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"Systemic financial risk: agent based models to understand the leverage cycle on national scales and its consequences"

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ABSTRACT

Dr. Stefan Thurner's report analyses the development, buildup and unfolding of financial market crashes using a dynamic agent based model. The model simulates relevant conditions under which agents behave in financial markets and allows one to see how excessive leverage (the use of credit for speculative investments) is a prime source of vulnerability and can act as the catalyst for a crash. The model demonstrates how crashes result as a consequence of synchronization effects of the different actors in financial markets. The report concludes with recommendations, most notably the need for radical improvements in the transparency of creditor- debtor relationships between financial market participants, which would reduce the chance of synchronization.

What is at stake in a financial crisis?

This report analyses the results of simulations using an agent based model of financial markets to show how excessive levels of leverage in financial markets can lead to a systemic crash. In this scenario, plummeting asset prices render banks unable or unwilling to provide credit as they fear they might be unable to cover their own liabilities due to potential loan defaults. Whether an overleveraged borrower is a sovereign nation or major financial institution, recent history illustrates how defaults carry the risk of contagion in a globally interconnected economy. The resulting slowdown of investment in the real economy impacts actors at all levels, from small businesses to homebuyers. Bankruptcies lead to job losses and a drop in aggregate demand, leading to more businesses and individuals being unable to repay their loans, reinforcing a downward spiral that can trigger a recession, depression or bring about stagflation in the real economy. This can have a devastating impact not only on economic propserity across the board, but also consumer sentiment and trust in the ability of the system to generate long-term wealth and growth.

To do something about crises you need to understand them

There is no global consensus on how best to manage or prevent financial crises from happening in the future. Nonetheless, policymakers need to develop strategies that are designed to at least reduce the severity of their impacts. In order to stregthen the financial system, making it more resilient to potential abuses in the future, it is critical that we understand the mechanism by which pervasive practice like

excessive leverage can present system-wide danger. Unlike forest fires or other sudden-onset natural disasters, financial markets are complex social systems, built on the repeated interaction of millions of people and institutions, and are subject to systemic failure,currency crises, bank runs, stock market collapses, being just a few of the terms indicative of the recent fallout. Often, this risk arises not through the failure of individual components in the system, such as the closing or collapse of a single bank or major financial institutions, but rather due to the "herd behavior" and network effects contained in the actions of large fractions of market participants. Such synchronization in behavior leads to many people underaking the same actions simultaneously, which can exacerbate price movements and the overall level of volatility in the system. This can significantly weaken a well-functioning financial market, potentially causing the booms, busts, and bankruptcies that are now familiar.

The need for Agent Based Models (ABM)

Recent experience has called into question the previously widely-accepted belief that the economy traveled on a steady-state growth path, with minor flucuations above and below a stable growth rate. The global financial crisis has led many to suggest that the booms and busts that have characterized our global economy over the past two decades may be the norm rather than the exception. As a result, the traditional general equilibrium models, which have guided our economic thinking are increasingly suspect. These models prove vulnerable to the herd behavior, information assymetries, and externalities that may quickly catapult minor fluctuations into widespread market failure. Systemic risk factors like those embedded in cases of high leverage, such as synchronization effects, strong price correlations, and network effects are of great concern to investors, and should concern policymakers when attempting to re-design policies capable of avoiding future disasters. The approach of many financial institutions, politicians, and investors to risk management in the industry has been built upon such traditional equilibrium concepts, which have been proven to fail spectacularly when most needed.

Among the most promising approaches to understanding systemic risk in complex systems are agent based models (ABM), a class of models used to explain certain phenomena via a bottom-up approach which, contrary to general equilibrium theory, does not require a steady state, but rather structures interactions between non-representative agents via a set of behavior rules. This report demonstrates that ABM offer a way to systematically understand the complicated dynamics of financial markets, including the potential for downward spirals to be generated by the synchronised actions of economic actors. In particular, the report shows that ABM could explicity describe the peculiar danger of using leverage to fund speculative investments. It also demonstrates how levels of leverage in the system are directly linked to the probability of large scale crashes and collapse, such that price volatility rises with leverage and even minor external events can trigger major systemic collapses in these environments. It suggest the importance of understanding the endogenous social dynamics of traditionally "financial" arena in order to more fully grasp the systemic risk for which gradual improvements in traditional economics cannot yet account.

Agent Based Models

To better approximate real-world outcomes with stylized models, ABM run repeated simulations, generating data whether there currently is too little for meaningful analysis, allowing agents to change their

behavior based on interactions with other agents, leading to a host of important findings. By running and analysing millions of simulations, each approximating millions of potential interactions between actors, insight is gained into the collective outcome of the system. This can be further analyzed by changing the decision rules affecting those interactions and even applying different regulatory measures to gauge their potential effects. Applied to the financial system, this process reveals how the likelihood of default among investment funds depends heavily on these regulations, specifically a maximum permissible leverage level. Similarly, the analysis also shows how banking regulations such as the Basel accords can influence default rates. The models demonstrate that such regulatory measures can, under certain circumstances, lead to adverse effects, which would be hard to foresee otherwise. These simulations also allow the possibility to follow the progress of a new regime installed after a shockoccurs, and analyze its effect on recovery rates, typical wealth re-distributions, etc.

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.

Mechanics of ABM for the Financial Market

The model includes several different types of "agents" or economic actors whose interactions result in the economic activity being modelled. These actors include investors, banks, investment companies, and regulators, among others. One of the hallmarks of ABM in general is the use of non-representative agents. In other words, these agents will differ in several key respects, including their tolerance for risk, size of endowment, and their general investment strategy. These differences weigh on the interactions between the agents producing the types of outcomes that have macro-effects.

In this model, there are three basic types of investors: informed investors, uninformed investors, and investors in investment management companies. Informed investors (e.g. hedge funds) do research to guide their investment decisions and typically try to discover assets that are under- or overpriced by the market to take advantage of arbitrage opportunities. Intuitively, uninformed investors do not carry out any analysis to discover the "true" price of an asset, but rather, for the sake of argument, place essentially random orders. The third type of investor places his or her funds in investment companies that then invest the money in financial markets. These investors monitor the performance of the company and adjust their strategy based on this performance relative to their alternatives. These investors all "compete" in the same market; their relative shares depend on their relative performance. Banks and regulators play a different role in this model. Banks provide the liquidity, providing credit that allows investors to build leverage. Regulators present the constraints which restrict the extent of leverage allowable.

In this model market, the different types of investors are buying and selling a single asset, which pays no dividends for the purpose of simplicity. Both uninformed investors and informed investors compute their respective demands for the asset (i.e. how many shares they would like to purchase). The difference lies in the method. The uninformed traders are relatively unsophisticated, while informed traders attempt to determine a "mispricing signal", namely by how much the asset is under-valued or overvalued by the marketplace (i.e. how big is the opportunity for arbitrage). Investors survey the performance of each fund and invest or withdraw money from these funds accordingly. Meanwhile, banks and the regulatory

constraints set the maximum levels of leverage available to traders. This process continues and firms whose wealth falls below a certain level fold and are quickly replaced. With an ABM, this process is repeated many times over.

How Does a Crash Occur?

In scenarios of high leverage, investors can overload on risky assets, betting more than what they actually have to gamble. Although this is an obviously dangerous practice, it also creates a tremendous level of vulnerability in the system as a whole. Two events in particular can lead to a devastating collapse of a system under the weight of significant levels of leverage:

1. Small, random fluctuations in the demand of an asset by uninformed investors can cause the asset price to fall below its "true value", leading to the development of a "mispricing signal".

2. In order to exploit this opportunity for arbitrage, the investment funds capitalize on the high allowable leverage levels to take massive positions.

This combination is essentially a potential recipe for disaster. If the uninformed or "noise" traders happen to sell off a bit of this asset and the price drops further, the funds stand to lose large amounts of money. This prompts the firms to take even greater amounts of leverage, while other firms are even forced to begin selling off more of the asset to satisfy their margin requirements. Naturally, this will have the effect of further depressing the price, resulting in a vicious cycle of price drops, greater leverage, and more enforced selling of the asset (margin calls). Over a short period of time, what seemed like a stable system can cascade into a scenario in which the asset price crashes, causing major losses and bankruptcies by highly leveraged firms. Importantly, only in systems characterized by high levels of leverage can such small changes trigger such catastrophic collapses.

Main findings

Repeated observations resulting from millions of controlled simulations, varying key parameters along the way, lead to several key findings.

1. In an unregulated world there are market pressures leading to higher leverage levels, i.e. there are incentives for both investors and banks to increase leverage.

2. There exist counterintuitive effects of regulation: implementing different regulation scenarios, such as the Basel accords, are demonstrated to work well in times of moderate leverage, but deepen crisis when leverage levels are high. This is due to enhanced synchronization effects induced by the regulations.

3. The actions and relative performance of different market participants influences the actions of others, creating an ecology of market participants, which has effects on asset prices. These

mutual influences cause fluctuations which are observed in reality, but are ignored in traditional economics settings.

4. Volatility amplification: even value-investing strategies, which are supposed to be stabilizing in general, can massively increase the probability of systemic crashes given that leverage in the system is high.

5. While high levels of leverage are directly correlated with the risk of major systemic draw-downs, moderate levels of leverage can have stabilizing effects.

6. Dynamics of crashes: by studying the unfolding of crashes over time, triggers can be identified. Small random events, which are completely harmless in situations of moderate leverage can become the triggers for downward spirals of asset prices during times of massive leverage.

Main conclusions

The findings have several potential ramifications for public policy and the re-organization of the financial system into a more resilient and more stable generator of long-term wealth for society:

1. Global monitoring of leverage levels at the institutional level is needed and could be performed by central banks. This data should be made more accessible for research, perhaps with a time delay. Without this knowledge, the practice of imposing and executing maximum leverage levels is less effective.

2. Continuous monitoring and analysis of lending/borrowing networks is needed, both of major financial players and of governments. Exactly who holds whose debt should be made known to the public, and not just the financial institutions involved. Without this surveillance, imposing meaningful and credible maximum leverage levels is difficult to implement.

3. Imposition of maximum leverage levels should depend on debt structure, trading strategies and relative positions in lending/borrowing networks. It is clear that government regulation can play an important role in controlling portfolio risk levels by limiting leverage. Yet, this is no trivial undertaking as fully analyzing the trend-following strategies of investors would be very difficult due to the sheer variety of market participants and instruments currently being traded, particularly under today's disclosure standards. There may be more scope in providing more regulatory guidance to banks on disclosing their leverage allowances to certain types of investors.

Inherent limits of ABM

Agent based models are undoubtedly useful tools in engineering a unique approach to understanding complex, dynamic systems. Yet, there are shortcomings to this approach, ranging from the high degree of technical expertise necessary to issues of data, quality standards, validation, qualitative understanding.

1. Data requirements: ABMs help to identify relevant data. Usually this data is not readily available in the required form. Data is needed often in the form of networks, such as asset/liability networks, and those of ownership and financial flows, etc.

2. Quality standards: the sheer number of parameters usually necessary for robust results makes ABM opaque. It can be hard to judge whether:

    a. Unrealistic ad-hoc assumptions were made that could lead to unrealistic effects
    b. Parameters are introduced that are inaccessible in reality
    c. Initial conditions for computer simulations are actually realistic

1. Linking to reality: ABMs presently help to understand systemic properties qualitatively. To make them quantitatively useful ABMs must be scaled with real data. This requires tremendous joint

efforts in scientific research, data generation, and institutional cooperation. Unless these efforts are undertaken, ABMs will remain largely descriptive.

2. Validation: ABMs should not be expected to make actual predictions of financial crashes or collapse. Using massive computer simulations, ABMs may help to clarify levels of risk under given circumstances. They may illustrate relevant mechanisms that represent legitimate precursors to a crash that could otherwise go undetected.

Recommended research directions

ABMs have been helpful in achieving a qualitative understanding of financial system dynamics and unexpected systemic effects, as well as spotting lurking dangers within the regulatory framework or lack thereof within a system. To take advantage of the full potential of ABMs (i.e. to make them effective tools for assisting actual decision-making processes) it is necessary to scale them up and combine them with real data. This implies a significant coordinated scientific effort, both in econometric modelling and the generation and collection of quality data. Some of the tangible steps that must be undertaken include:

1. Data collection, storage, quality and availability: massive efforts should be undertaken in economic data collection, under strict quality requirements which then remain available for analysis by a large scientific community.

2. Network studies in economics: much of the systemic effects in economics have their origin in networks linking agents. These networks are largely left unexplored, but they are an essential input for modelling dynamic systems. Networks need to be analyzed according to the standards of network theory, which have been developed over the past decade.

3. Simulation platforms of financial regulation: consequences of exogenous events such as 'changes of rules' or disclosure requirements are only the beginning in the development of a systematic understanding. This field of research should be significantly boosted.

4. Linking to the real economy: ABMs of the financial markets should be paired with ABMs of other aspects of the real economy, to understand their mutual influences and feedback loops. Critical points of interface between financial markets and the real economy can be identified as potential avenues for beneficial regulation.

1 INTRODUCTION

1.1 What is leverage?

Leverage on the personal scale, in the financial markets and on a national scale - has contributed much - if not most - to the financial crisis 2008-2010, for scientific literature, see [1, 2, 3, 4]. Leverage is generally referred to as using credit to supplement speculative investments. It is usually used in the context of financial markets, however the concept of leverage covers a range of scales from personal life, such as buying a home on credit, to governments issuing public debt. Leverage - in the sense of making speculative investments on credit - is used in a wide variety of situations. It can be used for realizing ideas with credit, start up a company, finance a freeway or job-less programs, etc. The outcome of these investments is in general not predictable, they are speculative. The price of the home changes according to trends in the housing market, a new company can fail, and a freeway might not deliver the economic stimulus which was initially anticipated. No matter of how these investments pay off, the associated debt has to be re-paid, in form of principle and interest. In principle the risk associated with leverage is the risk of unrecoverable credits. This by itself is a trivial observation. The nontrivial aspects of leverage arise through its potential to cause, amplify and trigger *systemic effects*, which can turn into extreme events with severe implications on e.g. the world-wide economy. Leverage introduces 'interactions' between market participants which - under certain circumstances - can become strong, so that the system starts to synchronize. Synchronized dynamics can lead to large-scale effects. The risk associated with a potential downturn dynamics is the *systemic risk* of collapse. This makes the issue of leveraged investments a typical complex systems problem, which can not be treated with the traditional tools of mainstream economics.

The term “financial leverage” is however mostly used in the context of corporations, financial firms and financial markets. There it is mostly associated with the assets of a firm which are financed with debt instead of equity. One of the important motivations for this is that returns can be potentially amplified. Imagine a hedge fund with an endowment of 100 $ makes investments which yield an annual return of 10 %, i.e. 10$. The wealth of the fund is now 110$. Imagine now a scenario with leverage: the fund approaches a bank, and asks for a credit of 900$ at a rate of 5% p.a. It then makes the same investments with 1000$. At the end of the year the fund earned 100$, i.e. it now manages 1200$. It pays back the 900$ to the bank plus 45$ of interest. The wealth of the fund is now 255$ - it grew by a factor of 255 %. The situation looks less brilliant if in case of the leveraged scenario the investments would turn out to be -10 %. At the end of the year the fund would manage 900$, it would pay back the 900$ but could not service the interest, the fund is bankrupt, the bank has to write off the loss of 45$.

For notation purposes, let us discuss some widely used measures and notions of financial leverage. Measures of leverage:

- *Debt to equity ratio* This is the ratio of the liabilities (of e.g. a company) with respect to its (e.g. the shareholders') equity. In our example above, the debt to equity ratio would be $\frac{900}{100} = 9$. Another frequently used measure is the Debt to value ratio, relating the total debt to the total assets. Total assets are composed of equity and debt.

- *Assets to equity ratio* This is referred to as the leverage level which is denoted by λ.

$$leverage = \lambda = \frac{Assets}{Equity} \quad .$$

This definition IS USED in all of the following. Talking about values of portfolios and cash positions the same definition reads

$$\lambda = \frac{portfolio\,value}{portfolio\,value + cash} \quad .$$

In this notation it is always assumed that the cash reserves of an investor will always be used up for the investment first. Only when these reserves are used up, the investor searches for credit. In the above notation credit is seen as a negative cash position (loan). In the above example the leverage of the fund is $\lambda = \frac{1000}{100} = \frac{1000}{1000-900} = 10$. As another example consider a homeowner taking out a loan using say a house as collateral. If the house costs $100 and he borrows $80 and pays $20 in cash, the margin (haircut) is 20%, and the loan to value is $80/$100 = $80%. The leverage is the reciprocal of the margin, namely the ratio of the asset value to the cash needed to purchase it, or $\lambda = 100/20 = 5$. Or in the other notation $\lambda = \frac{100}{100-80} = 5$.

• *Debt to GDP ratio* In macroeconomics on national scales, a key measure of leverage is the (sovereign) debt to GDP ratio.

• *Construction leverage* Leverage that is obtained through specific combinations of underlyings and derivatives [9].

• *De-levering* is the act or sum of acts to reduce borrowings.

It is noteworthy that taking leverage can be associated to a moral hazard problem: Managers can leverage to increase stock returns of their companies which amplifies gains (and losses) which are related e.g. to their bonuses. Gains in stock are often rewarded regardless of method [10].

1.2 The danger of leverage

If you speculate with more than you own, you can lose more than you have

Without leverage, by speculative investments one can lose all one has, the maximum loss is 100%. The danger of leverage is that one can lose more than this. This leads to a loss which can drive the debtor out of business. Under normal conditions this loss is then taken (realized or paid) by someone, the creditor. In case the creditor becomes illiquid as a consequence of this loss, it is passed on. Often to some other institution or the public.

This risk of generating losses exceeding the wealth of the debtor originates traditionally from the following fact: credit for speculative investments (leverage) requires collateral. This collateral is often given in the form of the acquired investments. For example if a hedge fund uses leverage from a bank to buy stocks, these stocks are held by the bank as the collateral for the credit. Or if a homeowner buys a home with a mortgage, his bank will usually (co-)own the home as collateral. Imagine the homeowner buys a home with a value today at 100$. He finances it with a down payment of 10%. He owes the bank 90 $, his wealth in form of the house is 10$. Suppose the housing market goes bad and within a year the value of the house falls to 80$. His wealth is now $-10$$, and declares bankruptcy. The bank takes the loss by selling the house for 80$ and by writing off the 10$ of credit as not recoverable. As a note on the side, a classical story during the last decade was worse. It could have been the following. A homeowner buys a home with a value at 100$ under the same conditions as above. The value constantly goes up, say to 150$

within several years. He thinks real estate is a good investment. His wealth is now 60$ and he decides to buy a bigger home with these 60$ as a 10% down payment. He sells the old house and takes 540$ credit for the new one. The bank is perfectly willing to do the deal. The same price drop happens as before, the value of the house drops from 600 to 480$. The bank becomes nervous and asks the credit back, the homeowner sells the house for 480$ and owes the bank 120$, more than the cost at high time of his first house! He files for bankruptcy. The bank takes the loss.

The example shows an important aspect to bear in mind for later consideration: during boom times, e.g. a housing bubble, credit is easy to obtain. Prolonged growth and increase in value of collateral is tacitly assumed. Credit is provided - credit providers participate in the boom. In times of crisis as nervousness increases, leverage tightens and as a consequence of de-levering losses are realized. During boom times the sustainable value of collateral can be strongly distorted. Its combination with leverage becomes especially dangerous.

1.2.1 The role of leverage in normal times

Let us now focus on leverage take by financial institutions, such as hedge funds, insurances, investment banks etc. Usually leverage is used for professional, expert investments by informed investors. By informed investors is meant actors whose investments follow a period of research on financial assets. For example a value investing hedge fund finds out through research that a given company has better prospects than the financial assumes. The fund determines the (subjective) 'true' value of the company. If this value is higher than the observed market price, the fund will try to go long in the assets of the firm until the financial market as a whole prices the assets correctly. The fund will profit from the increase of asset price, and - if it was a rational fund - would sell the assets as the market price hits the 'true' value. In this case the research invested in estimating the true value better than the others will result in profit for the fund.

