capital withdrawn or invested, and r^{b} is the benchmark return of the investors. Obviously, investors cannot take out more cash than the informed investor has.

Initially all informed investors start with the same wealth of $W_h(0) = W_0$. At each new time step the wealth of the informed investor evolves according to

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t)-p(t-1)] + F_h(t) \quad . \tag{6.12}$$

Chapter 7

Implementation of regulatory measures

In this chapter we modify the baseline model and introduce regulation schemes. The first regulation scheme, called the Basle scheme, introduces a typical regulatory measure to reduce credit risk encouraged by the Basle II framework. For the second regulation scheme we construct an ideal world, where all leverage introduced risk – borrowed money from banks used for speculative investments – is hedged perfectly with options.

7.1 The Basle scheme

In the following we understand under the Basle scheme the baseline model with two modifications, i.e. the implementation of haircuts and spreads.

7.1.1 Haircuts

For a collateralized transaction, the volatility adjusted amount for the exposure (E^*) is calculated as follows[1]

$$E^* = \max[0, E(1 + H_e^{\text{cut}}) - K(1 - H_{\text{sec}}^{\text{cut}})] \quad , \tag{7.1}$$

where E is the exposure to a counterparty, H_e^{cut} is haircut on the exposure, K the collateral received from the counterparty and $H_{\text{sec}}^{\text{cut}}$ the haircut applied on the collateral. Unless both sides of the transaction are in cash (in the same currency), the volatility adjusted value for the collateral will be lower than the current value of the collateral and for the exposure it will be higher. For instance, in case of short selling, the exposure of the bank, if acting as market maker, must be volatility adjusted.

As haircuts could either be used standard supervisory haircuts[2] issued by regulatory bodies or internal estimates of banks. Permission by supervisors to use own estimates is conditional on the satisfaction of minimum qualitative and quantitative standards as laid out by the Basle II framework[3]. A simple approach used in practice for own internal estimates satisfying the Basle standards is the following model

$$H_{\text{sec}}^{\text{cut}} = \min\left[\max\left(H_{\text{min}}^{\text{cut}}, \Phi\sigma\sqrt{T} + c\right), 1\right] \tag{7.2}$$

[1]See (Bank for International Settlements 2006): §147.

[2]See (Bank for International Settlements 2006): §147 for recommendation on supervisory haircuts, e.g. haircut for equities listed on a recognized exchange is 25%.

[3]See (Bank for International Settlements 2006): §156-165 for qualitative and quantitative standards.

with $H^{\text{cut}}_{\text{sec}}$ being the haircut for the specific security, $H^{\text{cut}}_{\text{min}}$ the floor haircut, Φ the confidence interval, σ the historical volatility, T the holding duration, and c the sales costs for the securities.

To use the above model for internal estimated haircuts to adjust margin requirements, the maximum leverage allowed is no longer constant, but depends on volatility

$$\tilde{\lambda}_{\text{max}}(t) = \max\left[\min\left(\lambda_{\text{max}}, \frac{1}{\Phi\theta\sigma(t)}\right), 1\right] \quad , \tag{7.3}$$

where $\sigma(t)$ is the historical volatility defined as the standard deviation of the log-returns of the underlying security over τ time steps, θ is an arbitrary factor to scale the length of one time step, and where the confidence interval is defined as

$$\Phi = \frac{1}{\lambda_{\text{max}}\theta\sigma^*} \quad , \tag{7.4}$$

with σ^* set according to market conditions with reasonable low volatility.

Therefore maximum leverage, λ_{max}, can only be used if the historical volatility, $\sigma(t)$, is equal or below σ^*. With the parameters listed in table 7.1, a 99^{th} percentile or above confidence interval, as required according to the Basle II framework[4], is used if λ_{max} is set to seven or below, which is reasonable in reality for stocks. By adjusting the margin requirements, the volatility adjusted exposure of the banks is always zero and by neglecting the costs involved in selling the collateral, the expected loss is also zero.

To adapt the model to variable maximum leverage the informed investor's

[4]See (Bank for International Settlements 2006): §156.

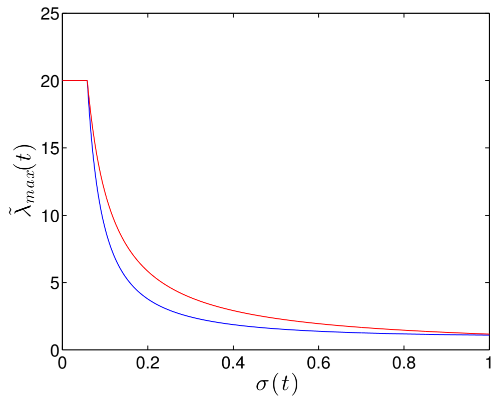

Figure 7.1: Maximum leverage function $\lambda_{max}(t)$ for all informed investors as a function of historical volatility $\sigma(t)$. The red curve shows the Basle scheme of equation (7.3), the blue curve shows the situation in the perfect hedge scheme of equation (7.22).

demand depends on the current price and the historical volatility, $D_h(t) = D_h(p(t), \sigma(t))$. Consequently, equation (6.3) changes to

$$D_h(t) = \begin{cases} (1 - \tilde{\lambda}_{\text{max}}(t))W_h(t)/p(t) & \text{if } m(t) \leq m_{\text{crit}}^{\text{short}}(t) \\ \tilde{\lambda}_{\text{max}}(t)W_h(t)/p(t) & \text{if } m(t) > m_{\text{crit}}^{\text{long}}(t) \\ \beta_h m(t) W_h(t)/p(t) & \text{otherwise} \quad . \end{cases} \tag{7.5}$$

Still the informed investor takes a long position if the asset is underpriced, a short position if the asset is over priced and reaches its maximum leverage if the mispricing is too large.

