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Modeling, Simulation and Control of Short-term Stock Market Dynamics

Henning Pedersen

Master of Science in Engineering Cybernetics
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Supervisor: Trond Andresen, ITK

Norwegian University of Science and Technology
Department of Engineering Cybernetics

Problem Description

Modeling, simulation and control of short-term stock market dynamics

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Preface

I would like to thank my teaching supervisor, Trond Andresen, for his ideas and inspiration whenever I needed help. His work and insight have been a platform for this report, and have also increased my interest in economics. The recommended literature has been an eye opener in many ways, especially the book “Irrational Exuberance”. Some illusions have definitely fallen to the ground.

As a student of technical cybernetics, my experience with economics has been limited. The mix of control theory and economy has proven to be a refreshing conclusion to the studies.

Abstract

Real-world stock markets exhibit periods of increased volatility and bursts in stock prices. This thesis is about creating similar dynamics in a model to gain insight into these potentially dangerous phenomena. A transaction tax able to stabilize the markets is briefly discussed. The relationship between rational and speculative traders is found to be crucial. If the speculative mindsets are allowed to dominate the markets, chaos is inevitable. Simulations show a direct relation between speculation and violent price movements. The discussed transaction tax is found to make the market more robust by targeting the most destabilizing form of trading - short-term speculation.

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1 Introduction

Thesis title: "Modeling, simulation and control of short-term stock market dynamics."

The work described in this report is based on a model of the stock market presented in a working paper by Trond Andresen (Andresen). The model includes short-term dynamics of stock trading, focusing on two types of traders: Fundamentalists (rational) and speculative traders (irrational).

The model will be explored and experimented with, and somewhat extended/modified to include some new features. These new features will allow the market to become temporary unstable due to increased speculative action, producing periods of higher price volatility (bursts), as seen in the real markets as early as the 18th century (Harrison, 1998). A new kind of tax on trading will be discussed, where the goal is to counter some of the effects of speculative trading in order to stabilize the market.

Instability in the markets with its crashes and booms cause considerable damage; Companies go bankrupt, jobs are lost, markets are paralyzed by fear etc. The model and this report were made and written to gain some insight into what creates this turmoil.

The following foundation provides a description of Andresen's Simulink model as well an explanation of the two mentioned trader mentalities. In the main part of the thesis (Composition) the model is experimented with in various ways. The results are presented with the help of simulation data and figures. It starts with some thoughts concerning the ideal stock market, where all traders are fundamental in their approach. Speculative traders are introduced to produce more interesting dynamics.

The model is then modified to include periodic instability in the market; producing price bursts (periods of increased volatility). Similar projects are briefly mentioned. The last part of the composition deals with a progressive tax suggestion. The thesis is concluded. Some ideas for further work are presented at the very end.

2 Foundation

This chapter provides an explanation of some useful terms, as well as the basis for the modeling found in the rest of the paper: A Matlab Simulink model of the stock market presented in a working paper by Trond Andresen (Andresen). The model is described and explained with my own words to fit the scope of this paper, but is the work of Andresen. The model serves as a platform and a starting point for the thesis, and most of my work has been done by modifying or extending it.

2.1 Fundamental approaches to stock trading

The fundamental mentality is based on what a stock, or a portfolio of stocks, is really worth. A popular measure of value would be the price/earnings-ratio, the P/E, where price is the price of the stock in the market, and earnings equals the dividends paid per stock. A low P/E indicates that the price is low relative to the earnings – the stock is cheap. A high P/E indicates that the stock price is high compared to what the stock actually pays in dividends.

A trader heavily influenced by the fundamental approach is likely to sell stocks considered expensive, and buy when the stock is considered to be cheap. If a stock is at, what is believed to be, its “real” or “sustainable” value, the trader will retain his current number of stocks.

The action which fundamentalism inspires is very similar to “tracking” in control theory. In an ideal market consisting only of traders with this mentality, the price of a stock would always reflect the real, sustainable value. It is not difficult to see that fundamental behavior stabilizes the market.

What is considered to be the real and sustainable prices of stocks have varied significantly over the last hundred years (Shiller, 2001). Such variations have been disregarded in this paper, as the model used considers short-term dynamics only (no more than a couple of years).

2.2 Speculative approaches to stock trading

Buying shares and holding them for dividend earnings is certainly not the only way to generate a profit in the market. Stock prices have a tendency to fluctuate, which gives room for speculation. Speculation can be explained as taking advantage of the fluctuations in price by buying and selling at the right times.

The most common speculation is probably the bandwagon mentality, which is based on the idea that the current trend will continue into the future. If the stock prices are rising right now, they will most likely continue to do so. In the same way, if the stock prices are decreasing, they will probably keep on decreasing. The profit is generated from jumping on board the bandwagon, hopefully riding the trend to where you want to be.