Note here that the value investing fund performs a price stabilizing role, which can be seen a service to financial markets. As it goes long in under-priced assets and short (if it can) in over-priced ones, due to its demand it drives the price of the asset toward its 'true' value. Note further that the 'true' value is a subjective estimate of investors. It can be wrong. It not only depends on the objective status of the company under investigation, but also on the behaviour of the collective of the other investors in the same asset. There are of course situations, when the collective of investors does not price the asset correctly over a longer time scale. An example when this is not the case is when a bubble is present. It can be that a burst of the bubble will eventually bring the price of a firm to its 'true' value, but the time scale can be too long to make profits for the fund. Even by finding the correct (absolute) 'true' value the fund can make losses. It is essential to also get the reaction time (time-scale) of the other market participants right. It is characteristic for times of crisis (panic) that these time-scales become short, and dynamics becomes synchronized.

This price stabilizing role of value investing investors is a service to markets in general since it reduces volatility of asset prices. Value investors reduce volatility. However, reduced volatility is not necessarily a sign of efficient markets. There is danger to the view that low levels of volatility indicate a functioning market its management and its regulation. This has been a fundamental misconception, which was famously declared by A. Greenspan [11].

It is well known that other investment strategies, such as trend following can have a price destabilizing effect. Trend followers reinforce price movements in any direction, leading eventual price corrections to overshoot. Trend followers play a role in bubble formation in financial markets. They are self-reinforcing: detecting an upward trend generates demand in trend followers, leading to increase of price, which reinforces the trend. The same is true for downward trends. For institutions interested in

moderate levels of volatility (such as regulators, governments, real sector) it would be natural to consider options to limit trend followers. A handle for this would be to impose maximum leverage levels for trend following strategies. Finding standards for controlling trend following strategies of investors would be hard to obtain under today's circumstances. However, one could think of disclosure procedures for banks when they act as leverage providers to trend followers. Quantification could happen by imposing disclosure of investment portfolios, and performance on a relatively short timescale.

Knowledge of stabilizing versus destabilizing forces would be essential information for regulators

To estimate the contribution of price stabilizing forces from value investors versus the destabilizing ones from trend followers, it would be essential to know the fraction at a given point in time of the demand generated by the respective groups. However, the fraction of value investors to trend followers is hard - maybe impossible - to find out without further disclosure requirements for (large) investors or leverage providers. At this point agent based models could become of great importance. The fraction of demand of value investors to trend followers is not constant, but depends on the performance of the two groups. If trend following is a good strategy at a time, it will attract more trend followers, and vice versa. This affects not only the asset prices but the relative fractions. Price and group sizes are co-evolving quantities, influencing each other. Agent based models are ideal to treat problems of this kind.

In such models, see e.g. [12], populations of value- and trend following investors can be simulated in computer 'experiments'. Investors can switch between value investing and trend following (and other strategies). These agents submit demand functions at various time-scales, a mechanism of e.g. market clearing leads to a unique (simulated) asset price. Given the demand functions of funds and the price at all times allows to compute the performance of the funds. Funds of one type who perform bad with respect to the other type will eventually switch strategies. In this way one obtains fluctuating group sizes of value- and trend following agents. Their fraction can be compared with volatility patterns in the price. The influence of exogenous interventions such as limits of leverage to one group or both can be systematically studied. This field of research pioneered by J.D. Farmer et al., see e.g. [12] should be significantly boosted and sponsored.

1.2.2 The role of leverage in times of crisis

We continue the following discussion for leverage-taking value investors in financial markets. The same basic structure holds true for leverage in e.g. the housing markets, or on national levels. The situation for trend following investors is less interesting since they are mostly price destabilizing. By looking at value investors one investigates 'the best of possible worlds'. A fraction of trend following investors will make the situation worse. Here one looks at an idealized 'optimistic' scenario to identify the fundamental dangers.

Imagine a leverage-taking value investor. The leverage provider (e.g. a bank) allows a range of credit, caped by a maximum level of credit, say a maximum leverage of 5. If the fund finds no under priced assets on the market, its demand is zero, it will not be long in any asset. As soon as it finds under priced assets it will buy and hold them, until they approach their 'true' value. The actual demand in that asset depends generally on two aspects: First, how big is the mispricing. The more the distance of the observed market price from the 'true value', the larger is the demand in the asset - given the fund is behaving rationally. Note that this is an optimistic assumption - certainly very often massively violated by numerous investors. Second, how much does the investor 'believe' the 'true value'. If it believes strongly that he computed or assessed the mispricing correctly, it will increase its demand strongly with every unit of mispricing. This is termed an 'aggressive' investor. If he is not so sure about the correctness of the mispricing, she will not increase her demand as rapidly, she is a 'moderate' investor.

Now assume that an investor finds an investment opportunity e.g. she detects an under priced asset. Given her level of aggression, she first invests a fraction of her wealth in the opportunity. Assume the mispricing gets bigger (price falls). The investor takes bigger and bigger positions in the asset (now making losses!). As all her funds are used up for these positions, the investor approaches a bank for credit, and keeps leveraging, until the demand is satisfied, or until no more credit is available. This happens in this example at a leverage level of 5. If the price goes up, the investor makes profit under leverage. If the price continues to go down, the bank will now ensure that the maximum leverage level is not exceeded. It will start recalling its credit. This is called a *margin call*. At her maximally allowed leverage level, the investor is now forced to sell assets on the market to maintain the maximum level of leverage. The investor reduces its demand, even though its investment strategy would suggest to increase it. Selling assets tend to drive the price down. If the investor holds a significant fraction of the asset, this price drop can turn out to be self-reinforcing (selling into a falling market), and it can be forced to sell off assets again to keep the maximally allowed leverage.

A single fund is however unrealistic altogether. To come toward a systemic understanding of the danger of leverage, let us look at an example slightly more complicated: assume 2 funds, one aggressive, one moderate. Both have detected a mispriced asset, and hold long positions. The aggressive fund has reached its maximum leverage level 5. The price drops slightly due to some external effects. The aggressive fund now has to sell, kicking the price down a little too. This drop in price lowers the value of the portfolio of the moderate fund, and - at same credit volume with its bank - experiences its leverage going up. Assume the price change to be so big, that the moderate fund now reaches its credit limit. It therefore has to sell off assets into the falling market too.

It is clear how this can lead to cascading effects to all leveraged investors who are invested in the same asset. However, these effects are of course not limited to the same asset. There are spill over effects. Assume the example as above. The aggressive fund, if it is invested in more than one asset, has the choice to sell other assets in its portfolio. If it has to sell off at massive rates, the sold assets will drop. Funds invested in these assets might then be forces to shrink their portfolios. The same cascading effect takes place as above, but now involving many assets. Note, that these assets might be otherwise completely unrelated. Even if the assets would usually tend to show no correlations (even anticorrelations in returns), as a result of the cascading deleveraging and spill over effects, their correlations in (negative) returns will become positive, possibly large. Cointegration emerges, a systemic scenario unfolds.

Let us continue the example on a systemic. During the selling into falling markets, a sufficiently leveraged fund can face illiquidity quickly. Its default and bankruptcy can create losses for the bank since it will in general not get the extended credit back entirely. Note that the collateral for the credit the banks often holds has the assets in its possession. The credit that can get paid back is e.g. generated through the selling of these assets. The loss is usually taken by the bank. If these losses become severe, either because the bank has extended leverage to a variety of funds (who now all perform badly), or because the bank itself (as a 'hedge fund of its own') has made investments in now falling assets, banks themselves can - and will - get under stress and default.

Naturally banks are connected through mutual credit relations. These asset and liability 'networks' are extremely dense, and can contribute a further layer of systemic risk [13, 14]. These networks have been empirically studied for an entire economy in [15, 17, 16, 18, 19, 20]. It was found that they typically display a scale-free organization and are consequently highly vulnerable against the shortfall of one of the 'hubs', i.e. the big players. Realistic networks of these kinds have been used to simulate contagion effects and contagion dynamics through these banking networks [17]. It was shown that the most sensible measure which correlated to the systemic danger of an individual bank within the system, is the betweenness centrality of the bank [21]. Banks with high betweenness centrality can bring down the entire banking system - due to consecutive situations of illiquidity in the system - given there are no interventions. We

refrain from commenting on effects of the real economy under collapse of the financial system. Due to the importance of the matter, academic research has to be boosted in this direction.

Systemic effects of the network of leverage providers - and banks need to be better understood

1.2.3 Insurance of risks to leveraged investments

The objective of the following two suggestions for mandatory leveraged investment hedges is to force the default risk onto financial markets, and to avoid the present situation that effectively the public sector has to serve as the ultimate risk taker for leveraged financial speculations.

In theory potential losses of leverage providers can be hedged (insured). Again sticking to the scenario of financial markets. There are two ways of strategies for hedging. One is insuring the collateral, the other insures the credit. Within the current financial framework both ways are possible in principle but suffer severe problems which make them questionable in practice. In particular these safety measures are costly. Effectively investors would either have to pay higher interest rates for leverage to the leverage provider - who will roll over its hedging costs to the investors, or will directly pay the premiums for credit default swaps. This implies that leverage becomes effectively less attractive for both sides: the provider has the burden of monitoring investor's performance, of designing adequate hedges and has to bear its immediate costs. The investors suffer less favourable interest rates for the used leverage, or they have to pay premiums for CDSs which works against the investors performance.

New role of regulator: enforce hedges for leveraged investments

• *Hedging collateral:* If collateral for leveraged investments are e.g. stocks, they can be hedged by conventional derivatives. Premiums for the appropriate derivatives will be paid for by the holder of the collateral, e.g. the banks. The costs for these hedges will have to be rolled over to the investor in form of higher interest rates. It is possible that these rates become unattractively expensive. Naturally, it must be avoided that the leverage provider itself is e.g. engaged in derivative trading, that it could for example write options. It is necessary that the risk is transferred from the leverage provider institution to the financial market.

The implementation of mandatory collateral hedging of the leverage provider could be implemented through an extended disclosure requirements for banks. They would report the collateral and the size of the extended credit, together with the type of hedge to the regulator or Central Bank. These requirements impose indirect costs to the leverage providers and would make leverage more expensive. It would be imperative that all providers to leverage have the same disclosure requirements.

• *Hedging the credit:* The actual risk of credit default from the side of the investor could be dealt with e.g. credit default swaps (CDS). These CDSs would be sold on the financial market. The premium for these instruments would be paid by the investors. Markets would estimate, assess and monitor the default risk of individual investors and would determine the corresponding premiums. This could lead to an implicit 'rating' of investors. In particular the prices for CDSs for the different investment companies could be used as an indicator of the perceived (from the market) level of aggressiveness. Naturally, more aggressive funds will have higher default rates. The issue of implementation of disclosure rules for such a strategy in today's financial markets could be more associated with technical problems. Investors would have to declare the actual credit

The difficulty with CDSs is, as for the collateral hedge, that the portfolio and the debt structure chosen by the investor can change on relatively short timescales. To avoid costly permanent readjustments it could become necessary to use more complex instruments than ordinary CDSs. Maybe even new instruments for exactly this purpose could be introduced.

Counterparty risk: Realistic or not, these measures for insurance will work only as long as the corresponding counterparties are liquid. The associated risk of financial collapse of counterparties is called counterparty risk. In the case of the collateral hedge the risk is that the issuer of the option disappears, in case for the credit hedge, there is the default risk of the buyer of the CDS. Usually, counter party risk is hard to anticipate because a wide range of scenarios can lead to the disappearance of them. It is consequently almost impossible to price counterparty risk and to hedge for it.

Insurance possibilities against systemic collapse do not exist within the financial system itself.

From a systemic point of view leverage-investment hedges could be highly desirable for two reasons: First, they would transfer the credit / collateral risk from the leverage provider to the financial market. It would reduce the probability for the public sector to cover losses in form of e.g. bank defaults. Second, they would make leverage more expensive and less attractive and would reduce its use to relatively save investments. To estimate the influence of hedge costs on leveraged investments, again, agent based models could be the method of choice to incorporate systemic and non-linear effects, which would be not trackable within traditional game theoretic or equilibrium approaches. It is a priory not clear to what extend the practice of leverage will get reduced depending on the hedging costs. It is a research question in its own right to think about the consequences of making disclosed data of CDS premiums or leverage levels of institutions available to all market participants.

1.3 Scales of leverage in the financial industry

Typically leverage becomes high in boom times and lowers in bad times. This can imply that in boom times asset prices are overpriced and too low during crisis. This is the leverage cycle [11]. Leverage dramatically increased in the United States from 1999 to 2006. A bank that wanted to buy a AAA-rated mortgage security in 2006 could borrow 98.4% of the price, using the security as collateral and pay only 1.6% in cash, i.e. a leverage ratio of 60. The average leverage in 2006 across all of the US$2.5 trillion of so-called toxic mortgage securities was about 16, meaning that the buyers paid down only $150 billion and borrowed the other $2.35 trillion. Home buyers could get a mortgage leveraged 20 to 1, a 5% down payment. Security and house prices soared. Today leverage has been drastically curtailed by nervous lenders wanting more collateral for every dollar loaned. Those toxic mortgage securities are now leveraged on average only about 1.5 to 1. Home buyers can now only leverage themselves 5 to 1 if they can get a government loan, and less if they need a private loan. De-leveraging is the main reason the prices of both securities and homes are still falling. The leverage cycle is a recurring phenomenon, [22]

A typical scale of leverage in investment banks just before the crisis was almost about a factor of 30. Many of these borrowed funds to invest in so-called mortgage-backed securities. Leverage levels of the 5 largest investment firms in the US rose from about 17 in 2003 to about 30 in 2007. The risks of these leverage levels are reflected in the fate of these companies in late 2008. Lehman Brothers went bankrupt, Merrill Lynch and Bear Stearns were bought by other banks, or changed to commercial bank holding companies, as Morgan Stanley and Goldman Sachs.

A typical value of leverage obtainable for trading in foreign exchange markets is a factor of 100, meaning that with one dollar owned, one can speculate with 101 dollars.

1.4 Scales of leverage on national levels

For most western economies present leverage levels range between 50 and 100 % of GDP, Japan being higher at around 200 %. To which extend such levels are sustainable under crisis - i.e. at times when governments might be confronted with major bank bailouts, or with the fact that outstanding debt from other governments has to be written off (in case of defaulting countries) - is under heavy debate. It is

noteworthy to mention that sovereign governments in control of their monetary policy, have three ways of managing their debt when under severe stress. They have three possible mechanisms for de-leveraging: they can (i) default, they can (ii) inflate their debt away (this is e.g. not possible for countries in the Euro zone), or they could finally - given a competent and efficient government and public support - (iii) decrease spending and increase production and efficiency.

What are Agent Based Models?

Agent based models allow to simulate the outcome of the aggregated results of social processes, resulting from the overlay of actions of many individual agents. Individual agents behave according to a set of *local* rules, or randomly. Usually this means that an agent - who interacts with other agents - can take decisions, which in general depend on (or are determined to some extend by) the interactions with the others. Random decisions of agents are decisions which are uncorrelated to interactions with others or other events.

For an example think of a simple opinion formation model. All agents can take one of two decisions: vote for A or vote for B. Every agent has several friends. All friendships are recorded in the friendship network. At every time step of the model a particular player X checks how many of his fiends say, they would vote for A. If a big fraction of his friends vote for A, player X will also say in the next time step that he would also vote for A, even though maybe in the previous time step he has voted for B. His local neighbourhood (better the *state* of his neighbourhood) made him change his mind. This is done simultaneously with say 1 million agents, and for 1000 times. It can now be checked, how often a majority for A forms. This can then be repeated under different initial conditions - i.e. how many people voted for A in the *first* time step. It can further be checked how the connectivity of the friendship network influences the probability for a final outcome of A winning, etc. In this example a random decision of an agent would be that he votes for A or B depending on throwing a coin and not copying what the majority of his friends are doing. This model is clearly not of practical interest here, but serves to illustrate the structure of an agent based models: Compute the probability of an outcome (election of A or B) under the knowledge, that people have a given communication network, and that they tend to copy the behaviour of their friends.

The basic idea is that often one has a clear concept of how most people act *locally* under given circumstances, but the outcome of the collective action is unknown. Such models can be seen as 'in-silico experiments'. Often they are the only source to understand a problem. In the above example it is impossible to let people vote a thousand times. In computer experiments this is no problem and can nowadays be carried out on laptops. It is clear that agent base models only work if the basic rules of interaction (here adaptation of opinions) is to a large scale correct. If this part is modelled erroneously, the outcome can only be of little or zero value.

1.5.1 What they are

Agent based models consist of a set of agents of a certain type. In this work, the different agent types will be banks, informed investors, investors to funds, regulators, etc. Usually every type is populated with many of these agents. These agents are in mutual contact with each other. A bank lends to an investor which leads to a money flow from bank to investor. The investor invests the money in the stock market which leads to a money flow from the investor to another agent owing the stock, etc. The agents all are equipped with behavioural rules, e.g. that if the bank recalls borrowed money at a particular time, the borrower will pay it back in the next time step. If this rule is broken, there are other rules which manage the breaking of rules. For example if a loan is not paid back because the borrower illiquid, the borrower is declared bankrupt. Bankruptcy implies e.g. that all assets of the borrower will be sold at the stock market, the proceeds will be shared between the lenders, the difference to the outstanding loans will be written off by the banks. The essence of agent based models is to model the interactions of the agents right. In a

typical agent based model there can be several dozen of rules which govern these interactions. It might seem that the given set of rules implies a deterministic model. This is by no means so. For example irrationality of agents can be modelled by random decisions of agents, which again mimics reality well. In this way models can mimic hypothetical worlds of only rational agents and how they differ from situations where a given fraction of decisions are made by pure choice. The latter can be used to model decisions with incomplete knowledge, ignorance, etc.

1.5.2 What can they do that other approaches can not?

Agent based models allow for estimating probabilities of systemic events, i.e. large scale collective behaviour based on the individual outcomes of locally connected agents. Their prime advantage is that they can generate data where there is none or too little to understand the system. The collective effects can be studied by running thouands of simulations. A sense can be reached about the effect that changing the interaction of rules between agents has on the collective outcome of the system. For example in this work, the likelihood of default of investment funds is shown to depend on regulation, e.g. if a maximum leverage is imposed. Likewise it can be shown how banking regulations (such as the Basel accords) influence default rates. With these models it can be demonstrated that such regulators measures can - under certain circumstances - lead to adverse effects, which would be hard to guess otherwise.

They allow to understand the concrete unfolding of events leading to a systemic change in the system. For example the origin, the development and the unfolding of a financial crisis can be related to all model parameters. In reality usually there is never all the relevant data present, which would allow you to identify the relevant parameters. The relevant parameters can be identified as the relevant ones. Also it is possible to follow the establishment of a new regime after a shock happened, such as recovery rates, typical wealth re-distributions, etc.

Some typical concrete questions that can be answered with an agent based model of financial markets would be: Can it be judged if one set of regulations is more efficient than another? How can systematic dangers be identified? What precursors have to be monitored? How can empirical facts be understood, such as fat tailed return distributions of asset prices, clustered volatility?, etc.

In short, agent based models are toy worlds which allow one can understands crucial dynamical aspects of complex systems such as the financial markets. As with toys in general they are useful to develop a concept and feeling of how things work, exactly in the sense of how a child acquires a clear concept of what a car by playing with toy cars. They are not meant to be used for the following.

1.5.3 What agent based models cannot do

Agent based models simulate actions and interactions of autonomous agents; but they cannot capture the full complexity of reality. They attempt to re-create and predict the appearance of complex phenomena, but should not be used to predict outcomes of future states of the world. They cannot explain inventions and innovations shaping and changing a given environment. Nor can they be scaled to realistic situations without considerable effort. Reasonable mappings of agent based models to real world situations requires large and competent modelling teams, of which there are very few. Greater support for these efforts is needed.