7.1.2 Spreads

To implement borrowing costs with zero benchmark interest rate in the model, a term accounting for the spread, S, is added to equation (6.12).

The informed investors always pay the borrowing costs for the previous time step. In case the informed investor takes a leveraged long position (M_h is negative), the wealth can be written as

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t) + M_h(t-1)S \quad , \tag{7.6}$$

and in case of short selling, where the demand is negative, as

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t) + D_h(t-1)p(t-1)S \quad , \tag{7.7}$$

where S is the spread in percent, e.g. 1%. The maximum amount of cash investors could take out of the informed investor (6.11) has now to be adjusted to

$$\tilde{M}_h(t) = D(t-1)p(t) + M(t-1)[1+S] \quad , \tag{7.8}$$

and

$$\tilde{M}_h(t) = D(t-1)p(t) + M(t-1) + D_h(t-1)p(t-1)S \quad , \tag{7.9}$$

respectively. This guarantees that obligations to banks are satisfied *before* demands of investors, according to the usual practice.

7.2 The perfect hedge scheme

Under the perfect hedge scheme we understand the baseline model with two modifications, i.e. implementation of hedging costs and limits to hedging costs.

7.2.1 Hedging

To offset unexpected losses due to loss of value of the collateral, banks buy options for the collateral for the loan to the informed investor. The costs for the options remain with the informed investors. Options are always bought for one time step only.

The option prices are determined using the Black-Scholes formula. The option price (P_h if it is a European put option, or C_h if it is a European call option), is calculated with the spot price of the underlying asset s, the strike of the option k, the risk-free interest rate r and the volatility of returns of the underlying asset (σ). In particular we have

$$\begin{aligned} P_h(t) &= P_h(p(t), \sigma(t), \lambda_h(t)) \\ &= P_h(s = p(t), r = 0, \sigma = \theta\sigma(t), T = 1, k = k_{\text{put}}(p(t), \lambda_h(t))) \end{aligned} \tag{7.10}$$

and

$$\begin{aligned} C_h(t) &= C_h(p(t), \sigma(t), \lambda_h(t)) \\ &= C_h(s = p(t), r = 0, \sigma = \theta\sigma(t), T = 1, k = k_{\text{call}}(p(t), \lambda_h(t))) \quad . \end{aligned} \tag{7.11}$$

For volatility σ we use the historical volatility $\sigma(t)$, defined as the standard deviation of the log-returns of the underlying asset over τ time steps. Volatility is multiplied by an arbitrary factor θ to scale the length of one time step,

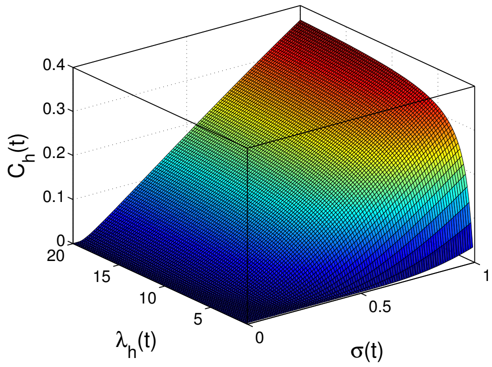

Figure 7.2: Black Scholes European call option pricing surface as a function of leverage and volatility.

which up to this point is not specified. The strike price is set such, that in case of failure of an informed investor and in case of large price drops the bank can sell the collateral at the price from the previous time step. In case the informed investor takes a long position the bank buys a put option with a strike at the current asset price, reduced by the equity ratio of the informed investor,

$$k_{\text{put}}(p(t), \lambda_h(t)) = p(t)\left(1 - \frac{1}{\lambda_h(t)}\right) \quad . \tag{7.12}$$

In case the informed investor takes a short position the bank buys a call option with a strike at the current asset price, increased by the equity ratio of the informed investor,

$$k_{\text{call}}(p(t), \lambda_h(t)) = p(t)\left(1 + \frac{1}{\lambda_h(t) - 1}\right) \quad . \tag{7.13}$$

To implement borrowing costs in the model a term with costs for the options is added to equation (6.12). The informed investors always pay the full hedging costs for the previous time step. In case the informed investor takes a long position, wealth changes to

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t) - D_h(t-1)P_h(t-1) \quad , \tag{7.14}$$

and in case of short selling, where the demand is negative, to

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t) + D_h(t-1)C_h(t-1) \quad . \tag{7.15}$$

The maximum amount of cash investors could take out of the informed investor has to be adjusted to

$$\tilde{M}_h(t) = D(t-1)p(t) + M(t-1)) - D_h(t-1)P_h(t-1) \quad , \tag{7.16}$$

for long positions and to

$$\tilde{M}_h(t) = D(t-1)p(t) + M(t-1)) + D_h(t-1)C_h(t-1) \tag{7.17}$$

for short selling. This again guarantees that obligations to banks are satisfied before demands of investors.