A trader heavily influenced by the bandwagon mentality will buy and sell stocks based on the previous price movement. If the price has increased slightly, the number of stocks he holds will be increased accordingly. If the price is in a steep, increasing trend, the trader will then buy a significant amount of shares. In the same way, a decreasing price trend will cause the trader to reduce his number of shares. In his model, Andresen assumes that the bandwagon mentality is the most dominant idea behind speculation, and disregards the others.

The common denominator that most forms of speculation share is this: Trading is done without taking the real or sustainable value of the stock into account. Imagine a market consisting only of bandwagon traders. A small price increase would then cause all the traders to start buying stocks, because they all believe the price will continue to increase. The excess demand would lead to a steeper price increase, and eventually the price will approach infinity. The Stock price would not be anchored to anything at all. It is not difficult to see that the bandwagon mentality can cause serious destabilization in the market.

In reality, a trader can operate both ways (fundamental and speculative). The model presented next does not include fundamentalists and speculative traders, but rather the aggregate of the mentalities of all traders in the market.

2.3 The simulink model

In his working paper (Andresen), Andresen develops the following model of short-term stock market dynamics:

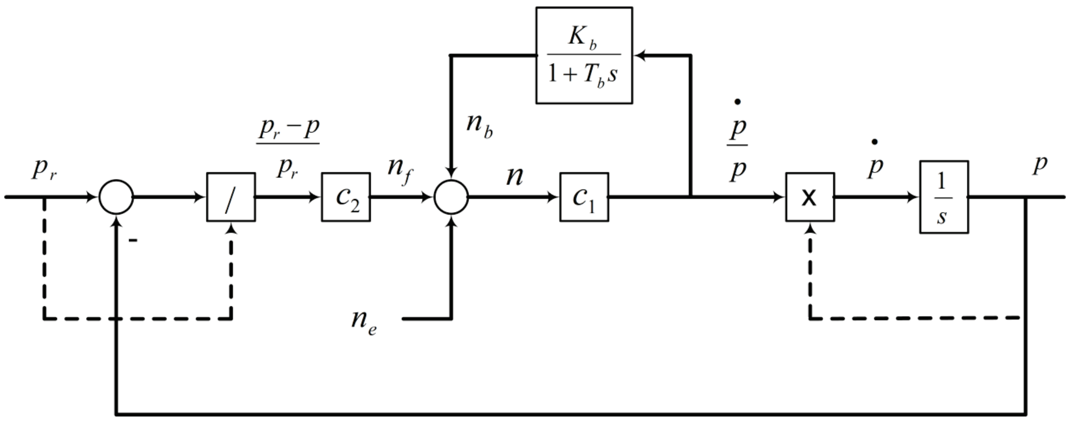

Figure 2.1 - Andresen's Simulink model of short-term stock market dynamics.

The following is an explanation of the symbols used in the diagram. Units are shown in brackets, [ ]. The brackets are empty if the entity is dimensionless.

p_r Real or sustainable P/E-ratio (price/earnings-ratio) for the stock [ ]. The P/E-ratio will from now on be called price for simplicity. Subscript *r* implies "real" or "reference".

p Current market price (P/E) of the stock [ ].

$\dot{p}$ Price change [day^{-1}]. The dot represents differentiation by time.

$\frac{\dot{p}}{p}$ Price change rate [day^{-1}].

s Differentiation operator [day^{-1}]

c_1 Constant factor [1/(number of stocks * day] transforming net demand into price increase rate. A surplus demand, either positive or negative, for stock is what drives prices up or down.

c_2 Constant factor [number of stocks] transforming price deviation into a fundamental demand for stocks. This factor determines the strength of the fundamentalist action.

K_b Constant factor representing the strength of the speculative behavior.

T_b Constant factor representing the time perspective of the bandwagon trader. The trader looks T_b days back in time to establish an opinion on what will happen to the stock price in the future.

n Surplus aggregate demand for stock [number of stocks]. The total demand is assumed to consist of the following three components:

n_f Surplus demand as a result of fundamental mentality in the market. This demand is fueled by a difference between the price and the real value of the stock. Subscript *f* implies “fundamental”.

n_b Surplus demand as a result of bandwagon mentality in the market. This demand is fueled by the price change rate. Subscript *b* implies “bandwagon”.

n_e Surplus demand due to insecurities or disagreement regarding the real or sustainable value of the stocks, due to variation between the traders as to what action to take when faced with information, and due to the influence of external events like news, rumors etc. This demand for stock is assumed to be a zero mean stochastic process and will act as an ever present price perturbation in the market. Subscript *e* implies “error”.

2.4 The model explained

The model is based on the idea that the aggregate surplus demand for stock (n) drives the price up or down. If, at a given moment, the net demand (stocks wanted – stocks for sale) is positive, the price will increase. If the number of stocks for sale exceeds the appetite of the buyers, the price will decrease.

As previously mentioned, demand caused by fundamentalism (n_f) stabilizes the system. Bandwagon demand (n_b) has the exact opposite effect. At any given time, the demand for stock will primarily be driven by a mix of these to mentalities. There is a third type of demand (n_e) represented in the model, but it is not driven by a separate mentality. The error demand can be view as a model correction, representing insecurities, modeling errors, news/rumors etc.