Agent based models are models they are not reality. Agent based models cannot be used to predict outcomes of future states of the world. They cannot explain inventions and innovations shaping and changing a given environment. They cannot be scaled to realistic situations without considerable effort. Reasonable mappings of agent based models to real world situations need large and competent modelling teams, of which there are very few. It would be wise to focus efforts in these directions.

A clear danger is that agent based models are often in transparent. This is due to the fact that it can be very hard to judge if particular rules are implemented realistically. What becomes essential is to test these models against real data. This means that certain dynamic patterns that are generated by the model - which are also observable in the real world analogon - have to be compared to real world data. For example in an agent based model of the financial market, time series of model-prices have to show the same statistical features as real time series. If clustered volatility or fat tailed return distributions are not found in a model of financial markets, for example, this would indicate that the model missed essential parts and is not to be trusted.

1.5 Failure of economics and the necessity of agent based models of financial markets

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. Based on this scheme financial institutions devoted considerable resources to modelling risk. However, they typically did this under the assumption that their own impact on the market is negligible, or that they were alone in contemplating a radical change in policy. In other words they did not take feedback loops and synchronization effects into account and therefore their basic assumption of independence and uncorrelatedness turned out to be a poor approximation. This was especially relevant in the time of crisis when risk models were most needed. A single institution, such as e.g. Lehman Brothers, had an enormous impact, and a group of institutions unknowingly acting in tandem had an even larger impact. When these impacts are taken into account the result can be dramatically different from that predicted by standard VaR (value at risk) models based on statistical extrapolations of returns from past behaviour.

Systemic risk is a classic complex systems problem: It is an emergent phenomenon that arises from the interactions of individual actors, generating collective behaviour at a system wide level whose properties are not obvious from the decision rules of each of the individual actors. Typically the individual agents believe they are acting prudently. Systemic risks occur because financial agents do not understand (or care) how their behaviour will affect everyone else and how synchronization of behaviour builds up. Such mutual influence leads to nonlinear feedbacks that are not properly taken into account in classical models of risk management. Very much against the usual intuition, it becomes possible that these nonlinear effects may lead to situations where the very policies designed to reduce individual risks may themselves lead to the creation of extreme risks, eventually able to bring the entire system down. Recent events in financial markets provide a good illustration on many different levels.

The current crisis is very likely the result of a combination of several components, such as the boom of use of supposedly risk-reducing derivatives, excessive use of credit and a high degree of lack of transparency through the use of complicated and often overlapping agreements, and finally a significant portion of criminal behaviour. Practically it is not possible for the individual agent to collect and monitor the relevant data which would be necessary to model the potential systemic risks. Further, a point which is severely underrepresented in current risk models is the possibility of disappearing counterparties. Especially in good times counterparty risk is often not taken into account properly in derivative prices, or other financial agreements. Practically none of the current risk models took defaults properly into account, because none of them addressed the complicated couplings and feedbacks of the interconnected components of the financial system.

Most models of risk are based on idealized assumptions which might be reasonable to a certain degree during times of little or no change. Under these circumstances assumptions such as the efficient market hypothesis, or the general equilibrium scenario might provide a useful framework to develop tools and methods for managing risk - for times of no change. Although these concepts might work under *equilibrium conditions* – they may become completely useless - sometimes even counterproductive - at times of change, stress and crisis. In the aftermath of the current financial crisis reforms of the financial

system are actively being discussed. Many of these reforms are hindered, however, by the simple fact that what policies would be optimal is unknown.

To address these questions the traditional tools associated to economics and financial economics such as game theory, no-arbitrage concepts and their thereof derived partial differential equations, as well as classical Gaussian statistics will not be sufficient. Risk management derived from these concepts such as VaR and eventually regulation schemes such as Basle I or II, ignore systemic effects, such as synchronization or feedback. These schemes have clearly failed during the recent crisis. It is essential to look at feedback loops, synchronization mechanisms, successions of events, and statistics of highly correlated variables. A fantastic setup to understand these issues is provided by so-called agent based models, where a set of different agents interact in a computer simulation. In this report such a model of financial agents is studied, which was introduced recently in full detail.

Rather than continue pursuing the standard game theory approaches, the need for agent based models arises because of the nonlinearities in the decision rules, payoff functions, and the nonlinear actions between the agents, which are simply too complex to treat with game theory-based models. This is further complicated by network effects. The utility of agent-based models in this context comes about because of the complicated interactions and dynamic feedback that leverage introduces. Agent based models allow to study dynamic systems and the detailed unfolding of typical scenarios in the simulations. Further they allow to generate data where there is none: simulations can be run thousands of times under various conditions, and assumptions, something which could never be done in the real world. From the study of the system under various conditions one can learn how the systems behave under different forms of regulation for example.

The essence and the main difficulty for agent based simulations is to capture not only the properties of the agents properly, but also the interactions between them. Agent based models further have to be built from variables and parameters, which - at least in principle - have to be accessible in the real world. Another difficulty is to calibrate agent models against real data, i.e. to set the scales of influences between agents to realistic values. These issues can be most relevant, since systemic properties of complex systems often depend on detailed balance of relations between parameters. Lastly, agent based models often make clear which parameters are relevant and dominant and which ones are marginal. As a consequence agent based models can be used to define which data is needed to be collected from real markets, and to which level of precision.

1.6 Secondary Impacts and the Global Context

Financial markets are heavily intertwined with the global economy, which in its present form depends on them. A crisis in the financial industry, the banking industry in particular, could have impacts that cascade into a broad range of different industries. Crisis in the financial industry can often lead to a tightening of credit, and therefore ideas and creative potential can not be realized - which can lead to a slowdown of economy. Related impacts are typically measured in bankruptcies, unemployment, loss of investment. Ultimately such a situation could engender social unrest.

The fear of such a succession of events is one of the reasons for many governments to bail out defaulted financial institutions lately. However, these interventions - which are effectively nothing else but an active engagement (of the worst side) of governments in leveraged speculations on the financial markets- come at a tremendous price: The danger of illiquidity of governments. A state of illiquidity leads to situation that governments can no longer pursue their core activities, such as providing infra structure, finance education, health systems, pensions, etc. Such a failure bears the risk of generating social unrest. Defaulting countries can kick other countries into default through cascading effects, which might be at the edge of happening at the present time with Greece, Portugal, Spain and Italy. Which of two scenarios - one

of no governmental bank bailouts or solidarity with defaulting countries, the other being the opposite - is more likely to lead to larger and more prolonged losses in the end is impossible to say with the limited present knowledge of the dynamics of financial markets and their links to economy. All the more it is imperative to channel collective efforts to understand these mechanisms. One of the starting points will be to extend agent based models of financial markets and try to link them to agent based models of the economy. Current main stream economics has been incapable of making useful contributions in this direction [23].

2 A SIMPLE AGENT BASED MODEL OF FINANCIAL MARKETS

For the new architecture of any future financial system it is essential to understand the dynamics of leveraged investments. In the following section discuss a model phrased in terms of financial markets. Many results generated there can be straight forwardly applied to other forms of leveraged investments - of course only after taking into account the necessary modifications, identifications etc., appropriate for the particular setup. Such identifications for leveraged investments on national scales will be discussed in Section 6.5.

2.1 Overview

The following section reviews a recent agent based model of the financial market, that allows to pinpoint at the systemic risk of the use of leverage [7]. The model does not claim to be a realistic representation of financial markets. It is designed for making clear the basic mechanism under rather stylized conditions. This short overview introduces the 'agents' of the model, they will all be described in more detail in the following sub sections.

The model assumes a collection of interacting types of financial agents. These agent types are investors in financial assets, banks, investors to investment companies and regulators. Within a type of agent, there can be a variety or spectrum of heterogeneity, e.g. investors will in general differ in their investment strategies, their risk aversion, banks will differ in their willingness to extend credit under given situations etc. In the model it is assumed that all investors interact through buying and selling on the financial market. This means that the price formation is governed through a simple market clearing mechanism. This means that at every time step when trading takes place, there will be a unique price for a given financial asset. For simplicity, think of financial assets as stocks or shares of a company, traded publicly. In the model no derivatives or more complex assets will be used. Trading happens such that all investors interested in a financial asset submit their *demand function*, i.e. the quantity of shares they want to buy, given that the asset has a certain price, p. The demand function is a function of the price, usually the higher the price of an asset the smaller the demand. The combination of all demand functions of all market participants - under the assumption of market clearing - yields a unique price of the asset.

The set of investors is partitioned into three types of investors, which will be described in more detail below: informed investors, poorly uninformed investors, and investors in investment companies.

The first kind of investor can be thought of as investment funds such as hedge funds, mutual funds or investment banks who base their investment decisions on research. In particular they try to find out whether the assets of a firm are over- or underpriced at a particular time. Research may involve visiting firms, performing market analysis, etc. In case they spot an underpriced asset the informed investor will

assume that the market will sooner or later find out that the asset is underpriced, and will eventually price it correctly, i.e. the price of the asset will tend to rise in the future. If the informed investor detects a supposedly overpriced asset, she might want to 'go short' in the asset, and wait for it to be priced correctly by the market, i.e. wait till it falls.

Investors of this kind basically try to estimate a 'true price' of assets. The difference of the actual price (as quoted in the market) and the estimate of the 'true price' will be called the *mispricing*, or *trading signal*, throughout the paper. Investors will in general differ from each other in two ways. First, they will differ in their opinion how 'correct' their assessment of the true price of the asset is. Second, they will differ in their view of how much that piece of information is worth, i.e. how much are they willing to speculate on their estimation of the 'true price'. An investment firm which is willing to speculate much on a given mispricing or trading signal will be called an 'aggressive' firm, a more risk averse, cautious firm will place moderate bets on their assessed mispricing. Often investors of the informed kind will use their know-how for speculating for others. For this service they generally take fees, often divided into a fixed fee and a performance fee. Typical fees before the financial turmoil were in the range of 1-4 % performance fee (of the capital invested) and 10-30% performance fee (from the actual profits made).

At this point it may be argued that a model of this kind is severely unrealistic because it ignores so-called trend followers. The model pursued in [7] is in a certain way the best of all worlds. The studied effects on price fluctuations, crashes, etc., and the role of leverage played, can only be amplified by the presence of trend followers, who are known to destabilize the system. The situation in the real financial world will always be more unstable than in the presented model. The importance of the model lies partly in the fact that even in a world of investors, who contribute to price stability through their behaviour, leverage can be devastatingly dangerous.

The second type of investors are poorly- or uninformed investors. These are investors who do not base their investment decisions on solid research or other forms of estimating the 'true prices' of assets, but - as a collective - place basically random orders (demands). This is either because they do not do any research, or because their research is not providing a reasonable trading signal - the trading signal is 'noise', so this kind of investor is here called a *noise trader*. It is assumed that these random investments follow a very slow trend toward the 'true price' of the asset. More precisely the demand of poorly informed traders (noise traders) shall be modelled such that the price tends to approach a 'true price' of the asset in the long run. In technical terms the noise traders will be characterized by a mean reverting random walk, which will be specified in detail below. This mean reverting behaviour is again an optimistic assumption in terms of stability of asset prices. This mean reversion is introduced to mimic efficient markets, i.e. the wide spread textbook believe, or dogma, that markets tend to price assets correctly [24]. That markets are not efficient is a well established fact [25], which has been famously expressed by A. Greenspan in 2008 [11].

The third kind of investors are investors, who invest their cash in investment firms, such as mutual funds or hedge funds. These fund will then invest this capital in financial markets. Investors who invest in funds generally believe that these funds are informed investors, which allows for higher profits, and justifies the fees. Investors to funds can be individuals, banks, insurance companies, governments, etc. In general they will monitor the performance of the fund they invested in, together with the performance of alternatives for their investments. If a fund performs well, investors will keep their investment there, maybe will increase their stake. If the fund performs badly, investors will redeem their investments. The model below introduces these investors who constantly monitor the performance of their investments. How the investment is monitored will be described in detail. There are no other forms of investors in the model financial economy.

The fraction of investments made by informed vs. uninformed investors is constantly changing and depends on the performance of the informed investors. If they perform well, they will experience an influx

of capital from their investors (of the third kind) and will additionally leverage this capital. Consequently the relative importance of informed investors will increase. In times when informed investors are performing badly the fraction of uninformed investors will increase.

In our model economy banks play the role of liquidity providers in the sense that they extend credit to investors to leverage their speculative investments. They do this in the form of short term loans. These loans are often provided for one day only, but are automatically extended for another day under normal circumstances. The size of these loans (leverage) largely vary across industries, see above. Investors use the cash from these credits to boost their investments, i.e. they will inflate their demand by the leverage factor. Aggressive funds will use more leverage in general than risk adverse ones. Banks earn interest on these loans. In reality banks also play the role of direct investors to investment funds, or they behave as if they were hedge funds themselves. This is often done to avoid regulation. In the following it is assumed that only informed investors use leverage.

Finally, there are regulators. These are not modelled as agents per se, but as a framework of constraints under which the above dynamics unfolds. These constraints regulate issues such as the maximum of leverage that can be allowed for speculative investments, the size of capital cushions for banks (e.g. for a Basle I like regulation scheme). These constraints are treated as variable parameters in the model, which allows to directly study systemic risk under different regulation schemes. For example two fictitious worlds can be compared, one in a tightly regulated setting, the other without regulation. In these worlds one can measure the respective systemic financial stability, in terms of collapses of investment funds or banks, price crashes, etc. Also one can directly compare the consequences of price characteristics in the different worlds.

2.2 The specific model economy

In the following agent based model there is a single financial asset which does not pay a dividend. There are two types of agents who buy and sell the asset, noise traders and value investors which are here referred to as 'hedge funds'. The noise traders buy and sell more or less at random, but with a slight bias that makes the price weakly mean-reverting around a fundamental value. The hedge funds use a strategy that exploits mispricings by taking a long-position (holding a net positive quantity of the asset) when the price is below its perceived fundamental value. A pool of investors who invest in hedge funds contribute or withdraw money from hedge funds depending on their historical performance relative to a benchmark return; successful hedge funds attract more capital and unsuccessful ones lose capital. The hedge funds can leverage their investments by borrowing money from a bank, but they are required to maintain their leverage below a fixed value that is determined in the model. Prices are set using market clearing. Now the components of the model can be described in more detail.

2.3 Variables in the agent based model

Table 1: Summary of parameters used in the model.

Variable	Description
General parameters	
N	Number of total assets in the particular stock
H	Number of informed investors in the economy
B	Number of banks in the economy
I	Lending relationship between banks and informed investors (matrix)
p	Asset price
m	Mispricing of the asset (perceived)
Informed investors	
D_h	Demand in asset of informed investor h (in shares)
D_{nt}	Demand in asset from uninformed investors (in shares)
V	Perceived fundamental value of the asset
W_h	Wealth of informed investor h
β_h	Aggressivity of informed investor
C_h	Cash position of informed investor h
L_h	Size of loan of informed investor h
W_{min}	Minimum level of wealth before bankruptcy occurs
T_{wait}	Time before defaulted fund gets replaced
λ	Actual leverage of informed investor
Banks	
W_b	Wealth of bank b
λ^{MAX}	Maximum leverage
Noise traders (uninformed investors)	
ρ	Parameter characterizing mean reversion tendency of noise traders
σ	Volatility of noise trader demands
Investors to Funds	
σ_τ	Time to compute variance for price volatility
r^{bm}	Benchmark return for investors
r_h^{perf}	moving average parameter for performance monitoring
b	performance based withdrawl/investment factor
κ	Volatility monitoring parameter
F_h	performance based withdrawl/investment to informed investor h
r^{NAV}	Net asset value of fund (informed investor)
γ	slope of log-return distribution

2.4 Price formation

We use a standard market clearing mechanism in which prices are obtained by self-consistently solving the demand equation. Let $D_{\mathrm{nt}}(p(t))$ be the noise trader demand and $D_h(p(t))$ be the hedge fund demand. N is the number of shares of the asset. The asset price $p(t)$ is found by solving

$$D_{\mathrm{nt}}(p(t)) + \sum_h D_h(p(t)) = N, \qquad (1)$$

where the sum extends over all hedge funds in the system.

2.5 Uninformed investors (noise traders)

We construct a noise trader process so that in the absence of any other investors the logarithm of the price of the asset is a weakly mean-reverting random walk. The central value is chosen so that the price reverts around fundamental value V. The dollar value of the noise traders' holdings is defined by $\xi_{\mathrm{nt}}(t)$, which follows the equation

$$\log \xi_{\mathrm{nt}}(t+1) = \rho \log \xi_{\mathrm{nt}}(t) + \sigma\chi(t) + (1-\rho)\log(VN). \quad (2)$$

The noise traders' demand is

$$D_{\mathrm{nt}}(t) = \frac{\xi_{\mathrm{nt}}(t)}{p(t)}. \quad (3)$$

Substituting into equation (1), and letting χ be normally distributed with mean zero and standard deviation one, this choice of the noise trader process guarantees that with $\rho < 1$ the price will be a mean reverting random walk with $E[\log p] = \log V$. In the limit as $\rho \to 1$ the log returns $r(t) = \log p(t+1) - \log p(t)$ are normally distributed when there are no hedge funds. For the purposes of this paper we fix $V = 1$, $\sigma = 0.035$ and $\rho = 0.99$. Thus in the absence of the hedge funds the log returns are close to being normally distributed, with tails that are slightly truncated due to the mean reversion.

2.6 Informed investors (hedge funds)

At each time step each hedge fund allocates its wealth between cash $C_h(t)$ and its demand for the asset, $D_h(t)$. To avoid dealing with the complications of short selling we require $D_h(t) \geq 0$, i.e. the hedge funds are long-only. This means that when the mispricing is zero the hedge funds are out of the market. Thus, to study their affect on prices we are only interested in situations where there is a positive mispricing.

The hedge fund's wealth is the value of the asset plus its cash,

$$W_h(t) = D_h(t)\,p(t) + C_h(t). \quad (4)$$

On any given step the hedge fund may buy or sell shares of the asset and the cash $C_h(t)$ changes according to

$$C_h(t) = C_h(t-1) - \left[D_h(t) - D_h(t-1)\right]p(t). \quad (5)$$

If the hedge fund uses leverage the cash may become negative, and the hedge fund is forced to take out a loan whose size is $L_h(t) = max[-C_h(t),0]$. The leverage of fund h is the ratio of the value of the assets it holds to its wealth, i.e.

$$\lambda_h(t) = \frac{D_h(t)\,p(t)}{W_h(t)} = \frac{D_h(t)\,p(t)}{D_h(t)\,p(t) + C_h(t)}. \quad (6)$$

The bank tries to limit the size of its risk by enforcing a maximum leverage λ_h^{MAX} . In purchasing shares a fund spends its cash first. If the mispricing is sufficiently strong, in order to purchase more shares it takes out a loan, which can be as large as permitted by the maximum leverage.

Suppose the fund is using the maximum leverage on time step t and the price decreases at $t+1$. If the fund takes no action its leverage at the next time step will exceed the maximum leverage. It is thus forced to sell shares and repay part of the loan in order to reduce the leverage to λ_h^{MAX} . This is called ``making a margin call''. We require that the hedge funds attempt to stay below the maximum leverage at each time step. We normally keep the maximum leverage constant, but we also investigate policies that adjust the maximum leverage dynamically based on time dependent factors such as price volatility, see Section 2.8.

Our hedge funds are *value investors* who base their demand on a mispricing signal

$$m(t) = V - p(t), \quad (7)$$

where as before V is the perceived fundamental value, which is held constant to keep things simple. All hedge funds perceive the same fundamental value V . Each hedge fund computes its demand $D(t)$ based on the mispricing at time t . The hedge fund's demand function is shown in dollar terms in Fig. 1. As the mispricing increases the dollar value of the fund's position increases linearly until it reaches the maximum leverage, at which point it is capped. It can be broken down into three regions:

1. *The asset is over-priced.* In this case the fund holds only cash.