7.2.2 Limits on hedging costs

Banks set limits on hedging costs. These limits are determined by hedging costs under market conditions with reasonably low volatility σ^*, the current price of the asset, and the maximum leverage allowed by the bank. In case the borrower takes a long position we get

$$P_{\max}(t) = P(p(t), \sigma^*, \lambda_{\max}) \quad , \tag{7.18}$$

for a maximum put price and in case of short selling, we get

$$C_{\max}(t) = C(p(t), \sigma^*, \lambda_{\max}) \quad . \tag{7.19}$$

Consequently, the maximum leverage $\tilde{\lambda}_{\max}(t)$ is determined by solving the equation

$$C(p(t), \sigma(t), \lambda_{\max}^{\text{hedge}}(t)) = C_{\max}(t) \quad , \tag{7.20}$$

or by solving the equation

$$P(p(t), \sigma(t), \lambda_{\max}^{\text{hedge}}(t)) = P_{\max}(t) \quad , \tag{7.21}$$

respectively. To limit the maximum leverage with an upper bound the maximum leverage becomes

$$\tilde{\lambda}_{\max}(t) = \min\left[\lambda_{\max}, \lambda_{\max}^{\text{hedge}}(t)\right] \quad . \tag{7.22}$$

To adapt the model to limits on hedging costs, demand equation (7.5) is used with maximum leverage as in 7.22 instead of maximum leverage as in 7.3.

$\rho = 0.99$
$\sigma = 0.035$
$V = 1$
$N = 1 \times 10^9$
$\lambda_{\text{max}} = 1, 2, ..., 20$
$\beta_h = 5, 10, ..., 50$
$r_b = 0.005$
$a = 0.1$
$b = 0.15$
$W_0 = 2 \times 10^6$
$W_{\text{crit}} = 2 \times 10^5$
$T_{\text{reintro}} = 100$
$\tau = 10$
$\theta = 5$
$\sigma^* = \sigma/3$
$S = 0.0005$

Table 7.1: List of the parameters used in the model.

Chapter 8

Simulation results

In this chapter we discuss the results of the simulations of the extended model described in the previous chapter. Section 8.1 discusses returns and correlations in accordance with Thurner et al. (2009). Section 8.2 explains the results of three time series, the historical asset volatility, the informed investors wealth, and the cost of capital for the informed investors. Section 8.3 shows the simulated impacts of the regulatory measures on a number of indicators both for the performance of informed investors and for the market overall. As performance indicators of the informed investors are discussed, the average probability of default, cost of capital for the informed investors, the rate of return of informed investors and the informed investors management fees. By management fees we understand a 2% management fee and a 20% performance fee. As market indicators are shown: The standard deviation of log-returns as asset volatility and the respective excess kurtosis as a measure for market stability, average amount of shares traded per time step

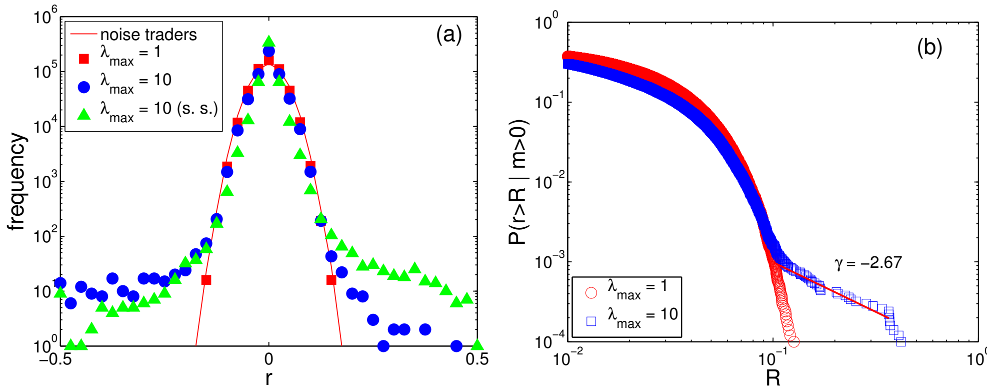

Figure 8.1: The distribution of log-returns r of the baseline model (with parameters from table 7.1). (a) Density of log-returns $p(r|m > 0)$ in semi-log scale. The unleveraged case (red squares) nearly matches the case with only noise traders' (red curve). When the maximum leverage is raised to ten (blue circles), the distribution becomes thinner but the negative returns develop fat tails. With short selling (demand equation (6.4)) the distribution becomes even thinner and the tails become heavy on both sides. (b) Cumulative distribution for negative returns, $P(r > R|m > 0)$, in log-log scale. For $\lambda_{\max} = 10$, a power law is fit in the indicated region, a line is shown for comparison.

by an informed investor as a measure for market liquidity and the amount of losses to banks or counterparties.

8.1 Returns and correlations

The statistical properties of price returns are considerably altered with increasing leverage.