The particular mix of fundamentalism and speculation determines whether or not the market is stabile. Using control theory, Andresen has come up with the following expression called the “relative damping factor”:

$$\xi = \frac{1 + c_1 c_2 T_b - c_1 K_b}{2\sqrt{c_1 c_2 T_b}} \qquad \text{(Equation 1)}$$

Information on how it was derived can be found in his paper. It can be used to determine stability properties for a certain set of parameters (used in chapter 3.4)

3 Composition

The models in this chapter have been built and simulated in Matlab Simulink Version 7.2 (R2008b), with a fixed-step size of 0.001 with an ode1(Euler) solver.

3.1 The ideal stock market

The perfect stock market is primarily supposed to do one thing: Channel fresh capital into promising projects (Andresen). The ideal market is thought to be so efficient that no opportunity for speculation is available (Lucas, 1978). The traders are fully rational, and information is immediately available to everyone at the same time. Any imbalances in price would be corrected fast, leaving no incentive for extra research, studying charts, uncovering errors in price etc. The trading volumes would be low or zero.

Such a market can easily be illustrated with a slight modification of Andresen's model (Figure 3.1). All the traders would then be fundamental, and the real value of a stock available to every trader. The only demand left in the model would be that which is generated from perfectly informed, rational traders.

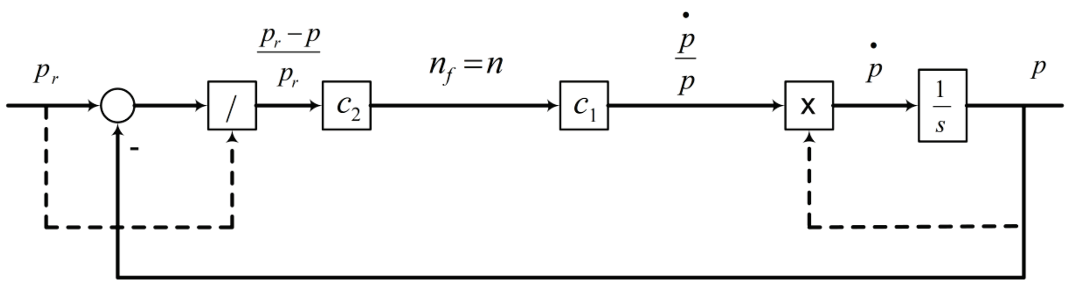

Figure 3.1 - Model of the ideal stock market where all traders are fundamental.

It can be seen that the stock price will reflect the real value perfectly (like an efficient tracking system with little or no noise). A change in price, minute or significant, would be interpreted as a change in real worth. Nothing else can really affect the price. It follows that a crash or a boom is interpreted as a sudden, significant change in the actual value of the stock(s).

However, a simple model like this does not fit well with what can be observed in real markets. For instance: A quick look at the 2008 statistics from Oslo stock exchange reveals that equity issues amount only to 13.1 billion NOK. Total turnover exceeds 2432 billion NOK (OSE statistics). In other words: Most of the activity in the Norwegian stock market has nothing to do with fresh capital being put into promising projects. Arthur (1996) concludes that enough statistical evidence has been gathered to seriously question efficient market theories.

3.2 The emergence of speculative trading

A trader population consisting of only rational, perfectly informed individuals is not very likely at all. This situation is even suggested to be "evolutionary unstable" (Maynard, 1982). There are numerous irrational ways of trading stocks (speculation), but the most important difference compared to the fundamental approach is this: The real and sustainable value of the traded stock is normally not taken into consideration.

Speculative traders are known by several names. Some call them 'chartists' (Lux 1998) for their efforts to gain statistical advantages by studying various types of charts, mainly based on stock price and trading history. For instance, certain formations in price history (like 'rectangles', "double/triple tops" and 'head-and-shoulder' formations) are interpreted in order to predict future movement. Another well known chartist key value is the 'RSI', or "relative strength index". The idea is that the longer a stock has increased in value, the more likely it is that the trend will reverse (and vice versa) (Frølich, 2001).

The term "noise traders" is also frequently used. It is explained by De Long (1990) as traders who possess different (often erroneous and irrational) expectations than the rational traders.

Some of the speculative traders could be called gamblers. The excitement of the possibility of earning a fortune, or at least quick money, can in itself be a significant incentive to trade stocks. Stories of simple men and women becoming wealthy over night can serve as fuel for gamblers. This kind of trading can be compared to lotteries, casinos, or even pyramid schemes.

Andresen's simulink model (figure 2.1) includes one of the most common types of speculative traders: Traders with bandwagon mentality (as explained in the Foundation part of the thesis). It also includes an error demand (n_e) to account for some of the effects of imperfect information distribution, information interpretation, model errors etc. The noise demand is implemented as filtered, band limited white noise (figure 3.2) in the simulations done in this paper.