2. *The asset is under-priced* with $\lambda_h(t) < \lambda_h^{MAX}$. In this case the dollar value of the asset is proportional to the mispricing and proportional to the wealth.

3. *The asset is under-priced* with $\lambda_h(t) = \lambda_h^{MAX}$. In this case its holdings of the asset are capped to remain under the maximum leverage.

Expressing all quantities at time t , the hedge fund demand can be written:

$$m < 0 \quad : D_h = 0$$

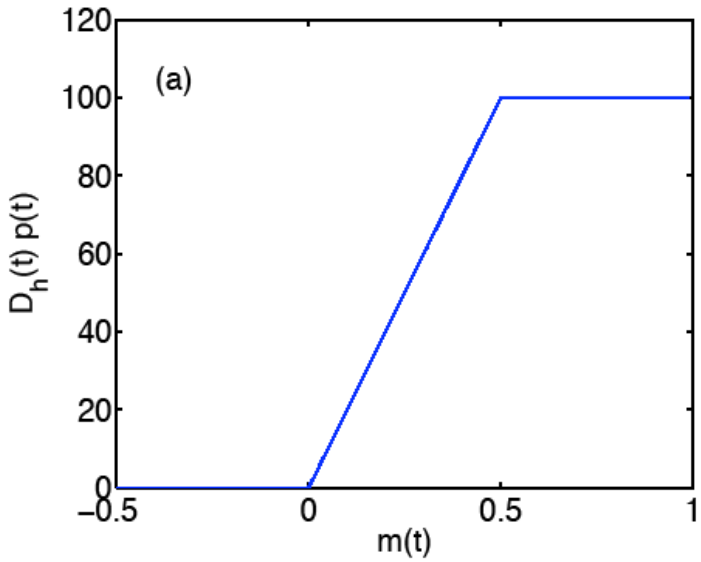
$$0 < m < m_{crit} : D_h p = \beta_h m W_h$$

$$m \geq m_{crit} : D_h p = \lambda_h^{MAX} W_h . \quad (8)$$

We call $\beta_h > 0$ the aggressiveness of the hedge fund. It sets the slope of the demand function in the middle region, i.e. it relates the size of the position fund h is willing to take for a given mispricing signal m. m_{crit} is defined as $m_{crit} = \lambda_h^{MAX} / \beta_h$. This is the critical mispricing beyond which the fund cannot take on more leverage. For larger mispricings the leverage stays constant at λ_h^{MAX}. If the price decreases this may require the fund to sell assets even though the mispricing is high. This is what we mean by making a margin call[1]. To compute the demand it is convenient to substitute equation (5) into equation (4), which gives

$$W(t) = C(t-1) + D(t-1)\, p(t). \quad (9)$$

This is useful because it means that in the expression for the demand everything except the price is known, and the price can be found using market clearing, equation (1).



[1] A more realistic margin policy would set a leverage band, which has the effect of making margin calls larger but less frequent. For example, if the leverage band is $(5,7)$, when the hedge fund reached 7 it would need to make a margin call to reduce leverage to 5. To avoid introducing yet another free parameter, we simply have the hedge funds make continuous margin calls, so that as long as the mispricing is sufficiently strong, they constantly adjust their leverage to maintain it at λ^{MAX}. Introducing a leverage band exaggerates the effects we observe here.

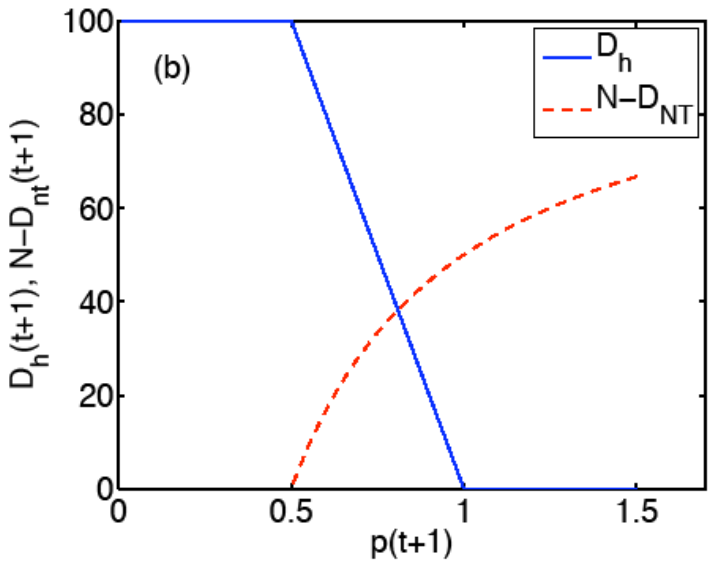


Figure 1: (a) Demand function of a fund as a function of the mispricing signal m defined in equation (7). (b) Market clearing: price and demand are determined by the intersection of the demand functions of noise traders and funds.

Investment firms typically generate their income through a performance fee α^{perf} and a management fee, α^{mgt}. While the management fee generally ranges from 1-5 % (for hedge funds) of the 'assets under management' ($W_h(t)$), the performance fee can be something between 5-40% of the generated profits. The fund's payoff P_h is

$$P_h(t) = (\alpha^{perf}(1 + r^{NAV}(t)) + \alpha^{mgt})W_h(t) \quad , \quad (10)$$

where r_{NAV} is the rate of return of the NAV over a specified time interval; W is the average size of the fund over that same interval.

2.7 Investors to investment fund

A pool of hedge fund investors (representative investor) contribute or withdraw money from each fund based on a moving average of its recent performance. This kind of behaviour is well documented,[2] and guarantees a steady-state behaviour with well-defined long term statistical averages of the wealth of the hedge funds. The performance of a fund is measured in terms of its Net Asset Value (NAV), which can be thought of as the value of a dollar initially invested in the fund. Letting $F_h(t)$ be the flow of capital in

[2] Some of the references that document or discuss the flow of investors in and out of mutual funds include [34,35,36,37,38].

or out of the fund at time t, and initializing $NAV(0) = 1$, the NAV is computed as

$$\mathrm{N}AV(t+1) = \mathrm{N}AV(t)\frac{W_h(t+1) - F_h(t)}{W_h(t)}. \quad (11)$$

Let

$$r^{\mathrm{NAV}}(t) = \frac{\mathrm{N}AV(t) - \mathrm{N}AV(t-1)}{\mathrm{N}AV(t)}$$

be the fractional change in the NAV. The investors make their decisions about whether to invest in the fund based on $r_h^{\mathrm{perf}}(t)$, an exponential moving average of the NAV, defined as

$$r_h^{\mathrm{perf}}(t) = (1-a)r_h^{\mathrm{perf}}(t-1) + a r_h^{\mathrm{NAV}}(t). \quad (12)$$

The flow of capital in or out of the fund, $F_h(t)$, is

$$F_h(t) = b[r_h^{\mathrm{perf}}(t) - r^{\mathrm{bm}}]W_h(t), \quad (13)$$

where b is a parameter controlling the fraction of capital withdrawn and r^{bm} is the benchmark return of the investors. The parameter r^{bm} plays the important role of determining the relative size of hedge funds vs. noise traders.

Funds are initially given wealth $W_0 = W(0)$. At the end of each time step the wealth of the fund changes according to

$$W_h(t+1) = W_h(t) + [p(t+1) - p(t)]D_h(t) + F_h(t). \quad (14)$$

In the simulations in this paper, unless otherwise stated we set $a = 0.1$, $b = 0.15$, $r^{\mathrm{bm}} = 0.005$, and $W_0 = 2$.

2.8 Setting maximum leverage

In most of the work described here we simply set the maximum leverage at a constant value. However, we explicitly test the effect of policies that adapt leverage based on market conditions. A common policy for banks is to monitor volatility, increasing the allowable leverage when volatility has recently been low and decreasing it when it has recently been high. We assume the bank computes a moving average of the asset price volatility, σ_τ^2, measured as the variance of p of over an observation period of τ time steps. Here we use $\tau = 10$. The bank adjusts the maximum allowable leverage according to the relationship

$$\lambda^{\max}(t) = \max\left[1, \frac{\lambda^{MAX}}{1+\kappa\sigma_\tau^2}\right]. \quad (15)$$

This policy lowers the maximum leverage as the volatility increases, with a floor of one corresponding to no leverage at all. The parameter κ sets the bank's responsiveness to changes in volatility. For most of the work presented the maximum leverage is constant, corresponding to $\kappa = 0$, in Fig. 4 of the main paper we compare the effects to $\kappa = 100$.

2.9 Banks extending leverage to funds

Here we assume that each fund has only one bank which extends leverage to it. There are no connections (influences) from one bank to another, other than the fact that both might be invested in the same asset through (different) funds.

2.10 Defaults

If a fund's wealth falls below zero it defaults, i.e. it can not repay its loans. A fund can default because of redemptions or because of trading losses, or a combination of both. The fund is then removed from the simulation. After a waiting period of T_{wait} a new fund is introduced with wealth W_0 and with the same parameters as the original fund. Further, whenever a fund falls below a non-zero threshold, somewhat arbitrarily set to $W_h(t) < W_0/10$, i.e. 10% of the initial endowment, it will be removed and reintroduced after T_{wait}. Using this threshold to reintroduce funds avoids the problem of ``zombie hedge funds'', i.e. funds whose wealth is very close to but not zero, who take a very long time to recover.

2.11 Return to hedge fund investors

Since the investor pool actively invests and withdraws money from funds, the NAV does not properly capture the actual return to investors. For example, by withdrawing money through time an investor may make a good return from a hedge fund that eventually defaults. To solve this accounting problem we compute the effective return r_{inv} to investors from their withdrawals by discounting the present value of the flows in and out of the fund. For any given period from $t = 0$ to $t = T$ this is done by solving the equation

$$F(0) + \frac{F(1)}{1+r_{inv}} + \frac{F(2)}{(1+r_{inv})^2} + \cdots + \frac{F(T)}{(1+r_{inv})^T} = 0. \quad (16)$$

Based on the sequence $F(t)$ of investments and withdrawals this can be solved numerically for r_{inv}. Note that if the simulation ends and the fund is still in business then $F(T)$ is computed under the assumption that all the holdings of the fund are liquidated at the current price. If the fund defaults then $F(T) = 0$.

During the course of a simulation a fund may default and be re-introduced several times, and it becomes necessary to compute an average performance for the full simulation. Suppose it defaults n times

at times T_i over the total simulation period, i.e. it existed for $n+1$ time periods. For each period where the fund remains in business without defaulting we compute the corresponding return $r_{inv[T_i,T_{i+1}]}$, and then average them, weighted by the time over which each existed, according to

$$\langle r_{inv} \rangle = \sum_{i=1}^{n+1} r_{inv[T_{i-1},T_i]}/(T_i - T_{i-1}), \qquad (17)$$

where $T_0 = 1$ is the first time step in the simulation, and by definition T_{n+1} is the ending time of the simulation.

2.12 Simulation procedure

The numerical implementation of the model on the tth time step proceeds as follows:

• Noise traders compute their demand for the time period $t+1$ based on equation (3).

• Hedge funds compute their demand for $t+1$ based on the mispricing signal $m(t)$ according to equation (8). Note that this must be done in conjunction with computing the new price $p(t+1)$ i.e. equations (1) and (8) are solved simultaneously. This includes computing the wealth $W_h(t+1)$, which involves the new cash holdings $C(t+1)$ and the leverage $\lambda_h(t+1)$.

• Investors monitor the NAV of each fund and make capital contributions or withdrawals.

• If the maximum leverage is not being held constant, banks compute the new maximum leverage.

• If a fund's wealth $W_h(t)$ falls too low it gets replaced as described in Section 2.10.

• Continue with next time step.

2.13 Summary of parameters and their default values

Parameters held fixed:

- number of assets: $N = 1000$

- perceived fundamental value: $V = 1$

- initial wealth (cash) of funds: $W_0 = C_h(0) = 2$. $L(0) = D_h(0) = 0$

- noise trader parameters: $\rho = 0.99$, $\sigma = 0.035$

- bankruptcy level: 10% of initial wealth W_0

- time to re-introducing defaulted fund $T_{wait} = 100$

- time to compute variance for price volatility σ_τ, $\tau = 10$ (see Section 2.8)

- benchmark return for investors, $r^{bm} = 0.005$

- moving average parameter for r_h^{perf}, $a = 0.1$

- investor withdrawal factor, $b = 0.15$

Parameters that we vary:

- number of funds and their banks: 1 or 10

- aggressivity of funds, values range from $\beta_h = 5$ to 100

- maximum leverage $\lambda^{MAX} = 1$ to 15

- volatility monitoring parameter $\kappa = 0$ or 100 (see Section 2.8)

We are now ready to implement the model into a computer simulation and study the dynamics of the emergent system. The most important results are collected in [7]. Here we give a more detailed overview.

2.14 An ``ecology'' of financial agents

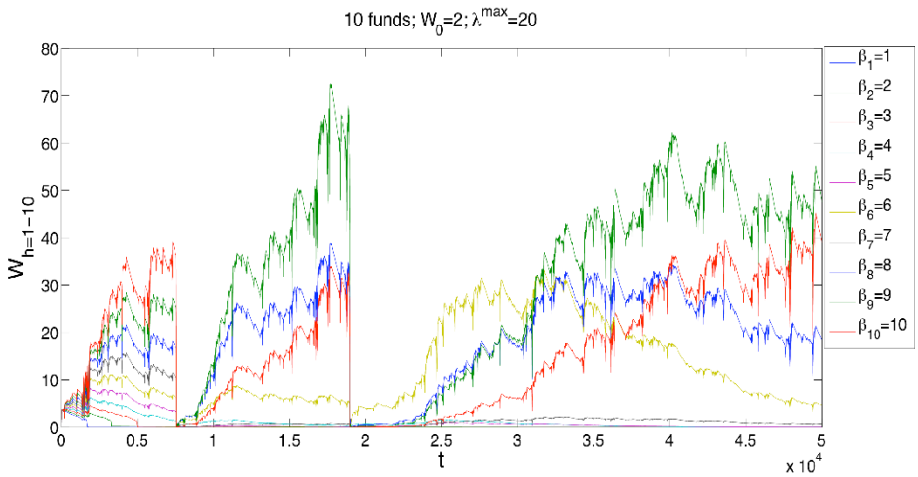


Figure 2: Wealth time series $W_h(t)$ for 10 funds with $\beta_1 = 1, \beta_2 = 2, \cdots, \beta_{10} = 10$, and $\lambda_b^{max} = 20$.

Fig. 2 shows the wealth time series for a system of ten competing funds with the aggression parameter β_h ranging from one to ten. Otherwise all their parameters are the same, including their initial wealth. To illustrate how leverage can drive crashes we have also raised the maximum leverage to $\lambda^{MAX} = 20$. During the initial transient phase the most aggressive funds grow rapidly, while the least aggressive shrink. This is not surprising: The aggressive funds exploit mispricings faster than the non-aggressive funds, make better returns, and attract more investment capital.

This situation continues until roughly $t = 7{,}500$, at which point there is a crash that causes the funds with $\beta = 8{,}9$ *and* 10 to default. The others take severe losses, bringing them below their initial wealth, but they do not default. Funds 8, 9, and 10 get reintroduced with W_0, and once again they grow rapidly. There is another crash at roughly $t = 19{,}000$, when once again funds 8, 9 and 10 default. Fund 6, in contrast, was not fully leveraged when the crash occurs and consequently it survives the crash taking only a small loss. This gives it a competitive advantage, and there is a long period after the crash where it is the dominant fund. With time, however, the other more aggressive funds overtake it. Meanwhile the other funds have all grown so small that they are effectively irrelevant. Although we do not show this here, with the passage of time fund 6 also dies out, leaving only the three most aggressive funds with any significant wealth.

This simulation might give the impression that it is always better to be more aggressive. This is not the case. We have also done simulations in which one fund uses a significantly larger aggression level than the others, e.g. $\beta_{10} = 40$. This also causes this fund to use more leverage, leading to a much higher default rate. In this case this fund is not selected at the end.

2.15 Generic results

2.15.1 Market impact and asymptotic wealth dynamics

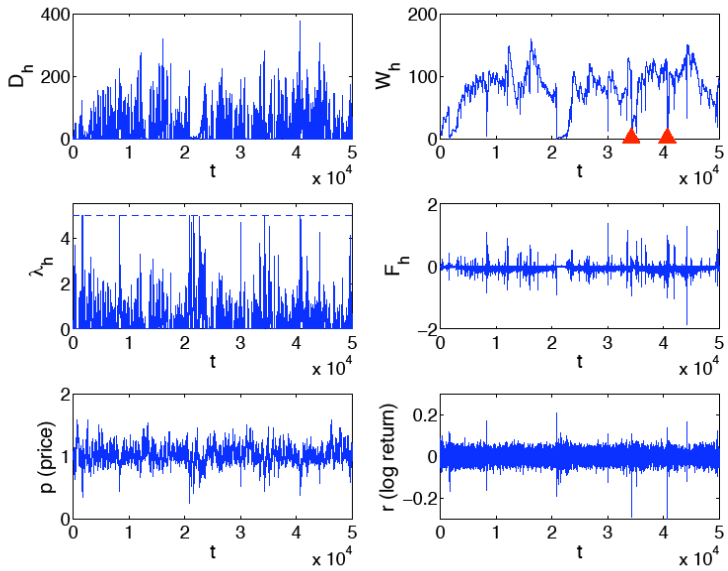


Figure 3: Time series of a fund for its demand, wealth, leverage, capital flow, loan size and bonds. Critical size here is seen to be around a value of 100. The fund has a $\beta_h = 10$ and a $\lambda_b^{MAX} = 5$; it was introduced at a size $W_h(0) = 2$.

To demonstrate that the model results in reasonable properties, in Fig. 3 we present results for a single fund in a parameter regime where the behaviour of the system is quite stable. We introduce the fund with a fairly low wealth $W_h(0) = 2$. The fund initially makes fairly steady profits and attracts more investment capital. Its wealth initially grows, both due to the accumulation and reinvestment of profits, but also because of the flow of new funds into the market. Once the fund size grows sufficiently large, in this case roughly $W = 100$, the growth trend ceases and the wealth fluctuates around an average value. As can be seen in the figure, the fluctuations are rather large: At some points the wealth dips down to almost zero, while at others it rises as large as $W = 200$. At time steps around $t = 34{,}000$ and $41{,}000$ the fund defaults (indicated by triangles).

The central reason for this behaviour is market impact. As the fund grows in size it becomes a significant part of the trading activity. This also limits the size of mispricings: As a mispricing starts to develop, the fund buys the asset, which prevents the mispricing from growing large, and there are correspondingly fewer profit opportunities. This effect increases with wealth, so that as the fund grows its returns decrease. Poorer performance causes an outflow of investment capital. The result is a ceiling on the size to which the fund can grow: If the fund gets too large, its returns go down and it loses capital. Nonetheless, it is clear from the simulation that the resulting steady state behaviour is only ``steady" in a statistical sense - the fluctuations about the average are substantial.

Note that the behaviour of the system is essentially independent of initial conditions. If we had introduced the fund with a wealth of $W(0) = 1$, for example, it would have taken it longer to build up the to critical wealth of $W \approx 100$, but after that the behaviour would have been essentially the same.

The parameter r^{target}, the benchmark return for the investors, plays a key role in setting the critical size of the funds. If r^{target} is small the funds will grow to be very large and they will take over the market, so that there are never large mispricings. As a result the fundamental price V forms an effective lower bound on prices. At the opposite extreme, if r_{target} is very large the funds will attract little capital and the behaviour will be essentially the same as it is when there are only noise traders. The interesting regime is in the middle zone where r^{target} is set so that the demand of the funds is of the same order of magnitude as the demand of the noise traders.