Figure 8.1(a) shows the distribution of logarithmic price returns $r(t) = \log p(t) - \log p(t-1)$ for four cases: Noise traders only, informed investors with no leverage ($\lambda_{\max} = 1$), and with substantial leverage $\lambda_{\max} = 10$, with and without short selling. With noise traders only, the log-returns are almost normally distributed. With unleveraged informed investors, volatility is slightly reduced but log-returns remain nearly normally distributed. When leverage is increased to $\lambda_{\max} = 10$, and a short selling ban is in place, the distribution becomes thinner but the negative returns develop fat tails. The asymmetry arises because informed investors are, with a short selling ban in place, only active when the asset is underpriced, i.e. when the mispricing $m(t) > 0$. With short selling allowed, the distribution becomes again more concentrated in the center and develop fat tails on both sides. Due to higher risk involving short selling, the distribution becomes again slightly asymmetric. This higher short selling risk arises because of the different risk profile of long and short positions. The potential losses from long positions are limited, since the price can only go down to zero. This is not the case for short positions, where the loss potential, at least in theory, has no limit.

Figure 8.1(b) shows the cumulative distribution for negative returns for two cases: Informed investors with no leverage ($\lambda_{\max} = 1$) and with substantial leverage $\lambda_{\max} = 10$. The cumulative distribution for the largest negative returns approximately follows a straight line in a double logarithmic scale, suggesting that it is reasonable to fit the tails of the distribution as a power law, of the form $P(r > R|m > 0) \sim R^{-\gamma}$.

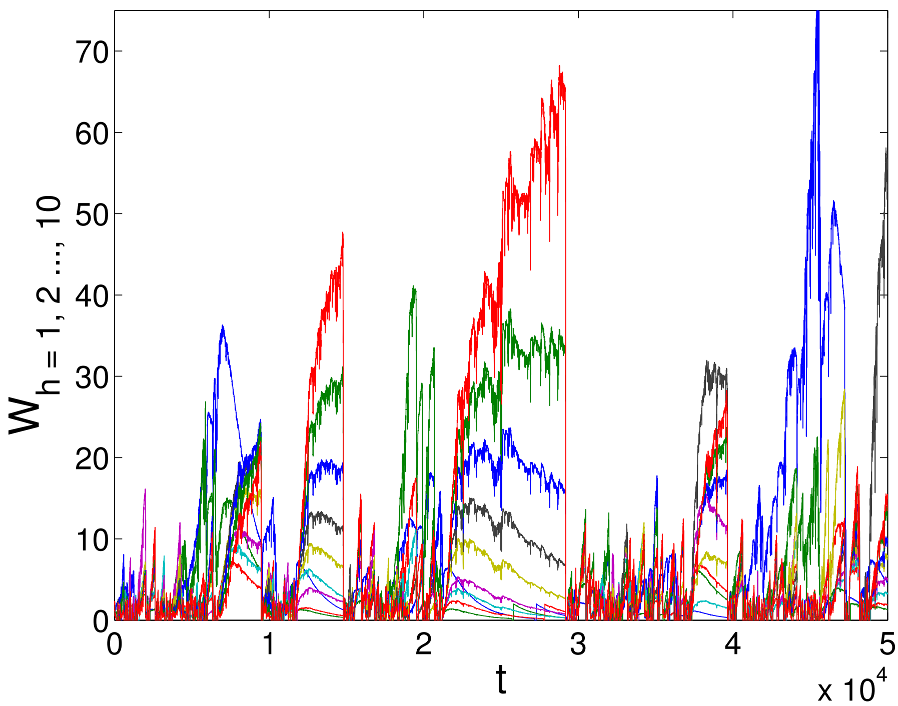

Figure 8.2: Wealth time series $W_h(t)$ for 10 informed investors with $\beta_h = 5, 10, \ldots, 50$, and $\lambda_{\max} = 15$ for all informed investors. The simulation was conducted for the perfect hedge scheme with demand equation (7.5), maximum leverage equation (7.22) and wealth equations as in (7.14) and (7.15). Simulation parameters are listed in table 7.1.