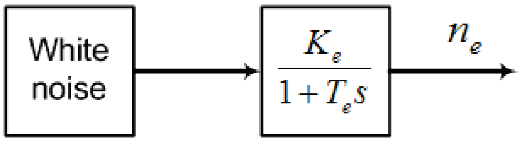

Figure 3.2 - Shows how the error demand (n_e) is produced in Simulink.

An illustrative expansion of the model could be to include bandwagon traders with different time perspectives. The resulting Simulink model would look like this:

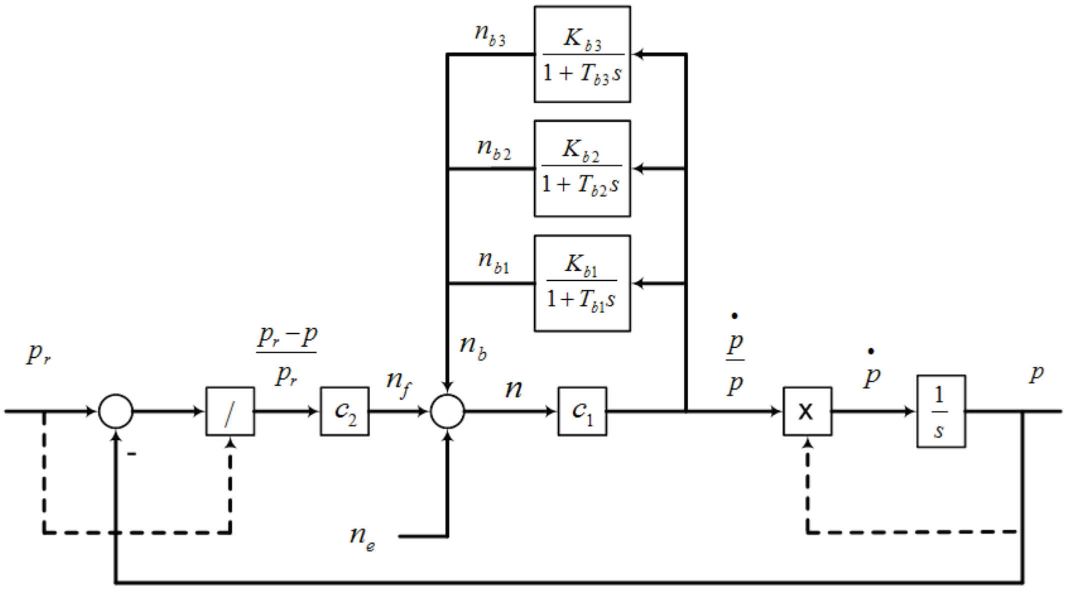

Figure 3.3 - The simulink model now includes bandwagon traders with different time perspectives

Parameter set 1

$K_{b1} = K_{b2} = K_{b3} = 13000$	$c_1 = 0.000074$	$c_2 = 72115.93$
$T_{b1} = 0.00128$	$T_{b2}=0.15385$	$T_{b3} = 1$
$K_e = 1000$	$T_e = 3$	$p_r = 20$