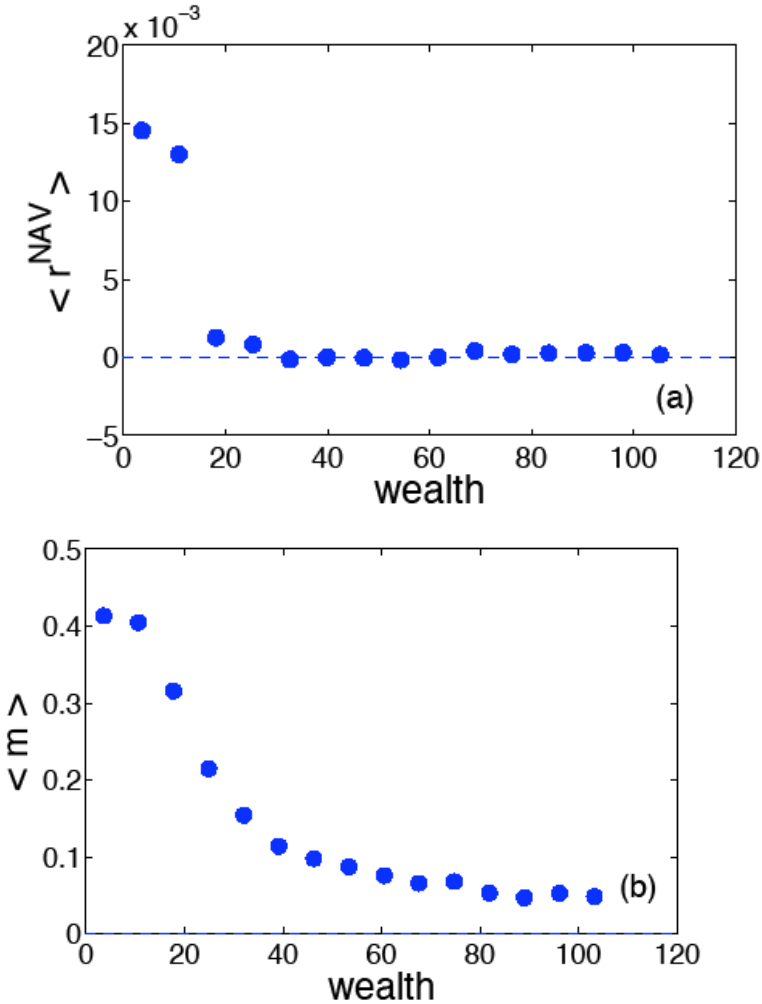
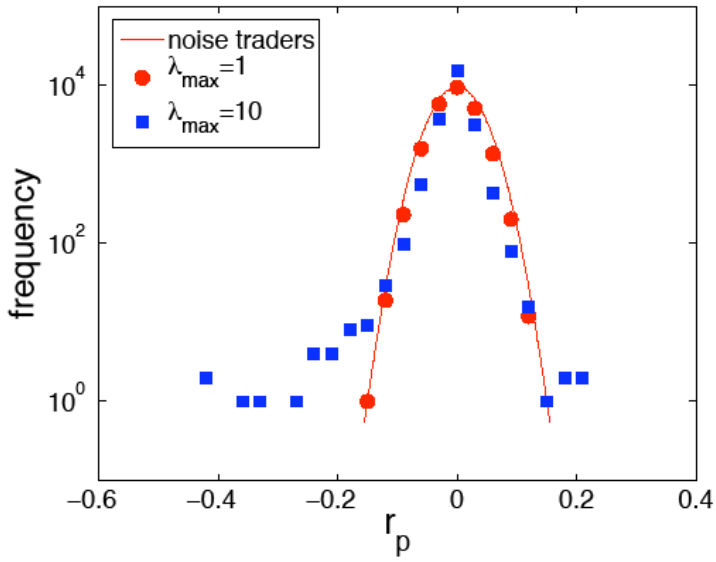
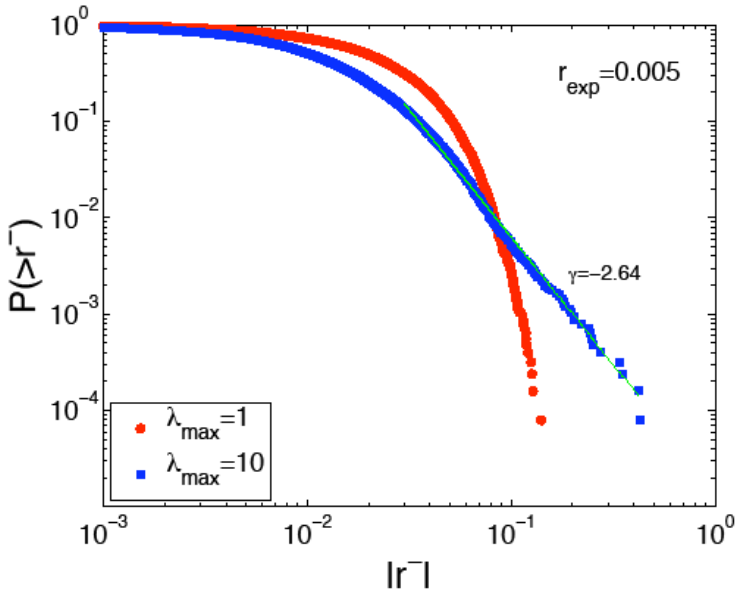


Figure 4: (a) Mean r^{NAV} of a fund conditioned on its wealth. (b) average mispricing $m = \log(V/p)$ conditioned on the funds wealth. Simulation: single fund, $\beta = 10$, $\lambda^{MAX} = 10$, $W_h(0) = 2$, $T^{wait} = 10$.

2.15.2 Volatility: heavy tails





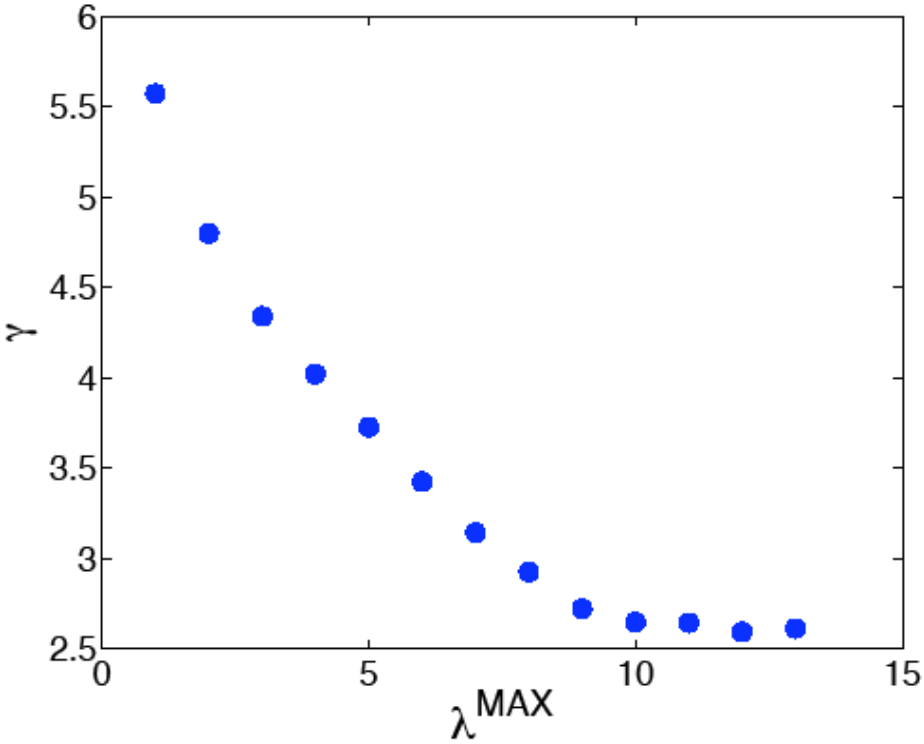


Figure 5: (a) Distribution of log returns r. Shown is the density $p(r)$ (conditioned on positive mispricing) in a semi-log scale. (b) cumulative density of negative returns conditioned on the mispricing being positive, $P(r > R \mid m > 0)$, in log-log scale. The red curve is the noise trader only case. For $\lambda_{max} = 10$ we fit a power law to the data across the indicated region and show a line for comparison. $T_{wait} = 100$, $r_{exp} = 0.005$, $\lambda_{max} = 10$; $\beta = 5, 10, \ldots, 50$. (c) γ as a function of λ_{MAX}.

The nonlinear feedback between leverage and prices demonstrated in the previous section dramatically alters the statistical properties of prices [7]. This is illustrated in Fig. 3, where we compare the distribution of logarithmic price returns with only noise traders to that with hedge funds but without leverage ($\lambda^{MAX} = 1$) to the case when there is substantial leverage ($\lambda^{MAX} = 10$). With only noise traders the log returns are normally distributed. When hedge funds are added without leverage the volatility of prices drops slightly, as it should given that the hedge funds are damping mispricings. Nonetheless, the log returns remain normally distributed. When we add leverage, however, the distribution becomes peaked in the centre and develops heavy tails. We show the case when $\lambda^{MAX} = 10$, where we see that the distribution of largest returns is roughly described by a straight line in the double logarithmic plot over more than an order of magnitude, suggesting that the tails can be reasonably approximated as a power law, of the form $P(r > R) : R^{-\gamma}$.

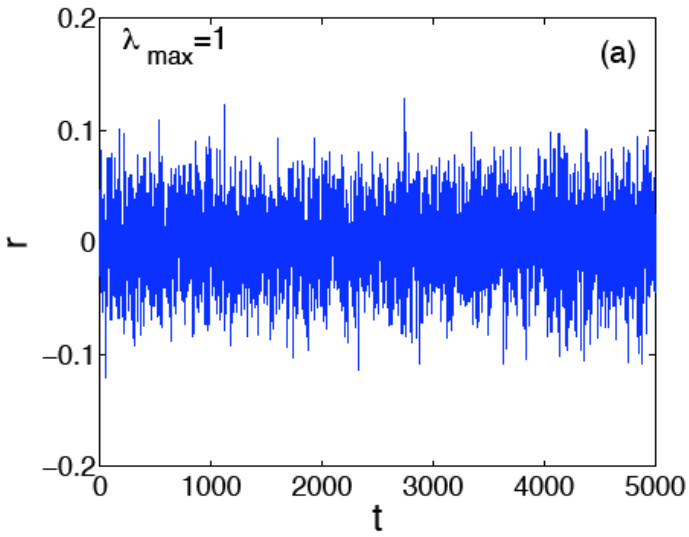
The transition from a normal distribution to a heavy tailed distribution as the leverage is increased occurs continuously: As we increase λ^{MAX} above one, the tails become heavier and heavier, and the centre

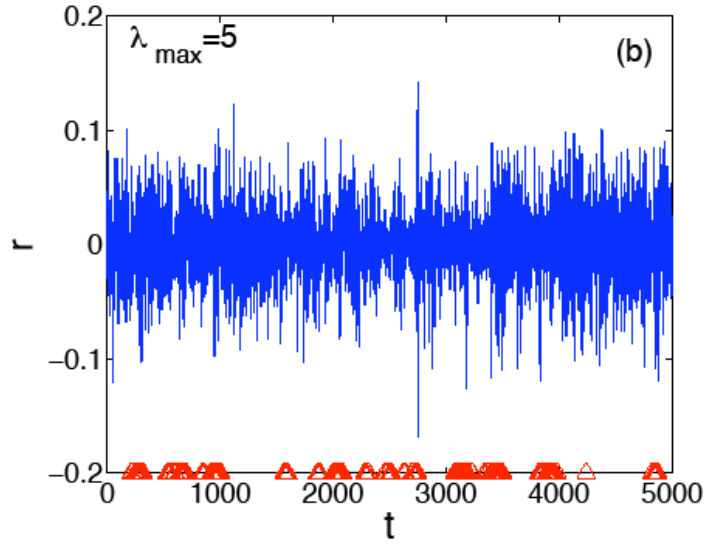
of the distribution becomes more and more sharply peaked. Increasing λ^{MAX} causes the tail exponent to decrease in a more or less continuous manner. For $\lambda^{MAX} = 10$, for example, we find $\gamma \approx 2.6$, which is slightly more heavy tailed than typical values measured for real price series [39,40]. For lower values of λ^{MAX} we get larger tail exponents, e.g. $\lambda^{MAX} : 7$ gives $\gamma : 3$, a typical value that is commonly measured in financial time series.

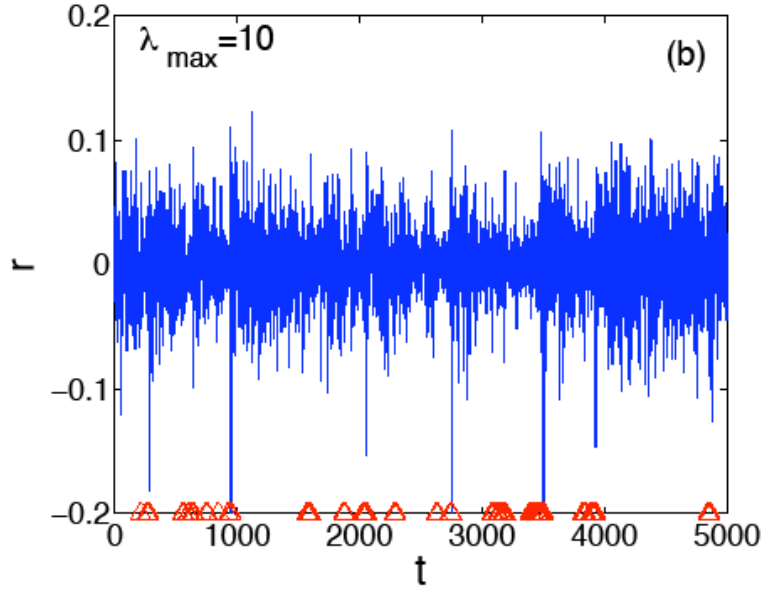
2.15.3 Clustered volatility

The origin of the phenomenon of clustered volatility in markets is another important mystery. Under the random walk model the rate of price diffusion v is called the volatility. Clustered volatility refers to the property that v has positive and persistent autocorrelations in time. In practice this means that there are extended periods in which volatility is high and others in which it is low. This model also produces clustered volatility in prices, similar to that observed in real markets.

In Figure 6 we show the log-returns as a function of time [7]. The case with $\lambda^{MAX} = 1$ is essentially indistinguishable from the pure noise trader case; there are no large fluctuations and only mild temporal structure, corresponding to the mean reversion of the noise traders. The case $\lambda^{MAX} = 5$, in contrast, shows large, temporally correlated fluctuations, which become even stronger for $\lambda^{MAX} = 10$.




λ max=5
(b)
0.2
0.1
0
−0.1
−0.2
r
0
1000
2000
3000
4000
5000
t


λ max=10
(b)
0.2
0.1
0
−0.1
−0.2
r
0
1000
2000
3000
4000
5000
t

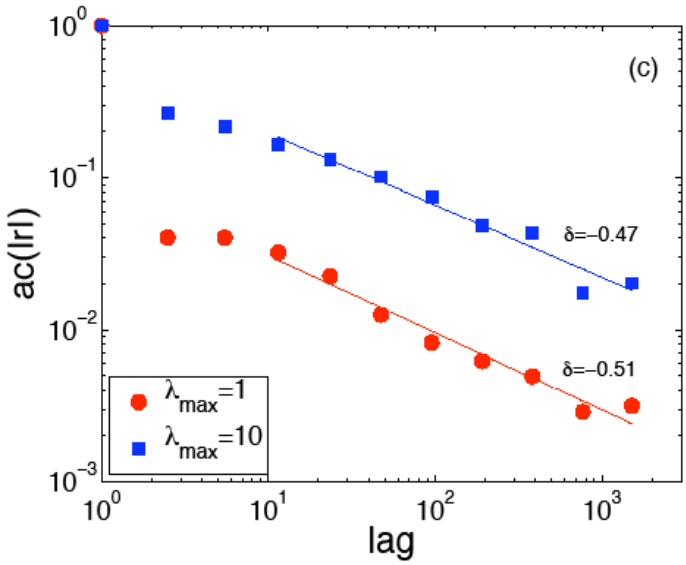


Figure 6: Log-return time series (a) $\lambda^{MAX} = 1$; (b) $\lambda^{MAX} = 5$; (c) $\lambda^{MAX} = 10$; Triangles mark margin calls in the simulation, indicating a direct connection of phases of large price moves with margin calls. (d) Autocorrelation function of the absolute values of log-returns for (a-c) obtained from a single run with $100{,}000$ time steps. This is plotted on log-log scale in order to illustrate the power law tails. (The autocorrelation function is computed only when the mispricing is positive.) Default parameter values.

To provide a more quantitative measure of the clustered volatility, in Fig. 4(d) we present the autocorrelation function of the absolute value of the returns for the parameter values shown in Fig. 4(a-c). Since the behaviour for noise traders only is essentially equivalent to that with unleveraged hedge funds, $\lambda^{MAX} = 1$, we show only the latter case. In every case we observe positive autocorrelations out to lags of $\tau = 2000$. Plotting the autocorrelation function on double logarithmic scale suggests power law behaviour at long lags, i.e. $C(\tau) : \tau^{-\gamma}$, as is commonly seen in real data [26]. For the pure noise trader case, or equivalently for unleveraged hedge funds, the first autocorrelation is roughly 0.03, a factor of roughly 30 less than one. Interestingly, after this it drops as roughly a power law, with an exponent $\delta \approx 0.5$. At $\lambda^{MAX} = 5$ the first autocorrelation is roughly 0.2, almost an order of magnitude higher, and for large values of τ it decreases somewhat faster, with $\delta = 0.76$. Finally, at $\lambda^{MAX} = 10$ the first autocorrelation is similar, but it decreases more slowly, with $\delta \approx 0.47$. Thus the behaviour as λ^{MAX} varies is not simple, but for large values of λ^{MAX} it is similar to that observed in real data.

2.15.4 Anatomy of crashes

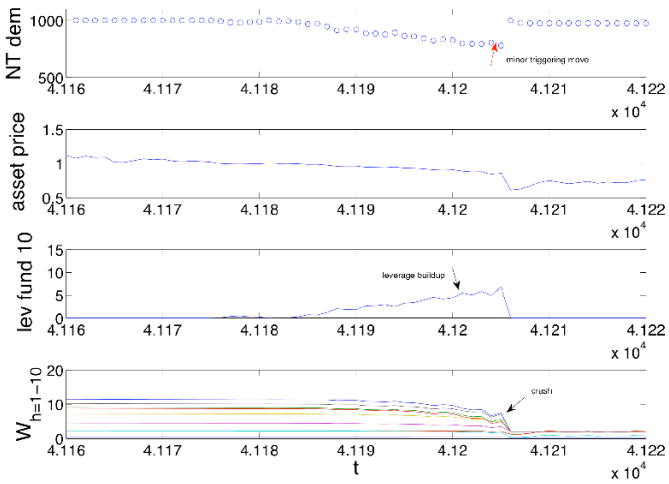


Figure 7: Anatomy of a crash: under the scenario of large levels of leverage a tiny - otherwise normal - fluctuation of the noise traders demand tips the system over the edge - it collapses. 10 funds, β in the range of $5:5:50$, $\lambda^{MAX} = 5$, $r_{exp} = 0.005$

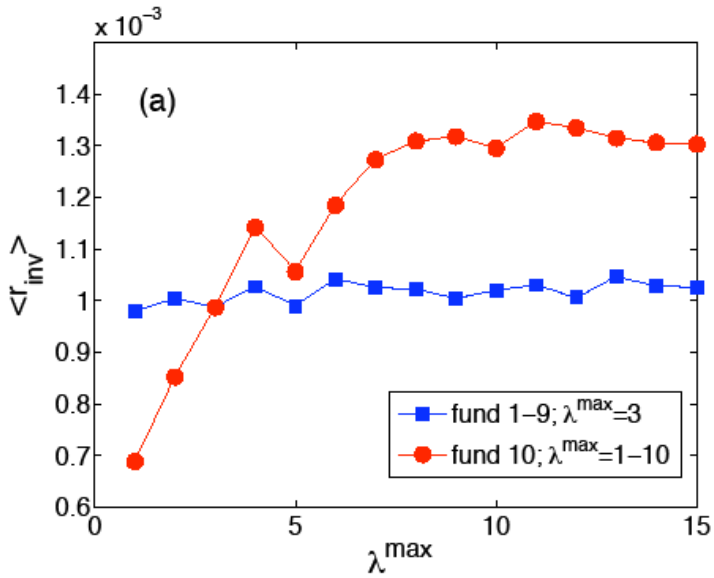
We now show how crashes are driven by nonlinear feedback between leverage and prices. In Fig. 5 we present a detailed view of what happens during a crash. At about $t = 41185$, due to random fluctuations in the noise trader demand, the price dips below its fundamental value and a mispricing develops, as shown in the top two panels. To exploit this the funds use leverage to take large positions. At $t = 41205$ the noise traders happen to sell, driving the price down. This causes the funds to take losses, driving the leverage up, and some of the funds begin sell in order to make their margin calls. This drives the price down further, generating more selling, generating ultimately a crash in the prices over a period of only about $2-3$ time steps. We thus see how crashes are inherently nonlinear, involving the interaction between prices and leverage.