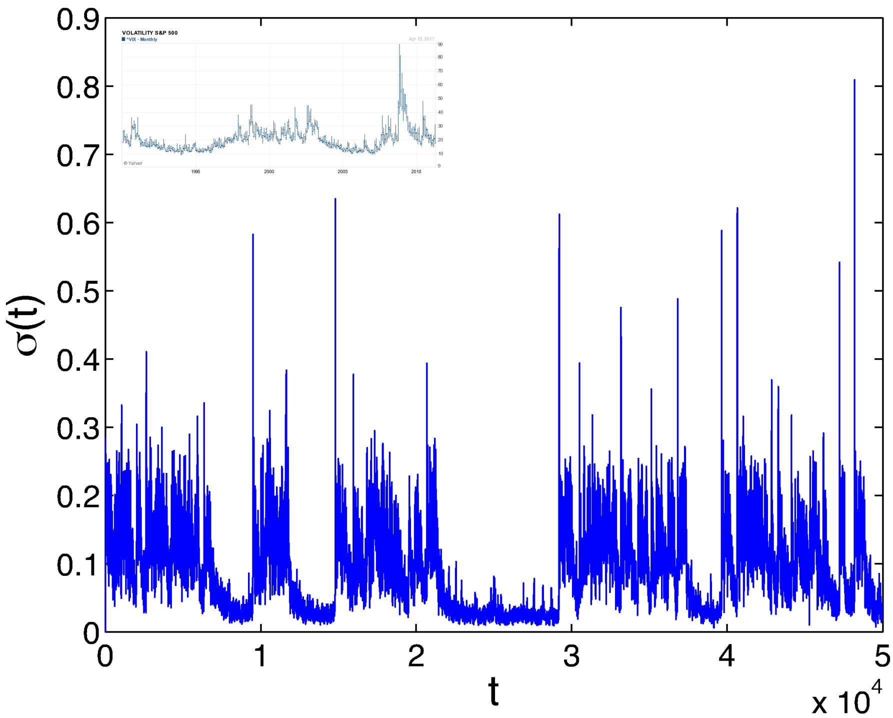

Figure 8.3: Annualized historical volatilities over 10 time steps for 10 informed investors with $\beta_h = 5, 10, \ldots, 50$, and $\lambda_{\max} = 15$ for all informed investors. The simulation was conducted for the perfect hedge scheme with demand equation (7.5), maximum leverage equation (7.22) and wealth equations as in (7.14) and (7.15). Simulation parameters are listed in table 7.1. To express in annualized terms it is assumed that one time step takes five days and a year has 250 trading days. The inlay shows the VIX (Chicago Board Options Exchange Market Volatility Index), a popular measure of the implied volatility of S&P 500 index options from 1990 to 2010.

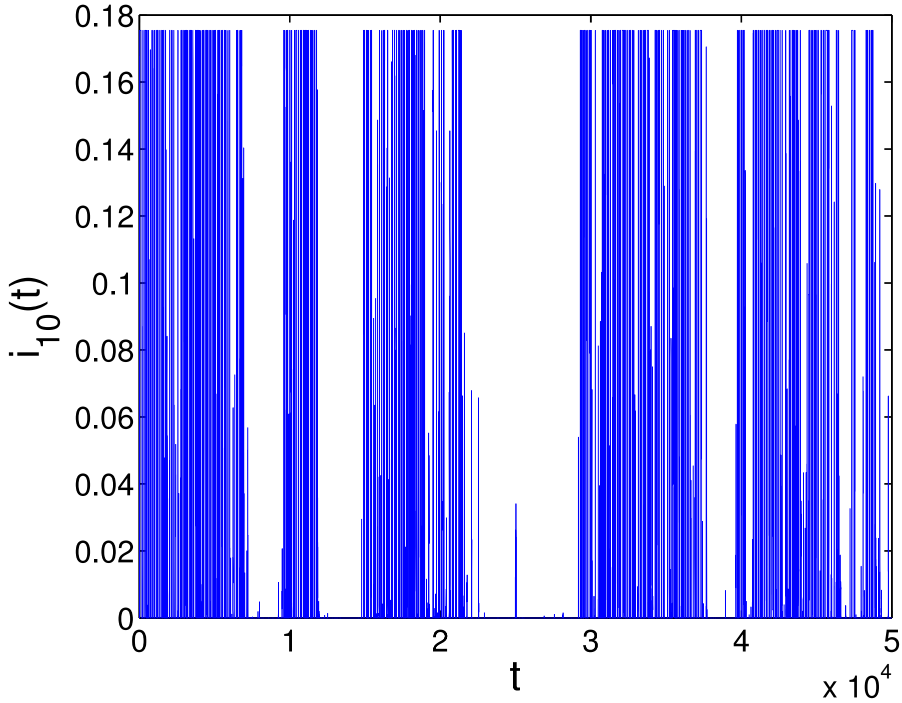

Figure 8.4: Series of annualized interest rates for the most aggressive informed investor with $\beta_h = 50$. The simulation was conducted with 10 informed investors with $\beta_h = 5, 10, \ldots, 50$, and $\lambda_{\max} = 15$ for all informed investors in the perfect hedge scheme with demand equation (7.5), maximum leverage equation (7.22) and wealth equations as in (7.14) and (7.15). Simulation parameters are listed in table 7.1. Interest rates are calculated as $i_h(t) = D_h(t)P_h(t)/M_h(t)$ in case the informed investor takes a long position, $i_h(t) = C_h(t)/p(t)$ if the informed investor is shorting, and $i_h(t) = 0$ if the informed investor is not borrowing. To express in annualized terms it is assumed that one time step takes five days and a year has 250 trading days.

8.2 Time series

All simulation results for the time series shown in figure 8.2, figure 8.3, and figure 8.4, were performed for the perfect hedge scheme with 10 informed investors with $\beta_h = 5, 10, \ldots, 50$ and a $\lambda_{\max} = 15$ for all informed investors. For the perfect hedge scheme we used demand equation (7.5), maximum leverage equation (7.22), and wealth equations as in (7.14) and (7.15). As parameters we used the values listed in table 7.1.

In figure 8.3 we show the time series of the annualized historical volatility of the underlying asset measured over a 10 time step period. Initially all informed investors have the same wealth $W_h(0) = 2$, as can be seen in figure 8.2 showing the wealth time series, and thus only a negligible influence on the market. In a market dominated by noise traders log-returns of the asset are close to being normally distributed with $\sigma = 0.035$ which results in a annualized volatility of $\sigma(t) \approx 0.175$. With volatility at this medium level, informed investors face higher borrowing costs from banks and thus take their time to gain a higher market share. After a period with volatility at medium level, informed investors manage to make higher returns and their wealth starts to grow. This is particularly true for the more aggressive informed investors as they are higher leveraged. As their wealth grows, informed investors have more impact, they themselves affect prices, driving them up when they are buying and down when they are selling or shorting. The stabilizing effect of the informed investors leads to a decrease in volatility with results in lower borrowing cost for the informed investors. Lower borrowing cost on the other hand allows them to use a higher leverage, which has a further stabilizing effect on the market resulting in even lower borrowing costs. This leads to a stable market condition with continuously low volatility and low borrowing costs for informed investors until an informed investor reaches a wealth at about $W = 70$ as can be seen best in figure 8.2, figure 8.3 and in figure 8.4 between $t = 20,000$ and $t = 30,000$. There are a series of crashes, which cause defaults, particularly for the higher leveraged informed investors. These crashes cause large price drops, up too 50%, resulting in volatility spikes. While informed investors waiting to get reintroduced, volatility level returns to a medium level being again mainly influenced by noise traders. With informed investors being reintroduced with initial wealth of $W_h(0) = 2$, the leverage cycle starts again. In case a crash wipes out all but the least aggressive informed investors, as happens around $t = 20,000$ and at about $t = 45,000$, most aggressive informed investors wait to get reintroduced, while lower leveraged informed investors manage to become dominant for extended periods of time.