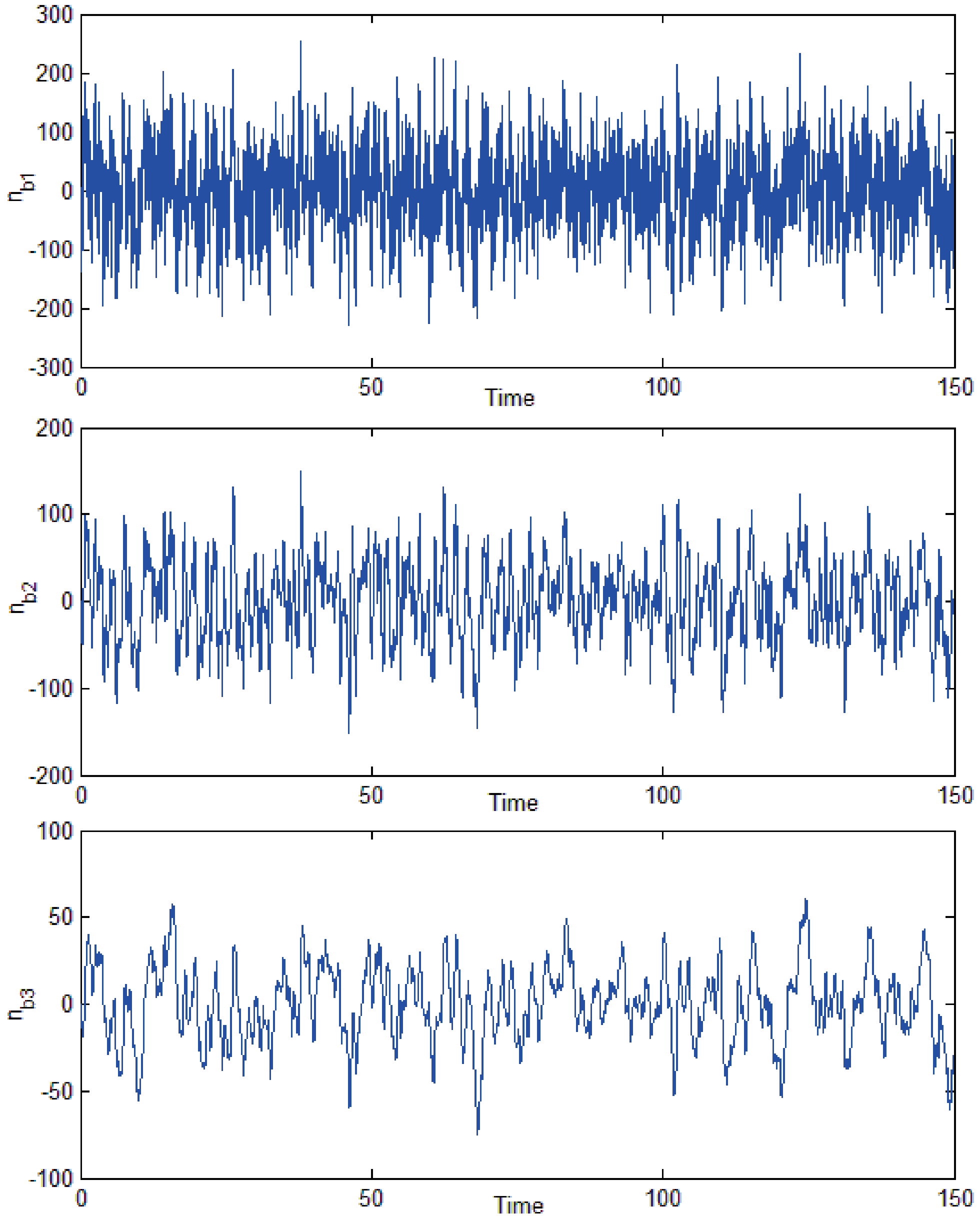

Figure 3.4 - The plots show demands created by bandwagon traders with half a minute (upper), one hour (mid), and one day (bottom) time perspectives. Their speculative strengths are the same to create comparable results.

The plots above show demands created by bandwagon traders with the following time perspectives: Half a minute (n_{b1}), an hour (n_{b2}), and a trading day (n_{b3}). In this simulation the speculative traders have been cut off from the market to create comparable results. Their demands do not affect the price, and equal speculative strength is specified. It is clear that the bandwagon traders with the shortest time perspectives create the biggest and most intense (destabilizing) demands. This realization is the basis for the tax proposal discussed later (chapter 3.4).

Experiments show that if a small number of speculative traders are introduced, they have the potential to not only survive, but also invade the population, even if they do not affect the prices (De Long, 1990). As the speculative traders increase in number and influence, they can also seriously affect prices and trends. This can go on to the point where the, so far, rational traders would be fools not to take advantage of the price movements created by speculation (Arthur, 1996). Rational traders would then, in a sense, be converted, to some extent, to behave as speculative traders. Such a shift in mentality could very well cause increased volatility, bursts and crashes as seen in the markets (Marchesi, 1998). The next step will be to include these mentality shifts in the model.

3.3 Shifts in trader mentality – Sporadic bursts

The purpose of this chapter is to document some changes made to the Simulink model (figure 2.1), producing similar results to those mentioned in chapter 3.3.1. After a time of relatively small variations in price, activity increases, sending the price into more violent ups and downs for a limited time (bursts). The opposite can also be seen: After periods of high volatility and increased trading volume, the market calms down.

3.3.1 Some existing models displaying sporadic bursts

Lux and Marchesi (1998) recognize that the market consists of chartists and fundamentalists. Their model includes three types of traders: Fundamentalists, positive chartists and negative chartists. Traders are allowed to switch from one strategy to another based on certain criteria of profitability and flows. Every trader monitors the past performance of the other strategies in order to adopt the most efficient one. The majority opinions of the other traders are also taken into account (flows), which enable bandwagon/herding behavior. The resulting simulations illustrate periodic "volatility clustering", or bursts. Furthermore, periods of increased volatility are perfectly correlated with periods of high numbers of chartists.

Kusch and Ydstie (1993) focus on the relation between the policy makers and the model makers. The idea is to have models that resemble the market with few errors. The models, which are the basis for forecasts, are continually updated and improved to better reflect our experiences and also improve our decisions (creation of policies). However, the implemented trading policies affect the market. When the market changes the models need to be updated. The new models indicate new policies, and so on. A poor model will lead to strange policies. This back and forth relation can cause temporary instability with resulting bursts much like the ones described above.

3.3.2 Changes in trading-approaches

The causes of increased or decreased activity in the stock markets are numerous, complex and intertwined (interest rates, media coverage, trends, trading availability etc). To model all of them is outside the scope of this paper, and I have decided to focus on one of the more intuitive – volatility. High volatility, which is a measure of risk, is considered scary and will cause traders to “sit back” until the market has calmed down enough for them to be comfortable (Sørum, 2009). Periods of low volatility (considered safe) will stimulate increased activity due to general confidence in the market. It also takes bigger quanta of stocks to reach a certain profit level when the price changes are small.