It is immediately clear that typically price fluctuations driven by random events of the noise traders will not cause big events. Many fluctuations have been bigger than the one which triggers the crash. The fluctuation only becomes systemically relevant, i.e. dangerous if it happens in a system which is highly leveraged. The leverage build-up from $0-10$ during time steps $t = 41185-41204$ is enough to allow for a crash triggered by a normal size fluctuation. This is a typical scenario - a crash is triggered by a trivial seemingly irrelevant event. The circumstances under which it happens however (the general leverage levels in the system) make it a trigger for system wide collapse.

3 EVOLUTIONARY PRESSURE FOR INCREASING LEVERAGE

Free market advocates often argue that markets are best left to operate in an unfettered manner. In this section we demonstrate that regulation of leverage is desirable from several different points of view. We first show that, under the parameter values investigated here, increased leverage leads to increased returns[3]. There is thus 'evolutionary pressure' driving leverage up, meaning that without exogenous regulation fund managers are under pressure to use higher leverage than their competitors. If this process is left unchecked, leverage rises to levels that are bad for everyone. This can lead to an increase in the number of defaults and lowers returns and profits for banks as well as for the funds themselves.

To illustrate this we do an experiment in which we hold the maximum leverage of all but one fund constant at $\lambda^{MAX} = 3$ while we vary the maximum leverage of one fund from $\lambda^{MAX} = 1$ to $\lambda^{MAX} = 10$. We then plot the returns to investors as a function of λ^{MAX} for the varying fund, as illustrated in Fig. 6.



[3] With very high aggression parameters, e.g. $\beta > 40$ this effect can reverse itself, because leverage becomes so high that defaults also become very high, lowering returns.

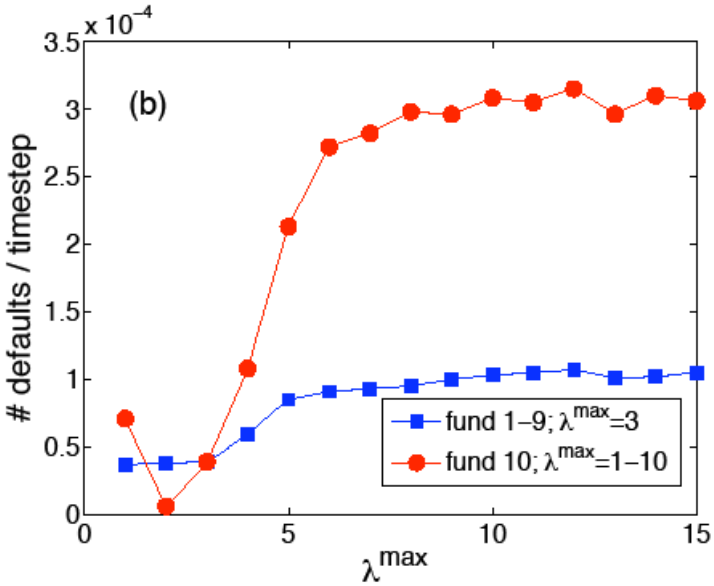


Figure 8: Results of a numerical experiment in which the maximum leverage $\lambda^{MAX} = 3$ for nine funds while λ^{MAX} varies from $1-10$ for the remaining fund. (a) shows the returns to investors and (b) the number of defaults.

We find that the returns to investors go up and down with leverage: All else being equal, when the leverage of a given fund is below the average of the other funds, the returns are below average, and when the leverage is above average, the returns are above average.

This result is not quite as obvious as it might seem, since as shown in Fig. 6(b), as the leverage increases, the default rate also increases. The NAV for a fund that defaults is by definition 0, corresponding to the fact that an investor who put a dollar in at the beginning and never took anything out loses everything. However, our investors redeem and add to their investments incrementally, so even in a situation where the fund defaults they may still on average achieve a good return. This is the reason why we have computed returns using Eq. 16, which properly takes this effect into account. We see that the enhanced returns of increasing leverage dominates over defaults, so that at least at these parameter values, there is a strong incentive for funds to increase leverage.

4 HOW LEVERAGE INCREASES VOLATILITY

We now explain how leverage increases volatility by stating the argument given in [7]. Let us begin with the case of noise traders alone, and assume for a moment $V = 1$ for simplicity. Market clearing requires that $D_{nt} = N$, and equation 3 implies $\xi = Np$. If we define $x \equiv \log \xi/N = \log p$, the noise trader process can then be written in terms of log prices as

$$x_{t+1} = \rho x_t + \sigma \chi_t. \quad (18)$$

Thus the price process is a simple AR(1) process. Defining the log return as $r_t = x_{t+1} - x_t$ and the volatility in terms of the squared log returns as $E[r_{t+1}^2]$, the volatility with a pure noise trader process is

$$E[r_t^2] = \frac{2\sigma^2}{1+\rho}. \quad (19)$$

In the limit as $\rho \to 1$ this converges to σ^2. Thus for $\rho < 1$ there is a very mild amplification.

Now assume the presence of a single hedge fund with aggressiveness β and assume a positive mispricing $0 < m = 1$, small enough that the price is slightly below V and the hedge fund is not at its maximum leverage, i.e. the hedge fund demand is $D_h p = \beta m W$. The market clearing condition can then we written as $NV\xi + \beta m W = Np$. With the mispricing being $m = V - p$ together with the definition $W_t = C_t + D_t p_t$, this gives the quadratic equation in m

$$-\beta D_t m_t^2 + [N + \beta(C_t + D_t V)]m_t + NV\xi_t - NV = 0. \quad (20)$$

At time $t+1$ we can make use of equation (9), $W_{t+1} = C_t + D_t p_{t+1}$, and write a similar equation for m_{t+1}, which is the same except for $\xi_t \to \xi_{t+1}$:

$$-\beta D_t m_{t+1}^2 + [N + \beta(C_t + D_t V)]m_{t+1} + NV\xi_{t+1} - NV = 0. \quad (21)$$

Solving these two quadratic equations (denoting the coefficients of equations (20) and (21) by $a = -\beta D_t$, $b = N + \beta(C_t + D_t V)$, $c = NV\xi_t - NV$ and $\bar{c} = NV\xi_{t+1} - NV$), the change in price can be written

$$p_{t+1} - p_t = m_t - m_{t+1} = \pm \frac{\sqrt{b^2 - 4ac} - \sqrt{b^2 - 4a\bar{c}}}{2a} : \frac{\bar{c} - c}{b} = \frac{NV(\xi_{t+1} - \xi_t)}{N + \beta(C_t + D_t V)}, \quad (22)$$

assuming that ac/b^2 and $a\bar{c}/b^2$ to be small, which is certainly true for large N. Comparing to the pure noise trader case, where $p_{t+1} - p_t = V(\xi_{t+1} - \xi_t)$, we see that the volatility is reduced by a factor $(1+\frac{\beta}{N}(C_t + D_t V))^{-1}$, which is less than 1 as soon as leverage is taken, i.e. $\lambda > 1$.

At maximum leverage the market clearing condition is $NV\xi + \lambda^{MAX} W = pN$. A similar calculation gives

$$p_{t+1} - p_t = \frac{NV(\xi_{t+1} - \xi_t)}{N - \lambda^{MAX} D_t}. \quad (23)$$

Both D_t and λ^{MAX} are positive. Comparing to the pure noise trader case, we see that now the volatility is amplified [7].

4.1 The danger of pro-cyclicality through prudence

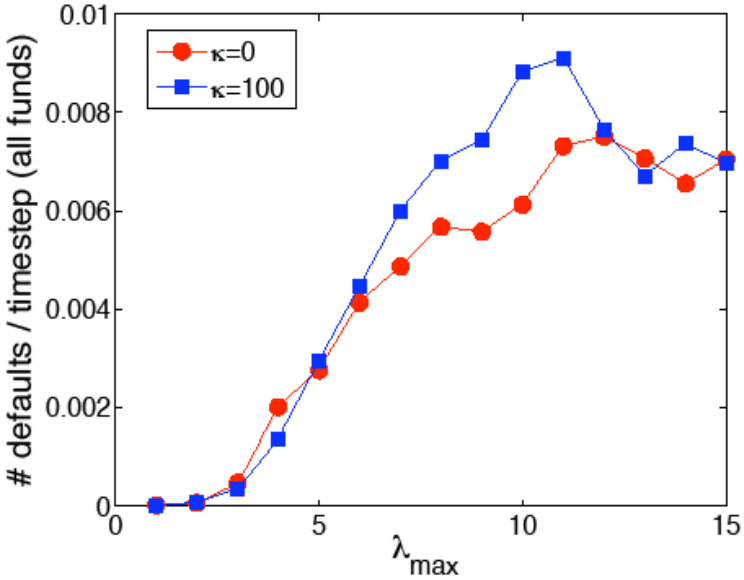
So far we have assumed throughout that the maximum leverage parameter λ^{MAX} is held constant. However, risk levels vary, so it is natural to consider policies that adjust leverage based on market conditions. We analyze two situations, one in which leverage providers monitor the value of their collateral. In case the volatility of the collateral gets high, a prudent lender will reduce its outstanding loan, and recall some of it. The other situation is to study a 'toy' implementation of the Basle I regulation scenario. Leverage providers - here banks - have to keep a capital cushion, i.e. they have to keep a ratio of about 10% of cash (with respect to their assets) in their vaults. Banks are forced to keep that ratio by the Basle agreement (e.g. [27, 28]). Potential pro-cyclical effects have been discussed in [29, 30]. With the agent based model described above we can now study the systemic effects of these practices.

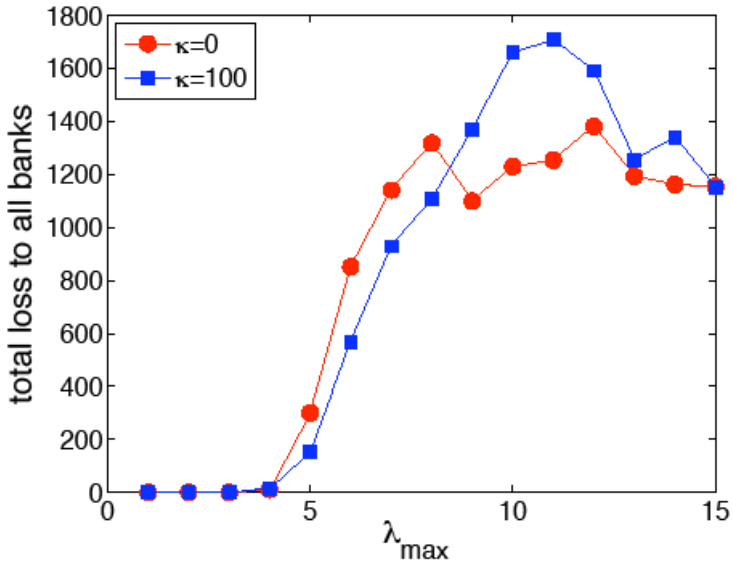
4.1.1 Volatility monitoring of collateral

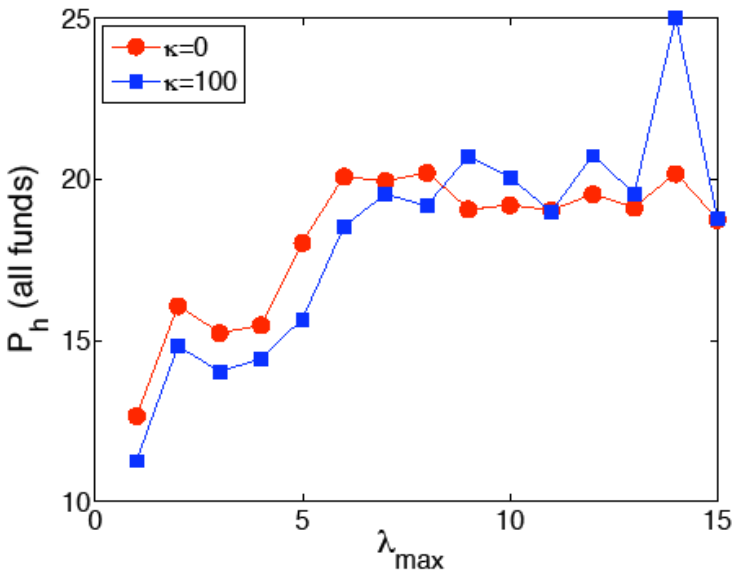
A common policy is for banks to monitor volatility, increasing the allowable leverage when volatility has recently been low and decreasing it when it has recently been high. We assume the bank computes a moving average of the asset price volatility, σ_τ^2, measured as the variance of p of over an observation period of τ time steps. Here we use $\tau = 10$ time steps. The bank adjusts the maximum allowable leverage according to the relation

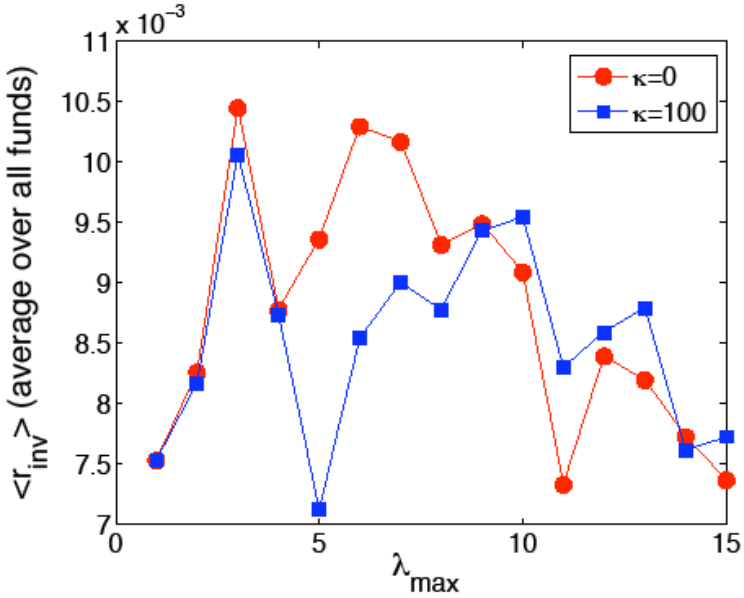
$$\lambda^{\max}(t) = \max\left[1, \frac{\lambda^{MAX}}{1 + \kappa\sigma_\tau^2}\right]. \quad (24)$$

This policy lowers the maximum leverage as the volatility increases, with a floor of one corresponding to no leverage at all. The parameter κ sets the bank's responsiveness to changes in volatility. For most of the work presented above the maximum leverage was held constant, corresponding to a $\kappa = 0$. In this section we use $\kappa = 10$.


0.01
0.008
0.006
0.004
0.002
0
defaults / timestep (all funds)
κ=0
κ=100
0
5
10
15
λmax


1800
1600
1400
1200
1000
800
600
400
200
0
total loss to all banks
κ=0
κ=100
0
5
10
15
λmax


κ=0
κ=100
P_h (all funds)
λ_max
25
20
15
10
0
5
10
15


x 10^-3
κ=0
κ=100
<r_inv> (average over all funds)
λ_max
11
10.5
10
9.5
9
8.5
8
7.5
7
0
5
10
15

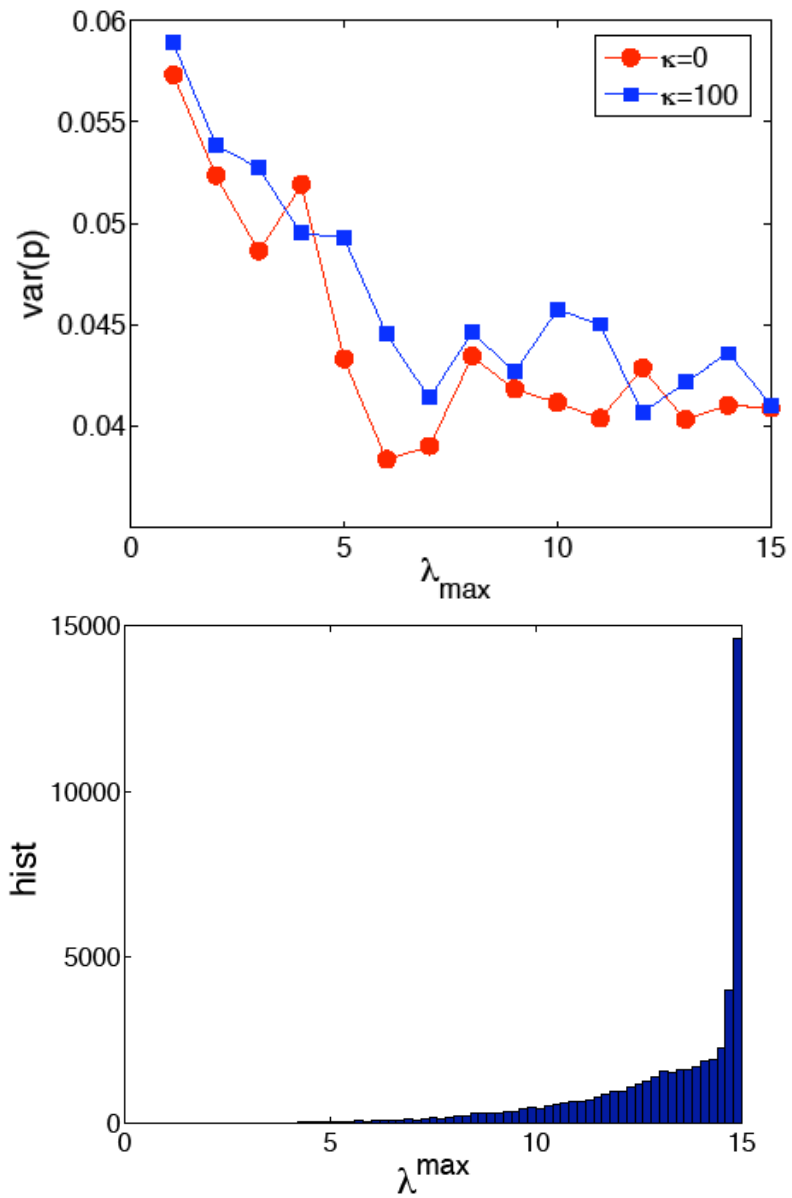


Figure 9: Comparison between constant maximum leverage (red circles) vs. adjustable leverage based on recent historical volatility, Eq. 24 (blue squares). 10 funds were considered with β values in the range of $\beta = 5,10 \cdots ,50$. (a) Defaults in the system. (b) Losses to the banks due to defaults (sum of all losses of all banks). (c) Average return to investors as a function of λ^{MAX} , the average extends over the returns over all funds. (d) Total return to all (10) fund managers assuming a with 2% management fee and a 20% performance fee. (e) Average variance of the price. (f) Distribution of the time-dependent $\lambda^{max}(t)$ in a simulation with λ^{MAX} in Eq. (24) fixed to $\lambda^{MAX} = 15$ and $\kappa = 100$. All results are averages over 10 independent runs.