8.3 Impacts

All computer simulations with the purpose to clarify the impacts of regulatory schemes were conducted for three cases: For the unregulated scheme, with discussed equations from section 6 with short selling (demand equation (6.4)). For the Basle scheme with demand equation (7.5) and wealth equations as in (7.6) and (7.7). And for the perfect hedge scheme we used demand equation (7.5), maximum leverage equation (7.22) and wealth equations as

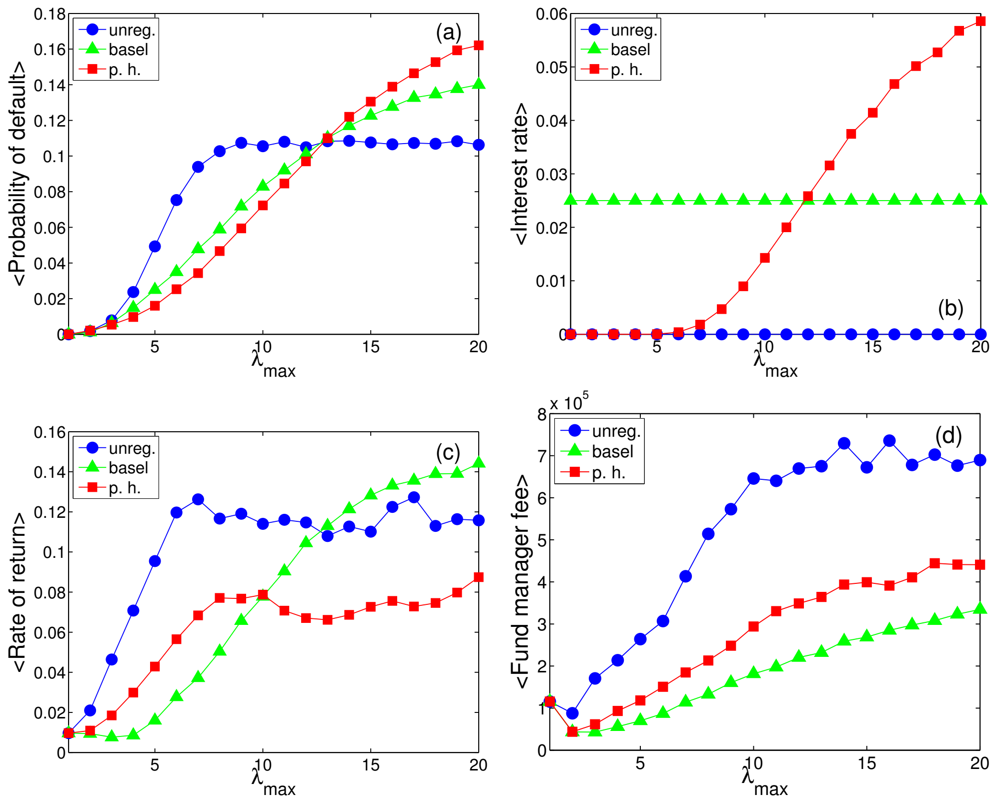

Figure 8.5: Impacts of regulatory measures on indicators for the most aggressive informed investor with with $\beta_h = 50$ as the maximum leverage varies. (a) Average annual probability of default. (b) Average annualized interest rate if the informed investor is borrowing from the bank. (c) Average annual rate of return if the informed investor is in business. (d) Average annual return to the informed investors management assuming a 2% management fee and a 20% performance fee. For all simulations we used 10 informed investors with $\beta_h = 5, 10, \ldots, 50$ over 5×10^5 time steps and the parameters listed in table 7.1. For all indicators it is assumed that one time step takes five days and a year has 250 trading days. The blue curves show the unregulated scheme with short selling (demand equation (6.4)). The green curves show the Basle scheme with varying maximum leverage according to equation (7.3). For the Basle scheme we used demand equation (7.5) and wealth equations as in (7.6) and (7.7). In the case of the red curves, banks hedge to offset risks from holding collateral. For the perfect hedge scheme we used demand equation (7.5), maximum leverage equation (7.22) and wealth equations as in (7.14) and (7.15). Simulation parameters are listed in table 7.1.