In short, the idea is to influence certain parts of the model with a new variable – price volatility. Volatility is analog with variance and the standard deviation. Producing variance or standard deviation in the model is a simple task, as can be seen in chapter 3.3.5.

3.3.3 Moving to a non-linear model

The market tends to be “underdamped with occasional instability” (Andresen). The linear model (figure 2.1) cannot dynamically switch between different modes of stability (the relative damping factor is, as discussed previously, constant). In other words, the relative damping factor must become variable in order to produce the desired results. This in turn means that one or more of the parameters c_1, c_2, T_b or K_b will have to become variable. Adjusting any of these values will stabilize or destabilize the system.

The changes in stability properties are driven by volatility. It is therefore reasonable that at least one of the mentioned stability parameters should be a function of price variance, which in turn depends on price. A modification like that will in any case result in a nonlinear model, and should enable periods of sporadic instability to produce the desired bursts in activity and price levels.

3.3.4 Dynamically adjusted parameters

The purpose of this subsection is to explain a Simulink mechanism created to regulate parameters based on price volatility. There are several uses for such a mechanism. It could be used to modify the strength of the speculative action (K_b), with the assumption that such behavior will increase until a certain level of risk is reached. When the traders become uncomfortable, activity is significantly decreased, lowering the risk enough to make speculative trading attractive again. This kind of behavior has recently been confirmed in the Norwegian stock market. A month by month comparison for 2007-2009 shows that the 2009 turnover has been cut in half (roughly) due to the 2008 turmoil in the financial markets (Sørum, 2009).

It could also be imagined that volatility has an effect on the time perspective (T_b) of the speculative traders. Periods of low risk could inspire the traders to think in shorter terms, while bursts and increased chaos will lead to an increased time horizon.

In the following examples I have, however, chosen to manipulate the variable c_1 for the following reason: The fear associated with a volatile market is assumed to affect all traders, not just the speculative ones.

It can be argued that any of the three mentioned modifications will produce the same result (sporadic bursts). In calm periods activity will increase, and speculative trading will become more dominant, destabilizing the market (and vice versa). This is easy to understand when K_b or T_b is the affected parameter. However, the same thing will happen if c_1 is chosen. While c_1 is a gain affecting all three types of demands (n_f, n_b and n_e), changing it will directly influence the price change rate, which in turn fuels the speculative traders. The result is a relative increase in speculative activity.

3.3.5 A Simulink mechanism for updating c_1

The mechanism consists of three parts: A variance estimator, a logistic function, and a filter.

Variance estimator

Variance can be produced in Simulink by using two blocks in the following way:

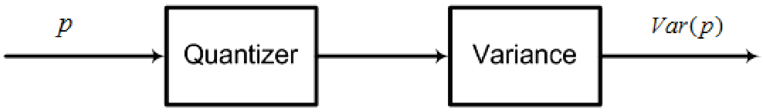

Figure 3.5 – Shows how variance is computed in the Simulink model. The variance block needs a quantized input in order to function.

The variance block needs a quantized input in order to function. The quantizer is set up with a quantization interval of 0.01. The variance block is set to "running variance" (checkbox). This part of the mechanism produces an estimate of the price variance.

Logistic function

A logistic function is used to translate price variance into the range of the parameter c_1.

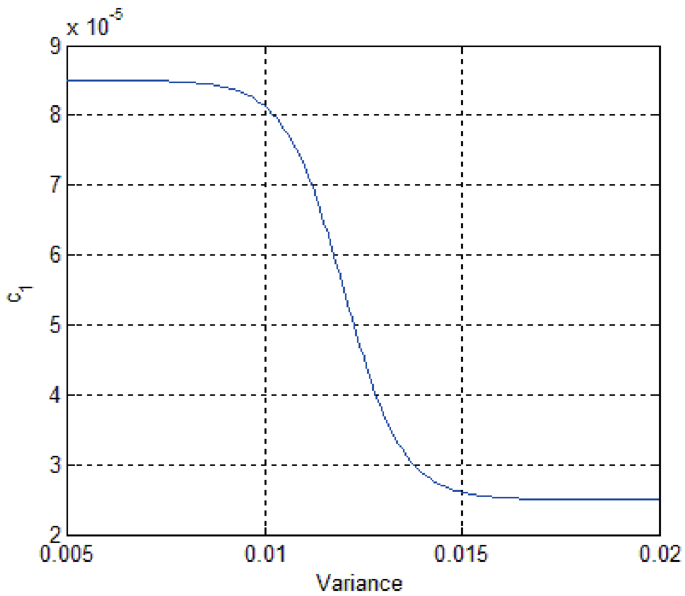

Figure 3.6 – The logistic function used to translate price variance into the range of the parameter c_1.

This type of function provides a max and min value for the parameter, as well as a smooth transition between them. The max value for c_1 should be high enough to create instability, and the min value should at least make the market look normal. The function was set up in such a way that the slope is positioned between the min and max input.