In Fig. 9 we compare the active leverage management policy of Eq. 24 to a constant leverage policy. We show a series of measures as a function of a hypothetical λ^{MAX} imposed (by an external regulator) on

the system. We see immediately that the adjustable leverage policy for low values of λ^{MAX} works as expected: The number of defaults in the system as well as the total losses taken by the banks are smaller for the active volatility monitoring strategy. Also expected is that this implies that returns to investors and returns to fund managers are lower than in the unregulated case.

The situation changes for higher λ^{MAX}, where the situation reverses and the adaptive regulation has a contrarian effect of what is initially intended. The number of defaults clearly is much higher for the prudent case (!). The same is seen for the total losses to banks in the system. The regulation has not much effect on the overall volatility in the asset price; it remains about the same in either case. Also seen in the figure is the distribution of $\lambda^{MAX}(t)$, which makes clear to what extend leverage is actually reduced by this mechanism.

4.1.2 Introducing pro-cyclicality through regulation through capital cushions

Banks have to keep capital cushions as a safety measure for liquidity problems. We perform a series of simulations to see what happens under such a typical regulation scheme, where the bank constantly has to monitor its capital-to-asset ratio,

$$\gamma(t) = \frac{\sum_h L_h(t)}{W_B(t)}, \quad (25)$$

where $W_B(t)$ is the wealth of the bank at time t, and $\sum_h L_h(t)$ is the total outstanding loans (made to e.g. funds for leverage). Banks are not allowed to exceed a maximum $\gamma^{\max}$ - they have to keep a 'capital cushion'. If $\gamma(t) > \gamma^{\max} > 0$, the bank adjusts $\lambda^{\max}(t)$ such that $\gamma(t) = \gamma^{\max}$ is ensured for the next time step. [4]

In Fig. 10 we see a set of measures plotted as a function of the maximum leverage, externally imposed. We study four scenarios, one where the bank is very 'rich' i.e. it has enough capital to always maintain its mandatory capital cushion. We do this by endowing the bank with $W_B(t=0) = 1000$ monetary units. The other scenarios are chosen, that the banks sometimes have to become active to maintain the ratio, and have to recall loans to do so ($W_B(t=0) = 200,150,100$). It is clearly seen, that this regulatory measure does not show much effect for small λ^{MAX}. However, for larger λ^{MAX} for the cases where banks become active, the number of investment firm defaults is much larger than for the unregulated banks. Of course the procedure of setting different $\gamma^{\max}$ levels (Basle parameters) and keeping the banks at the same cash level, would yield identical results. Also seen in the figure are the wealth levels for the funds, associated to the inactive or active banks. The ones which face less margin calls and can take more leverage on average are doing consistently better. The average of the actually uses leverage shows a clear peak. It arises through the fact that the bigger investment funds get, the less they rely on leverage.

[4] We mention that in these simulations the banks do not earn money since we set the interest rates to zero. This was done to keep most processes stationary. However, here we now introduce a non-stationarity because banks only lose money. This is an unrealistic feature which has to be dealt with in future extensions to the model.

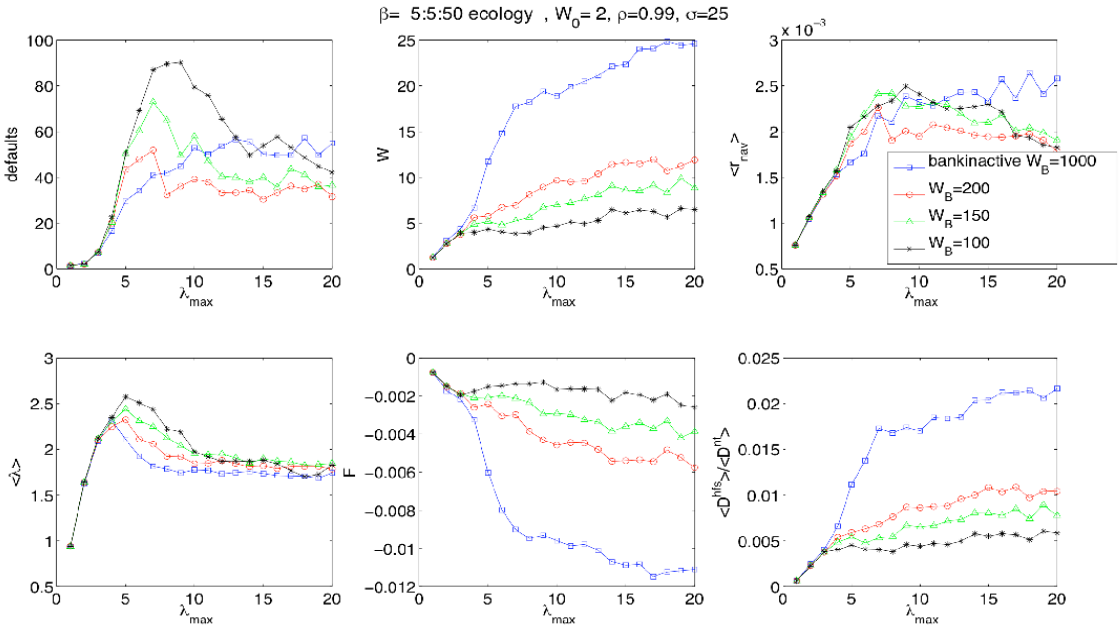


Figure 10: Comparison of regulated leverage providers to an unregulated one (blue), as a function of the maximum leverage λ^{MAX} in the system. (a) number of defaults of investment firms. (b) size of investment firms. (c) NAV. (d) average of the actually used leverage. Note that leverage is not always used to its maximum, it depends on the investors demand function, and its aggressiveness β in particular. (e) Capital inflow to the funds from the investors to investment forms. Negative values mean that funds are paying out to these investors (dividends). (f) Ratio of average demands from investment firms to noise traders.

Figure 11 shows the same measures as the previous figures. Now the most and least aggressive funds of the ecology are shown for both the unregulated bank (bank inactive) and the regulated bank For the unaggressive funds regulation works as it should, default rates are lower when banks are regulated. It is now interesting to observe a reverse effect for the aggressive funds: when banks are regulated defaults are higher. This is understood simply because in the regulated scenario aggressive funds (which take high levels of leverage) suffer severely from loan re-calls. These re-calls will sometimes trigger a downward spiral of asset price driving highly leverages firms into default, whereas firms with little or no leverage will suffer losses but will survive.

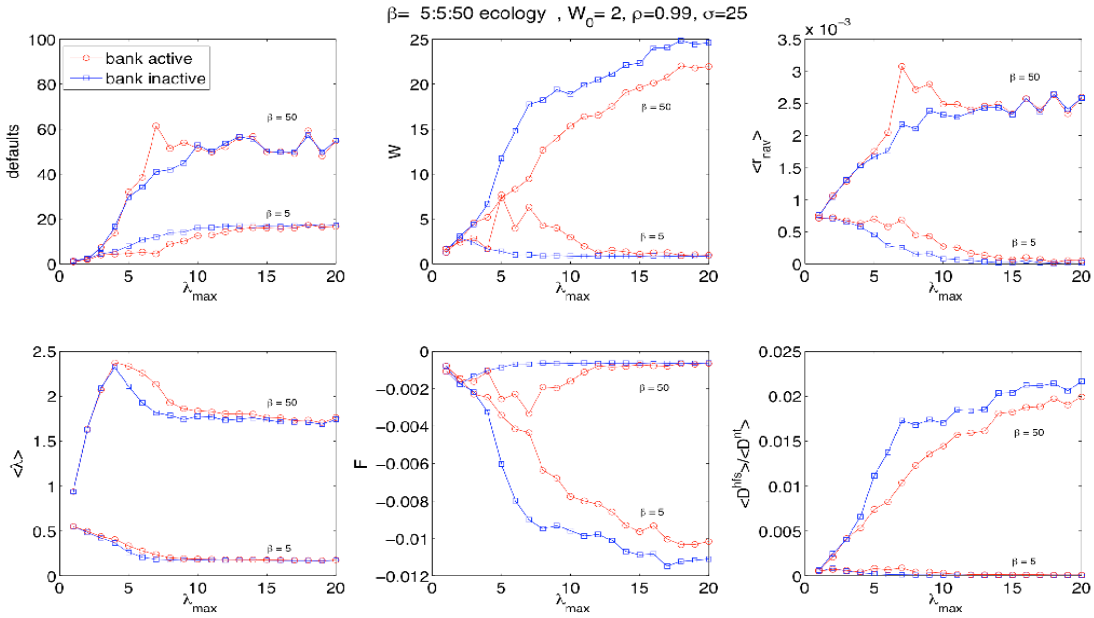


Figure 11: Comparison of the effect of regulated (red) versus unregulated (blue) banks on aggressive funds (indicated by their aggression level $\beta = 50$) and non aggressive ones ($\beta = 5$). The same measures as in the previous figure are shown: (a) number of defaults of investment firms. (b) size of investment firms. (c) NAV. (d) average of the actually used leverage. Note that leverage is not always used to its maximum, it depends on the investors demand function, and its aggressiveness β in particular. (e) Capital inflow to the funds from the investors to investment forms. Negative values mean that funds are paying out to these investors (dividends). (f) Ratio of average demands from investment firms to noise traders.

4.2 The process of de-leveraging

In the model above the process of de-levering is as follows. At every time step - after each trade in the asset - the actual leverage is computed. It is known to the lender (who holds the assets as collateral and knows the asset price from the market) and the investment firm. At this point the lender can take several decisions:

• recall the loan or parts of it because the actual leverage is higher than the one actually agreed. This is the margin call scenario

• recall the loan or parts of it because of liquidity issues of the lender, e.g. too high capital-to-asset ratio

• recall the loan or parts of it because of risk management consideration of the lender, e.g. that the collateral appears to be too volatile

The first of these cases is taken care of implicitly by the design of the demand function of the leverage taking investors. The other two cases are realized by the leverage provider lowering the leverage ratio for the next time step. The investor will in the next time step adjust his demand such as to meet this new ratio. Usually this is achieved through a reduction of demand in the asset, i.e. by selling the asset. Generally this will tend to drive the price of the asset down, and potentially the volatility up. Both consequences will be

felt by all investors invested in the same asset, and banks holding the same collateral. This might lead to new actions in the next time steps. In severe cases, and especially if the general leverage levels have been high, this might induce a feedback mechanism, which forces investors to sell large stakes of their assets within a few time steps, resulting in a massive decline of asset prices and an incline of defaults of investors, who can not pay back their debt by selling the now low-priced assets. The losses - credits which could not be paid back - are taken by the leverage providers - here the banks.

If none of the above takes place, the leverage provider renews the credit for an other time step. The fund takes as much of that credit as is indicated by its demand function.

5 LEVERAGE AND SYSTEMIC RISK: WHAT HAVE WE LEARNED?

Here follows a summary of the most important findings of the presented agent based model of the financial market [7]. This report showed qualitatively how different market participants such as informed investors, noise traders, leverage providers, and investors perform their roles in their co-evolving environments. It demonstrates how their performance influences actions of others, and study the effects on e.g. the formation of asset prices. Among many other features, these mutual influences cause price fluctuations and volatility patterns which are observed in real markets.

5.1 Triggers for systemic failure

The report shows that moderate leverage leads to a reduction of volatility in price formation. However the higher the leverage levels get, the more extreme price movements have to be expected. Further, it quantifies the relation in our toy-model economy. In this setting it could be demonstrated that even value investing strategies, which are supposed to be stabilizing in general, can massively increase the probability of crashes - given that leverage in the system is high.

The report looks in detail at the dynamics and the unfolding of crashes, in particular it identifies triggering events for crashes. Small random events, which are completely harmless in situations of low and moderate leverage can become the triggering events for downward spirals of asset prices during times of massive leverage.

It shows that the level of leverage directly correlates with likelihood of systemic failure. Further it shows that in an unregulated world there exists market pressure toward high leverage levels, i.e. there are incentives from the investors' and banks' side to increase leverage.

5.2 Counter intuitive effects

Two modes of regulation were implemented in our model economy. The first type was to introduce prudent banks, i.e. leverage providers, who constantly monitor the value of their collateral. If the value of the collateral - typically the assets bought by the leveraged investors - shows certain patterns, these banks will start recalling their loans (margin calls), forcing leveraged investors to sell the assets. Increased supply will tend to drive prices down. The pattern bank monitor in our model is the volatility of the asset.

The second type of regulation was to implement a regulation scenario of the Basle-type. This means that leverage providers have to maintain a capital cushion of say 8%. If the ratio of extended credits to

capital can not be maintained, the bank again enforces margin calls. This might lead to severe synchronization due to many investors being forced to sell at the same time - driving asset prices down. The capital ratio typically becomes relevant if banks lose capital through foul credits (of defaulted leverage takers)

In conclusion the report found that both types of regulation work well in times of moderate leverage, but turn into enhancing crisis when leverage is high. This is mainly due to enhanced synchronization effects induced by regulation of this type.

6 IMPLICATIONS - FUTURE RESEARCH QUESTIONS

6.1 The need for global leverage monitoring

Our findings to this point imply several immediate messages relevant for a future architecture of the financial world:

• Global monitoring of leverage levels on the institution level. This could be done by Central Banks. Data should be made available for research. Without the knowledge of leverage levels at the institution scale, imposing and executing maximum leverage levels is pointless.

• Monitoring and analysis of lending/borrowing networks, both of major financial players and of governments. It should be known who holds the debt of whom. Without this knowledge imposing maximum leverage levels becomes hard to implement.

• Imposing maximum leverage levels depending on debt structure, trading strategies and position in lending/borrowing networks. Through this measure, regulators could control levels of extreme risk by limiting leverage. This is by no means a trivial undertaking, and needs to be accompanied by massive future research, concerning implications of this step.

6.2 The need for understanding network effects in financial markets

Two types of network effects are immediately relevant for systemic risk in financial markets. Both of them are empirically poorly understood, and need to be boosted and brought into mainstream economic thinking. Without the detailed knowledge of these networks a regulation of leverage will be impossible. Massive efforts on concerted data aggregation with rigorous quality requirements are needed. The two types o networks are

• First, the lending relations between leverage providers and leverage takers. It is typical that one bank is the source of leverage to a series of hedge funds. If one of these funds comes under stress this might cause the bank to issue margin calls not only to the fund under stress but to all of the funds it extends credit to.

• Second, the asset-liability network between banks becomes relevant if one bank experiences losses or default. This might trigger contagion effects through the banking network, if no exogenous interventions occur [13, 17].

Given the knowledge of these networks - which could be in principle assessed by e.g. Central Banks - these networks could be fed into ABMs of the above kind as direct input. The implementation of these network structures into agent based models will open to a new level of complexity, and possibly opens a source of understanding hitherto unthought of types of systemic risks. In particular it can be expected that certain dynamics will now be influenced by the position of funds in the leverage provider-taker networks, and the position of banks in the asset-liability networks of bank. For example the risk for margin calls might become higher when taking leverage from banks with a high *node centrality* [17] than from banks which are not likely to be effected by liquidity contagion cascades between banks. These questions pose an important field for future research, both empirically as well as on the side of agent based modelling.

6.3 The need for linking ABMs of financial markets to real economy and social unrest

Crisis often occurs in one sector but often can percolate through other areas of life. How there mechanisms work is largely not understood. It would be of prime importance to link agent based models of financial models with ones for the real economy. These efforts would help to understand the mechanisms of unfolding dynamics of crisis through different scales: from financial crisis to economic crisis (reduction of production, demand, increase of jobless, decrease of purchase power, etc.) and eventually social unrest. It is further important to understand the feedback from a slowing down real economy to the financial industry (less demand for credit, less realization of ideas, less venture capital etc.). It would be especially interesting to couple such models to dynamics of social unrest [?] - which is certainly linked to economic wealth. One could think of coupling unrest scenarios along the following lines of different scales of crisis

• Collapse of investment firms: - hits investors to these firms (rich individuals, investment firms, other funds): Potential for immediate social unrest is low

• Collapse of banks and financial sector: - hits depositors (increased risk for social unrest) and hits liquidity of other banks - potential to cascading effects (contagion scenarios) in case of no interventions and bailouts with public money

• Collapse of governments: illiquidity can be dealt with in three ways: default, inflation, increase of productivity, efficiency, innovative power, etc. As soon as governments lose their ability to perform their core duties, revolutionary potential increases sharply

6.4 Systemic risk is not priced into margin requirements

Today systemic risk is not priced into margin requirements. This would be necessary to design self-regulating leverage regulation policies. Current regulation schemes are not self-regulating and lead to the described counterintuitive pro-cyclical amplification of crisis. Margin requirements must be a function of leverage loaned out by leverage providers. If a lender contributes to the total risk in the system over-proportionally, margin requirements should be automatically raised, i.e. the capital to loans ration must be increased.

Further, systemic risk induced through network effects is not priced into margin requirements. It is obvious that different network topologies of lending/borrowing networks and the individual position of leverage providers influence the total risk in the system. Much more scientific research is needed to understand these influences, before proper steps toward regulatory measures can be taken.

6.5 Extensions to leverage on national levels

Governments make speculative investments on credit. Given the recent developments in Greece it becomes clear that the concept of leverage also hold on national levels. However, there are also several important distinctions to be made with respect to the leverage scenarios described so-far. Nevertheless many of the conclusions drawn above hold equally on national scales. Let us list some differences and similarities

• Usually investments of governments are not made directly in the financial market, even though this has happened in recent years as well. The investments usually made, for example in infrastructure, public health, bank-bailouts, job-less programs etc. are also highly speculative. If a series of such investments do not yield the expected returns, countries can get under stress, e.g. facing liquidity problems, exactly as in the examples shown for the investment companies in the above ABM.

• Sustainable leverage is obtained usually through borrowing from the financial market, e.g. through bonds. This limits the risk of a direct margin call. Short term debt however needs to be refinanced, and a situation very much alike the margin call scenarios described above for investment firms may arise. This might come through strongly rising interest rates for governments under stress. Governments might be forced to repay debt and be unable to issue debt at realistic rates. The government is forced to de-leverage.

• Governments can default as investment firms above. In this case they are not able to leverage anymore, and can only rely on their present tax revenues.

• Governments have more options to de-lever than investment firms. In addition to default, they can (if they have the possibility to print money) inflate their debt away.

• De-leveraging of governments means to reduce scales of social investments, social and health benefits, (in some countries) pensions, etc. Consequences of governments under stress or default can lead to social unrest.

• Indirect governments engagements in financial markets are established through bank-bailouts. When governments act as ultimate risk takers of investment companies (bailouts) they are implicitly involved in financial speculation. This directly links stress in the financial markets with limitations of government actions.

6.6 Data for leverage-based systemic risk on national scales

For future research on implications of leverage on national scales and their risks, the following research questions should be addressed

• Identify lender-borrower relations in form of network structure on a national-financial institutional scale

• Identify orders of magnitudes of leverage, by institution, regionally, and globally

• Identify the active effective number and linkages of agents: in other words, identification of the owner relationships / structure of financial institutions and debt holders

• National credit structure: who holds whose risk? Assemble data whatever possible. If good data was available, one could try to feed these credit networks into existing agent based models.

7. OUTLOOK: TRANSPARENCY AND CONSEQUENCES FOR A NEW GENERATION OF RISK CONTROL

7.1 Breaking the spell: need for radical transparency

The agent based model described above makes one point very clear. In systems with structures like our current financial markets, crisis can and will emerge endogenously, i.e. triggered by the system itself. It does not necessarily need exogenous shocks to trigger and maintain the unfolding of a crises and the eventual collapse of the system. These effects happen far more often than predicted with current models of risk management.