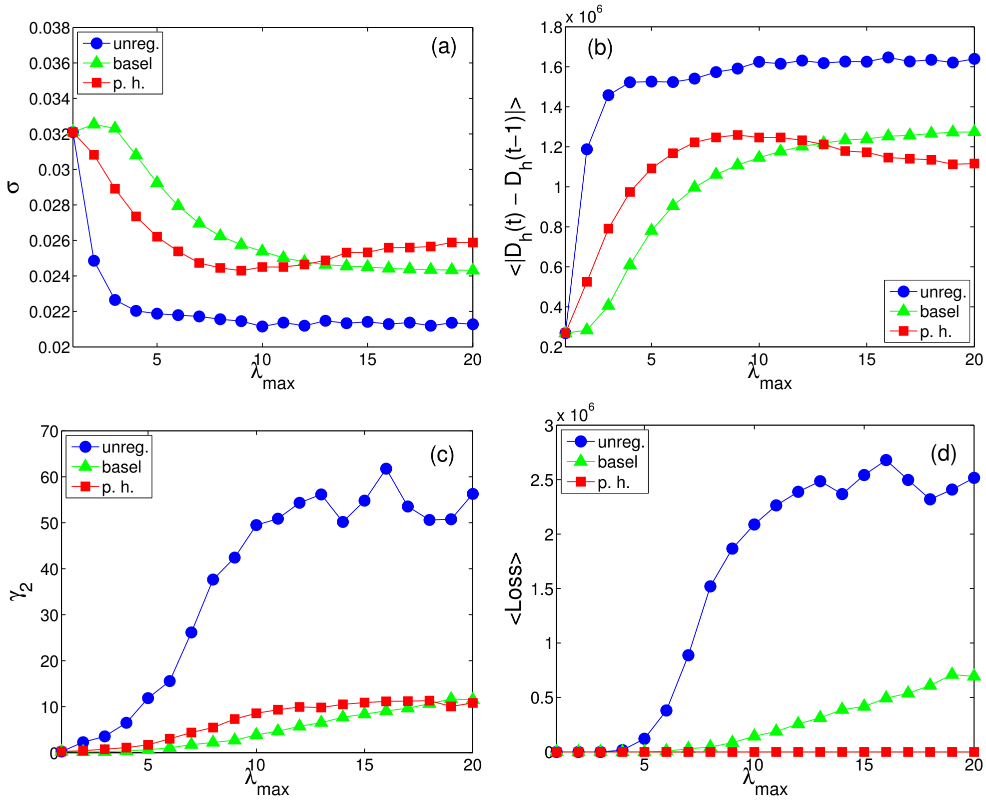

Figure 8.6: Impacts of regulatory measures on market indicators as the maximum leverage varies. (a) Volatility of the underlying asset. (b) Market liquidity of the underlying asset, measured by the average amount of shares traded by an informed investor per time step. (c) Market stability of the underlying asset, measured by excess kurtosis. (d) Annual losses to banks. For all simulations we used 10 informed investors with $\beta_h = 5, 10, \ldots, 50$ over 5×10^5 time steps and the parameters listed in table 7.1. For annual losses it is assumed that one time step takes five days and a year has 250 trading days. The blue curves show the unregulated scheme with short selling (demand equation (6.4)). The green curves show the Basle scheme with varying maximum leverage according to equation (7.3). For the Basle scheme we used demand equation (7.5) and wealth equations as in (7.6) and (7.7). In the case of the red curves banks hedge to offset risks from holding collateral as discussed above. For the perfect hedge scheme we used: Demand equation (7.5), maximum leverage equation (7.22) and wealth equations as in (7.14) and (7.15). Simulation parameters are listed in table 7.1.

in (7.14) and (7.15). For all simulations we used the parameters listed in table 7.1 and λ_{max} was varied from 1 to 20. For all indicators that are *annualized* it is assumed that one time step takes five days and a year has 250 trading days. As impact we understand the effect of regulatory measures on a number of indicators, both for the performance of informed investors and for the market overall.

Figure 8.5(a) shows the average annual probability of default for the most aggressive informed investor. In the unregulated scheme, without credit risk mitigation, probability of default reaches a maximum around a maximum leverage of 10, and stays at this high level plateau. In both cases, where banks use credit risk mitigation techniques, the situation for maximum leverage between 1 and 10 is significantly better but get's much worse above a maximum leverage of about 15. The perfect hedge scheme performs best for maximum leverage below 10, because banks restrict their lending policy more aggressive to an increase in volatility as can be seen in figure 7.1. Both the Basle scheme and the perfect hedge scheme show a higher probability of default than the unregulated case, because of the higher cost of capital for maximum leverage over 10.

Figure 8.5(b) shows the average annualized interest rate if the informed investor is borrowing from the bank. In the Basle scheme banks apply a minimal fixed credit spread around a benchmark interest rate to cover for unexpected losses. This results in higher cost of capital below a maximum leverage of about 12, in comparison to the perfect hedge scheme, where informed investors pay for the actual hedging costs of banks depending on leverage and volatility. In the Basle scheme banks overestimate the unexpected loss in case informed investors use low leverage and underestimate it, in case of higher leverage. Below a maximum leverage of 5 both the perfect hedge and the unregulated scheme (baseline model) have costs of capital close to zero.