A logistic function was implemented in Simulink using a custom function block, and created using the following Matlab code with 'var' as input:

```
c1max = 0.000085;
c1min = 0.000025;
steepness = 1350;
var_mid = 0.012;

c1= c1min - (c1min - c1max)./(1 + exp(steepness.*(var - var_mid)));
```

Filter

The output from the logistic function is passed through a standard low-pass filter with a time constant of 2 days (T_u = 2. u represents "update mechanism"). It takes time for the market to react to changes in volatility. Some traders are glued to the computer screens every day, some get a phone call once a week from their broker, some check up on their mutual funds once a month etc. The delay (from filtration) introduced in the update mechanism is assumed to be an average of the different time perspectives.

With the mechanism in place, the model looks like this:

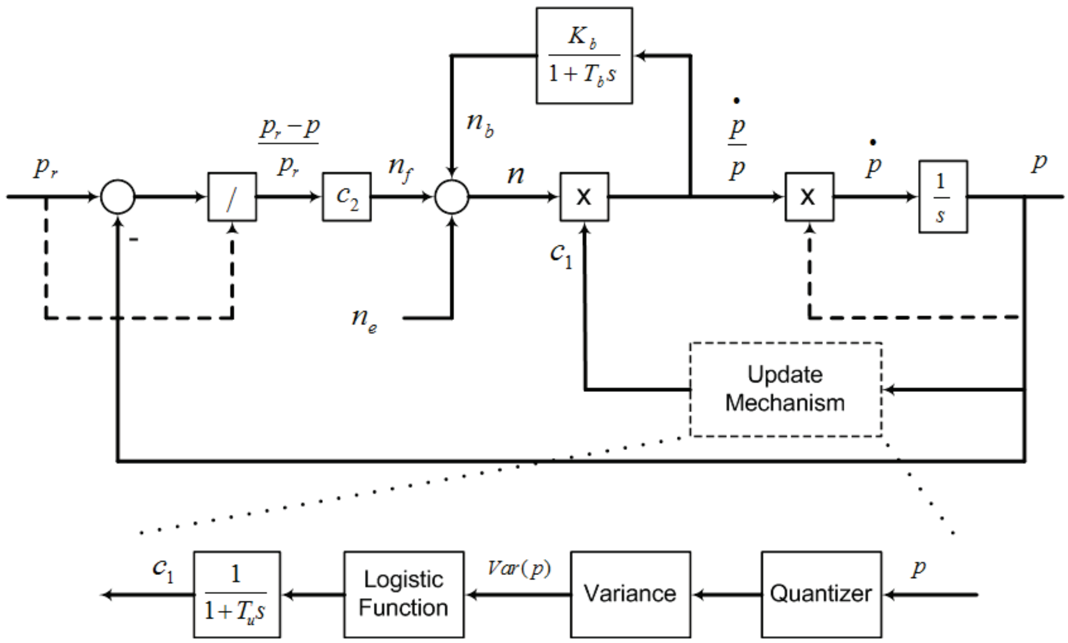

Figure 3.7 - The Simulink model used to create price time series displaying bursts.

3.3.6 Simulations with c_1 controlled by price variance

This simulation is based on the Simulink diagram shown in figure 3.7 and parameter set 2:

Parameter set 2

K_b = 14000 T_b = 0.00128 c_2 = 72115.93
K_e = 1000 T_e = 3 p_r = 20
T_u = 2

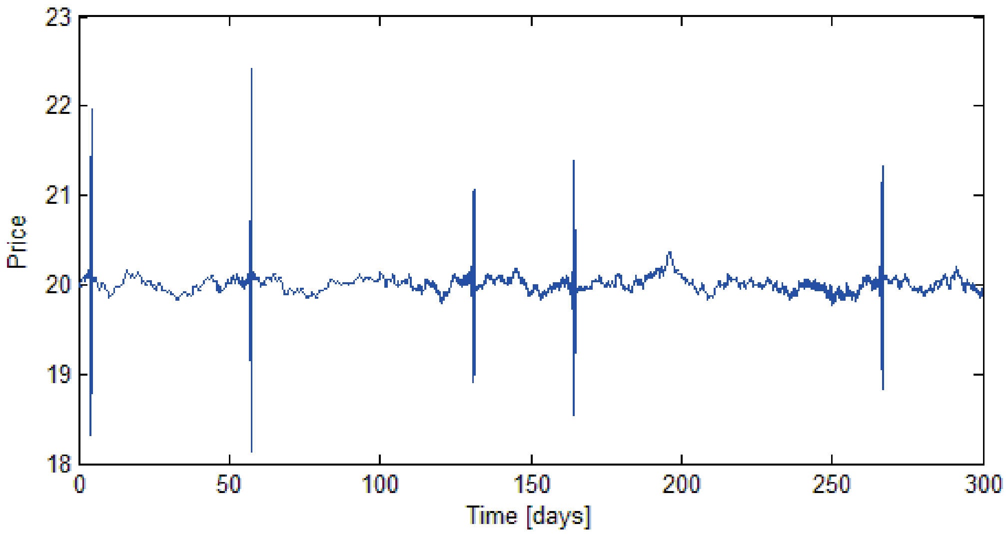

Figure 3.8 - Typical time series of the stock price. Bursts can clearly be seen.