The present model enables looking at the precise unfolding of such processes. The message is that the system, whenever system-wide leverage levels are high, becomes prone to amplifying small perturbations. The system starts to amplify small random events which are completely harmless and irrelevant in low-leverage situations. The amplifications can gain in weight and unfold into an *endogenous* extreme event. These amplifications happen through synchronization effects among individual agents. They all observe the same market information (i.e. asset prices) and under given circumstances, for example when liquidity starts drying up, they start behaving in similar ways - as if they were synchronized. The reason for this is that the rules (such as leverage contracts, lending conditions, margin calls, etc.) under which agents act (here for the informed investors) are the same across the system. To break up this synchronization - which finally is the ultimate reason for extreme events such as crashes - there exists one obvious setup:

The *complete* market information must become *fully* transparent to *all* participants. Today market information is obviously not transparent. It is only transparent in the sense that asset prices are available to all agents at the same time. What is generally not known to lenders and providers of credit is the complete portfolios of those who borrow for speculative investments. These portfolios must be made public to everyone. It is important to stress that not only the portfolios of those receiving the credit are needed, the information of who provides what credit to whom is of the same importance. If a bank provides large loans to risky funds, this bank should be publicly seen as risky too and should face a harder time to obtain credit as well. For such a bank it will be harder to receive deposits and to maintain a high share value. This reputational costs issue is necessary for the self-regulation scheme described below.

7.2 Self-regulation through transparency: an alternative regulation scheme

The following idea is simple to describe: a potential credit provider monitors not only the complete portfolio of its clients but also - in case he actually provides a loan - makes it public to whom he made it. The idea is that the levels of leverage will not become 'market levels' such as is the case today, but become individualized, i.e. - depending on client, provider and the complete surroundings. Such a scheme could entail the following steps.

Credit providers monitor the portfolios of their clients. They come up with a rating of the client based on this information.

Short term credit (leverage) is provided according to this rating. If the rating is high - leverage is provided - if low, it is recalled or interest on it is priced higher. Whatever the credit is, to whom the credit

was given is made public knowledge – possibly with conditions and depending on a qualifying purpose, such as scientific research. Failure to provide this information to the public is made a criminal offence.

Each financial institution monitors the assets and credits of the others - especially those it has relations with. If one bank sees that another bank is providing leverage to risky hedge funds, for example, it will reduce engagement with that bank, - recall its credits or deposits, or raise the interest rates. Under this scheme banks run reputation risk when loaning money to risky (or unethical) parties.

Central Banks provide credit to financial institutions, not on the federal funds rate as today, but rather on an individual basis, based on assets and liabilities of the particular institutions. These credits and rates between a Central Bank and institution are made publicly known to all as well. Central Banks provide credit to financial institutions not on the federal funds rate as today, but on an individual basis, again based on assets and liabilities of the particular institutions. These rates (Central Bank - institution) are publicly known to all as well.

Central Bank rates are known to the public - which gives depositors (and small shareholders) a way to assess the safety, prudence of their bank.

Bailouts with public money under this regime are ruled out.

This scheme leads to self-correcting dynamics. As a nice side effect under this scenario rating firms become obsolete: banks rate themselves. Depositors rate their banks. Rating has been delegated all too much to external rating firms in the past which has led to the known -partly absurd- problems, such as the creation of conflicts of interest, whereby firms pay the rating agencies for rating them, etc.

Within the proposed scenario it becomes the core-business of credit providers to check the credit worthiness of their borrowers, and lenders to keep a high rating in the eyes of their peers. Financial institutions would only survive and prosper if they assess the risk of others better than their peers, and, at the same time, reinforce this message across by opening their own books. This radical transparency would create incentives for a new culture in risk monitoring. The best performing institutions will be those with the best risk assessment.

Under this set of rules synchronization effects would be drastically reduced, since leverage terms, conditions, onset of margin calls, etc. are diversified. It remains to deepen agent based model studies of this new regime to quantify to which extent synchronization of market behaviour is reduced and how exactly this is reflected in reductions of default rates and total losses of financial institutions.

7.3 Toward a 'National Institute of Finance'

How could such a transparent world be implemented?

It would be necessary to set-up a database keeping track of all credits, transactions and repayments. On national scales data exists and is usually gathered by Central Banks. In Austria, for example, all credits above a certain size have to be reported by banks on a monthly basis, (large credit record). It would make most sense Central Banks to be responsible for providing coordination and oversight of such databases. On the basis of such data, information on outstanding credits could be made available on the homepage of banks in a standardized way, such that no hiding and polishing of position is possible. Central Banks could provide the data directly, so that there is a further incentive for individual banks to ensure that data is correct.

All financial transactions within e.g. the Euro area are recorded within the TARGET2 system. This information is also known to Central Banks and can be used e.g. to verify paying out and repayments of credits. This could again be used to increase incentives to avoid fraud. It would then need coordination to aggregate national data onto the global scale. This might call for a new institution, yet to be founded and endowed with the appropriate rights and powers.

In the United States there have been recent developments toward a 'National Institute of Finance' (NIF) [46], following the idea of the National Institutes of Health (NIH). The latter is perhaps the most comprehensive source of data on medicine and life sciences. For example, most high-quality genome data wherever obtained in the world is stored there and is open for science. Data is uploaded in a way that minimum quality standards are guaranteed. NIH is perhaps the richest resource of scientific data combined with best quality standards on the planet. First steps toward an NIF in the United States are underway. On June 21-22, 2010 a workshop on "Frameworks for Systemic Risk Monitoring" was organized by the Committee to Establish a National Institute of Finance (CE-NIF) co-organized by the Center for Financial Policy at the R.H. Smith School of Business at the University of Maryland and the Pew Financial Reform Project was held in Washington DC.

The essence of a National Institute of Finance would be to provide a database with the highest quality-standards possible and to make these data visible to all market participants, regulators and scientific researchers. It is mainly a technical challenge, not one of principle. It would of course be wise not only to bring financial data to this database, but to include all economic data on the scale of firms as well. The process of high-frequency data aggregation and the resulting new insights on the progress of an understanding of the systemic risk of the financial sector, would further make clear what further data needs to be recorded; including , perhaps data that is not even conceived of today.

8 SUMMARY

This report studied the effects of leverage on systemic stability in a simple agent based model of financial markets. It argues that this approach - unlike traditional approaches to risk management - allows to understand market mechanisms which can lead to large scale draw-downs and crashes. Even though the model is phrased in terms of financial agents acting in the financial markets, the essence of its findings can be transferred to national scales. This becomes especially important because of the active involvement of governments in the financial markets.

Governments make leveraged investments in at least two ways. First, they issue debt for performing their traditional role in financing infrastructure, economic incentives, innovation, education, etc. Second, several governments have chosen to become directly involved in highly leveraged speculations in the financial markets by bailing out financial institutions thereby increasing public debt. While these leveraged 'investments' might reduce some immediate potential of social unrest, it is everything but clear which scale of risks these actions might induce, in particular the risk of governments losing control: either through illiquidity and economic collapse, or through unpredictable political changes of groups using social unrest for their means. Since this later 'investment' can be very costly as experienced lately, and can jeopardize the liquidity of governments, it is imperative to understand the mechanisms and dynamics of leveraged investments and its dangers.

The report discusses immediate consequences of the findings in terms of possible policy implications for regulations of financial markets. Finally, it points out a series of research questions which have to be addressed massively to become able to rationally monitor and manage systemic risks. Most importantly from a scientific point of view are two issues, one related with data, the second with modelling: First, the specific aggregation and adaptation of specific financial network data under strict quality standards. Second, agent based models of the financial market, such as the one presented here, have to be extended to incorporate models of the real economy. This is necessary to gain an understanding of the possible feedback mechanisms between the financial industry and real economy. The study of these largely unexplored mechanisms might uncover unexpected insights in the unfolding of crisis and might provide starting points for its management or prevention.

Finally, the report concludes by showing how a new regulation scheme, based on complete portfolio transparency of all relevant financial players, opens a natural way to evade feedback mechanisms which has been shown to be at the root of crisis. The presented regulation scheme could revive a new culture of risk assessment among the majority of financial players, leading to a self-regulating systemic risk management, and at the same time evade the moral hazard problems created by external rating agencies.

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See also

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APPENDIX A: SOCIAL UNREST AND AGENT BASED MODELS

In the same way as financial markets are complex systems and show potential systemic large-scale effects, dynamics of social unrest do. As argued above, agent based models - provided they capture essential features - allow for an understanding of a series of fundamental issues of dynamics of social unrest. In particular these models may help to estimate the role of certain conditions that lead to the outbreak of phases of large-scale non-cooperative behaviour. One of these models, which was mentioned in the context of financial markets, is on the verge of becoming sophisticated enough to be of actual use.

For a discussion of the agent based model see Epstein [46]. In his strongly simplified ``world" there exist two types of actors, agents A, and cops C. The agents, representing people in a society can be found in two modes, they are either silent or they engage in rebellious acts, they take part in ``revolutionary" actions against their e.g. political or economical system. In the model it is not specified, what these systems are, the focus rests entirely on the dynamics of social unrest. Also what social unrest means in this context is not further explained in the model, all that counts is the number or fraction of agents actively participating in `revolutionary" actions at a given point in time. Let us call these agents ``active" which are in the revolutionary mode, while the others are called ``silent".

The role of the other type of actors, the cops is simply to remove (to ``jail") the active actors. Cops can spot active agents within a given range, and will arrest them when they encounter them. Each cop can arrest one active agent per time unit only, meaning that if many agents are active within a region with a limited number of cops around, the individual risk for active agents to be arrested becomes small. The agents can sense the presence of cops, which influences their decision of whether they are in the active or silent mode. The essence of models of this kind is the way agents decide in which mode they operate. In Epstein's model the decision process works as follows. Each agent has a certain ``grievance" which characterizes her. Grievance G is modelled as a product of hardship H and illegitimacy of a present regime I, $G = H * I$. The more hardship one has to bear the more grieve, the more illegitimate a certain regime, or certain surroundings are, the harder it is to bear these surroundings.

Any agent in the model that decides to become active faces the risk of being arrested, this risk being proportional to the ratio of cops versus active agents within a given region. The higher the number of police the higher the risk of being arrested, the higher the number of activists, the less likely the risk. Agents are further characterized by a random risk-aversion factor, quantifying their readiness to become active, given a certain probability of being arrested. The net risk for an agent to be arrested is called N. Agents are allowed to change their mode and their positions in the model. They change their mode from silent to active, whenever the difference of their grievance with respect to their risk of being arrested exceeds a pre-specified threshold, T, i.e. $S \rightarrow A$ if $G - N > T$. Cops are only allowed to change their positions.

These rules can be implemented in a simple computer algorithm to study the emerging properties of the model. Even though the model is undoubtedly a severe oversimplification of reality, surprisingly, it captures a series of known features of dynamics of social unrest. Again, as before, the agent based setup can now help to identify the key components, conditions and scenarios that lead to outbreaks of social unrest. It is not the intention of the model to predict a specific outbreak, or the time of an outbreak - which would be certainly impossible for any system. What can be studied, however, is the probabilities and detailed mechanism how, and under what circumstances social unrest unfolds, propagates and eventually ceases.

Some of the lessons that can be immediately learned from the model of Epstein [47] are:

• Free assembly of agents facilitates revolutionary outbursts

• Revolutionary outbursts tend to happen whenever a measure for social tension builds up. This measure is basically derived from an average of agent's grievance their risk aversion, paired with a high frequency of extreme grievance agents

• Abrupt legitimacy reductions correspond with large risk of outbursts, whereas gradual reduction (or decline) of legitimacy, such as constant reports on corruption within a regime, is much more stable in terms of outbreaks of social unrest.

• The distribution of drastic events over time (inter-event time of large scale outbursts) follows an approximate Weibull distribution

• The size distribution of drastic events (number of agents being active during an outburst) shows a nontrivial peak at high numbers, meaning that if there outbreaks of unrest they tend to be big.

• Effects on the reduction of the number (density) of cops in the system can be explicitly studied.

In summary, the findings of [46] suggest that the key elements for develop outbreaks of social unrest are associated with three elements: (i) Economical, social or political grievance which is composed of perceived hardship and perceived illegitimacy of the system. (ii) low risk of consequences of taking part in revolutionary action and (iii) low risk aversion and mobility of agents. The agent based model teach that not one of these factors is sufficient alone to dominate the risk of unrest, but indicates that certain ratios and combinations are able to determine when a system is ``ripe'' for social unrest. A system which is ripe for unrest then just needs a ``triggering'' event which starts a large-scale outbreak - as spark.

It is maybe within reach to design models as the above and isolate relevant measures which allow to estimate the risks for potential outbreaks of social unrest. It may also be possible with the use of novel data-mining techniques and data sources (such as mirrors of opinions on specific issues such as blogs, or opinion fora such as facebook, twitter, etc.)[5] to access some of the relevant parameters in real life so that the ripeness can be actually estimated. The actual triggering events for outbreaks, of course, will most certainly never be predictable.

Finally, let us mention that extensions to this model particular model are applicable to study unrest between groups, such as inter-group violence, dynamics of ethnic cleansing, and the role and usefulness of peacekeepers [46]. Again here it is by no means intended to apply these models to real situations such as what happened e.g. in the Yugoslav war, but to point out the core elements of dynamics, and parameters which - if they were accessible - could be used to manage the scale and the unfolding of inter-group violence.

Questions to be asked: What are typical pathways to social unrest? How can parameters for risk of outbreaks be accessed? How can the unfolding of social unrest be managed?

A.0.1 Pathways toward social unrest: Linking financial crisis and social unrest through agent based frameworks

[5]One such approach is followed in recent exploratory research activity at IIASA, involving the author.

In an increasingly globalised world, financial crisis undoubtedly has regional and in severe cases global consequences. Financial crises can contribute to a series of risks eventually leading to social unrest, be it directly or indirectly. The following sketches some pathways for this interaction. A particular model of financial agents and the role of leverage in financial markets will be presented in Section 2. Similar to the model of social unrest mentioned above this model will show how certain circumstances can lead to drastically inflated levels of risk for financial collapse. Whether collapse then occurs or not depends whether a triggering event of a certain type will take place or not. In case it does, and crisis unfolds it is known that often a process of deleveraging follows, which can have direct impact on social mood, and grievance as discussed above.

Examples of how painful this process can be has been seen in times following the financial crisis of Argentina in 2001, South East Asia in 1997 and lately in Greece 2009-2010, all involving outbreaks of social unrest of some kind and scale.

Pathways to high grievance: destroy expectations

High levels of grievance are often associated to unfulfilled expectations of people. Effects can be especially pronounced if the times needed for ``disillusioning" are short. It has been noted long ago, that [48] `` ... Revolution is most likely to occur when a prolonged period of rising expectations (material and non-material) and rising gratifications is followed by a short period of sharp reversal, during which the gap between what people want and what they get quickly widens and becomes intolerable ..." .

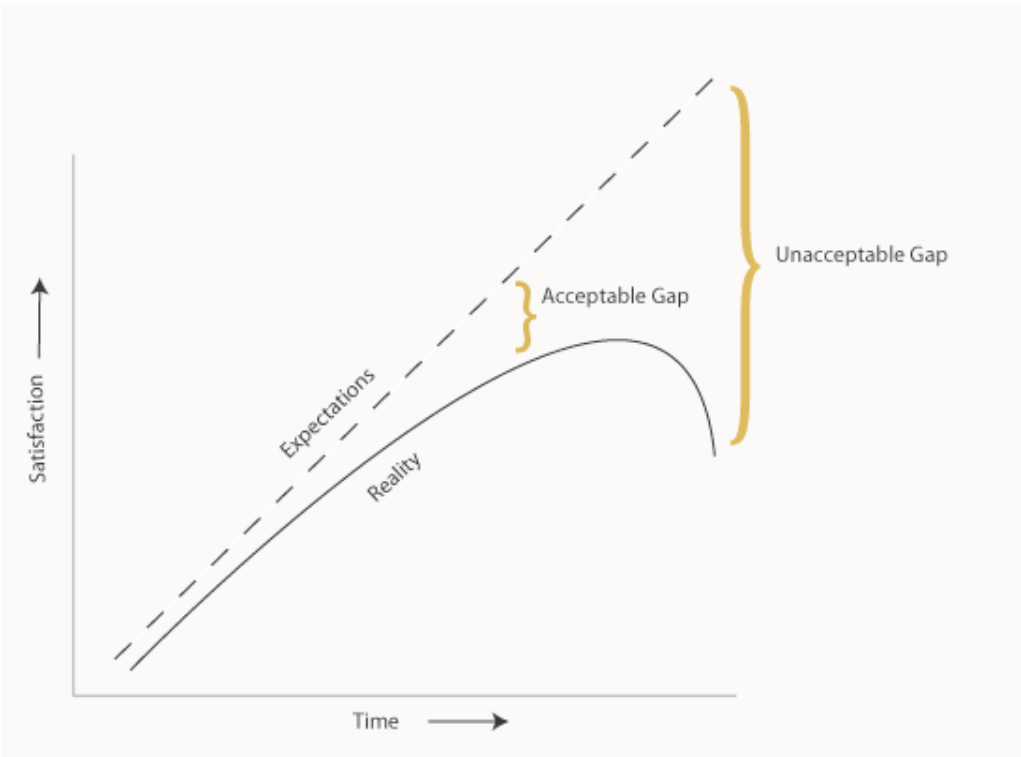

Figure 12: Davies J-curve.

source: http://www.globalpost.com/dispatch/commerce/090206/peasant-revolution-20

This concept has been made intuitive by the so-called Davies J-curve, see Fig. 4. On the y-axis the expectations of people are shown. The straight line corresponds to extrapolations of expectations people have; the full line represents reality, what people actually *can* have at a certain point in time, due to the present political, social and financial circumstances of the system. The size of the gap can be directly related to hardship, which plays an important role in the level of grievance in the above discussed model of social unrest. It is clear that the state of the financial system has direct implications on the gap. Financial crisis and its consecutive periods of a potential economic crisis and / or deleveraging can lead to a sharp downturn of the ``reality'' curve. In particular if the financial crisis has implications on basic needs of housing grievance can increase sharply. Drastic decreases in real estate prices can lead to mortgages which become unrealistic to repay leaving a feeling of financial inflexibility and potentially to lifelong debt and irrecoverable poverty. The same holds true for potentially lost private savings, e.g. through a hyperinflation scenario, which becomes realistic in times economies approach insolvency or when public money is used for recovery programs whose outcome is unsuccessful.

Ways to reduce legitimacy

Legitimacy can be seen as a major component for social unrest. Finance-related mechanisms which lead to a decline of legitimacy of a systems are not hard to find: Use of tax money to bail out defaulted financial institutions. Taxpayers are aware that they have had no share in profits of these firms, but find themselves now financing the risk of the ``rich''. Linkages of the political and financial worlds, such as the role of Wall Street in the bailout program, the role of former Goldman Sach employees in political decisions related to bailouts, etc. Further handling and open fraud of national accounts Greece by Wall Street firms. The actual and perceived lack of consequences of large scale fraud in politics and finance, bonuses paid with tax money, failure and corruption within regulatory bodies, etc.

A.0.2 Pathways to social unrest not directly related to financial crisis

There exist several important factors that directly affect the systemic risk of social unrest, which are not directly related to financial.

Reducing risk of consequences, ``reducing cops''

In the Epstein model it was shown that the reduction of ``cops'' (i.e. the consequences for actions against the system) can have a severe effect on the outbursts of social unrest. In the real world this does of course not necessarily mean real policemen, but the perceived negative total value of the consequences following the discovery of an action against the system. This involves education, deterioration, etc.

Reduce risk aversion

A relevant parameter is the risk aversion, i.e. how much they fear the consequences for subversive behaviour against a regime or system. Risk aversion is often seen as a parameter which depends on the levels of wealth of an individual. The poorer a person the more risk averse she is. Risk aversion also largely depends on how much a person perceives to be able to lose in a particular action or decision. Risk aversion in this sense bears an educational component to a certain degree.

Mobility: physical and information

Finally, mobility (physical or the ease of communication spreading) has been known to be a relevant factor for social unrest. The model of [46] produces further evidence for this and provides insight in the mechanism of why this is so.