Figure 8.5(c) and (d) show the average annual rate of return of the most aggressive informed investor and the average annual informed investors management fee in case the informed investor is in business. As expected, both figures show that the informed investors in the unregulated scheme have the best performance because costs of capital is zero. In the unregulated scheme the rate of return quickly reaches a maximum, around a maximum leverage of 7, and stays at this high level. Because of the management fee, which is proportional to the mean wealth of an informed investor, the informed investors management salary reaches it's maximum not below a maximum leverage of 10. Interestingly, in the Basle scheme the rate of return is lower compared to the unregulated and the perfect hedge scheme, below a maximum leverage of 10 and higher above a maximum leverage of 15. The informed investors management on the other hand would always prefer the unregulated or the perfect hedge scheme. The explanation for this is that the average returns for an informed investor are higher with lower wealth and market share of all informed investors. The performance fee in the Basle scheme does not compensate for the lower management fee because of the lower average wealth of the informed investor.

Figure 8.6(a) shows the asset volatility, figure 8.6(b) the market liquidity. The standard deviation of log-returns is used as a proxy for asset volatility and the average amount of shares traded per time step by an informed investor as a measure for market liquidity[1]. As expected, informed investors have the greatest impact on the volatility and the liquidity in the unregulated scheme, which allows for higher leverage on average. Interestingly, the impact of the informed investors in the unregulated scheme reaches it's maximum at a low maximum of leverage of around 4. At a maximum leverage of 2 it surpasses the impact of the regulated schemes. The large increase at a maximum leverage of 2 is due to short selling, which is not possible without leverage. Both ways to regulate the market significantly affect both volatility and liquidity. Informed investors in the perfect hedge scheme, with cost of capital for the informed investors reflecting the actually used leverage, have higher impact below a maximum leverage of 10 and a lower for higher maximum leverage than the Basle scheme. In the perfect hedge scheme the impact is, due to high cost of capital, decreasing with maximum leverage above 10.

Figure 8.6(c) shows the excess kurtosis of the log-returns as a measure for market stability. Again, as expected, informed investors in the unregulated scheme have the strongest stabilizing influence on the market. Interestingly, in figure 8.6(d), the average annualized unexpected losses to banks, clearly shows similar characteristics as shown in figure 8.6(c). As expected, banks, in the unregulated market, are affected of significantly higher losses due to the failure of informed investors. This similarity is due to the fact that large price fluctuations lead to losses for banks because the assets no longer cover the entire loan. In the perfect hedge scheme banks transfer the risk of

[1]See (Kerbl 2010): p. 12 for market liquidity.

unexpected losses to counterparties and do not have to cover for them.

Chapter 9

Concluding remarks

Econophysics is an interdisciplinary research area using methods from physics, in particular from statistical mechanics, in order to analyze problems in economics and finance. Agent-based models (ABM), which can be used to study complex systems, are an extension of the famous Ising model, a model of ferromagnetism in statistical mechanics. They are a class of computational models simulating actions and interactions of autonomous agents, which are employed to study their effects on the system as a whole. With ABMs gaining increasing popularity over the last two decades, they are about to become an accepted tool for the analysis of economic problems.

In the first part of this work, an overview of ABMs in finance and economics is presented, in particular different designs of artificial markets are discussed. In the second part an ABM is used as a toy model of the financial market to test the efficiency and dangers of credit regulation schemes.

The simulation results showed that Basle-type regulation works fine in situations of low leverage levels in the financial system, however they become destabilizing in scenarios with realistic leverage level. Furthermore an "ideal world", where all leverage introduced risk is hedged with options was designed. Even by assuming that option writers never default, it turned out that introducing the heavy requirement of complete hedging does not make the system systemically more secure.

List of Figures

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Zusammenfassung

Econophysics ist ein interdisziplinäres Forschungsgebiet, in dem Methoden aus der Physik, insbesondere aus der statistischen Mechanik, angewandt werden um Probleme im Finanzwesen und in der Ökonomie zu analysieren. Agenten-basierte Modelle (ABM), welche zur Untersuchung von komplexen Systemen verwendet werden können, sind eine Erweiterung des bekannten Ising-Modells, einem Modell des Ferromagnetismus in der statistischen Mechanik. Sie sind eine Klasse von Computermodellen zur Simulation von Aktionen und Interaktionen autonomer Agenten, die eingesetzt werden, um deren Auswirkungen auf das System als Ganzes zu studieren. Mit dem zunehmendem Gewinn an Popularität in den letzten zwei Jahrzehnten sind ABMs dabei, zu einem akzeptierten Instrument für die Analyse von wirtschaftlichen Problemen zu werden.

Im ersten Teil dieser Arbeit wird ein Überblick über ABMs im Finanzwesen und in der Ökonomie gegeben, insbesondere werden verschiedene Designs künstlicher Märkte diskutiert. Im zweiten Teil wird ein ABM als Spielzeug-Modell des Finanzmarktes genutzt, um die Effizienz und die Gefahren von Bankenregulierungssystemen für das Kreditwesen zu testen.

Die Simulationsergebnisse zeigen, dass die Basel-Regulierungsvorschriften gut in Situationen mit geringem *leverage* im Finanzsystem funktionieren. In Szenarien mit einem realistischeren *leverage level* haben sie aber destabilisierende Auswirkungen. Auerdem wurde eine “ideale Welt”, wo alle durch *leverage* hervorgerufenen Risiken mit Optionen abgesichert werden, entwickelt. Selbst unter der Annahme, dass Optionsaussteller nie zahlungsunfähig werden, stellte sich heraus, dass durch die Einführung einer vollständigen Absicherung das System nicht systemisch sicherer wird.

Curriculum Vitae

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