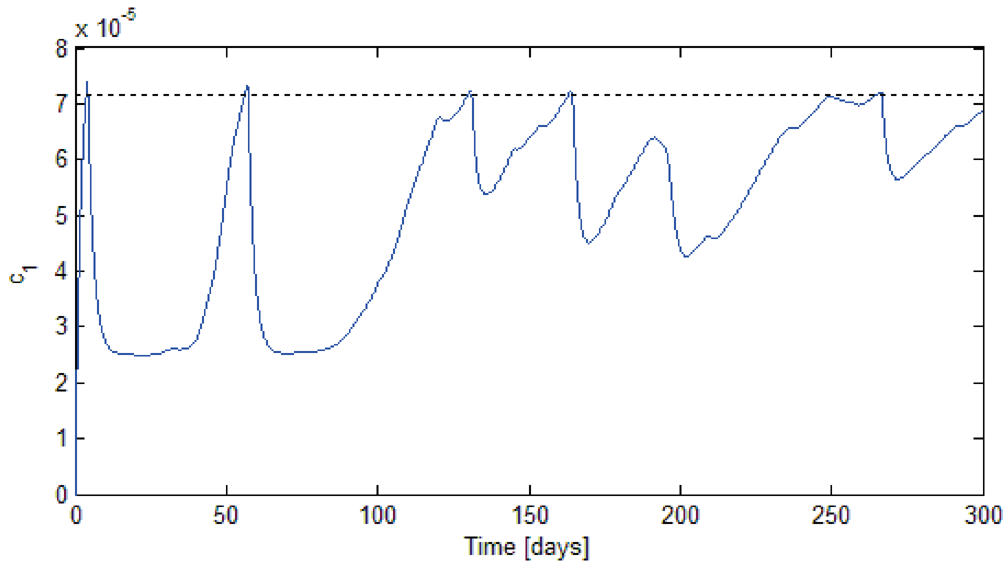

Figure 3.9 - Shows how the parameter c_1 varies with time. Notice what happens to the stock prices when c_1 passes the stability threshold market by the dotted line.

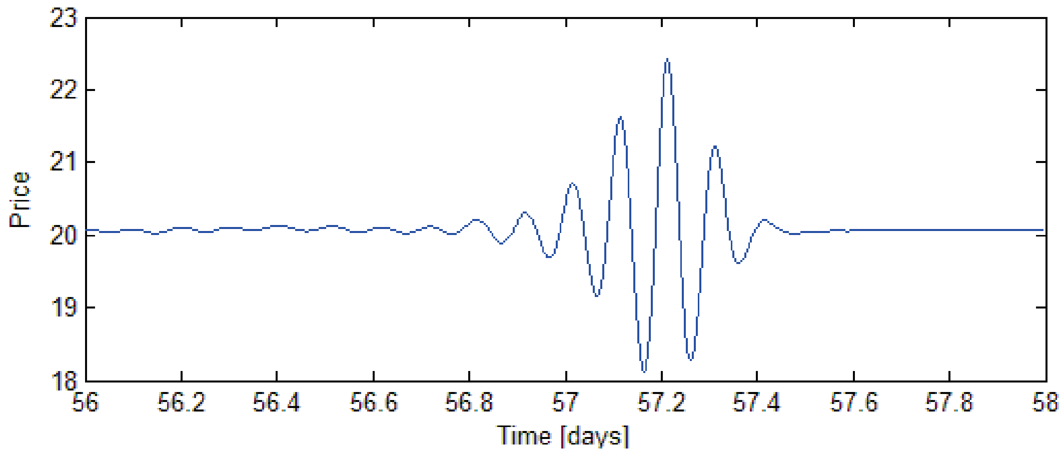

Figure 3.10 - Close-up of one of the bursts shown in figure 3.8.

Figure 3.8 shows the resulting price time series. The price mostly remains in its normal range at no more than 1-2% change per day. Occurrence of periodic instability and bursts can clearly be observed, where the price changes at more alarming rates. To better show the nature of these bursts, a close-up of one of them has been provided (figure 3.10). It can also be seen that these bursts coincide with c_1 breaking the stability threshold of approximately 7.15×10^{-5} marked by the dotted line (figure 3.9). The threshold can be computed from equation 1, with the "relative damping factor" = 0.

The simulation above serves only as an example. It is possible to modify the amplitude, frequency, and duration of the bursts by tweaking the logistic function, the filter time constant (T_u), speculative strength (K_b) etc.

3.4 A progressive transaction tax

The purpose of this chapter is to discuss a progressive transaction tax on trading that would mostly affect the traders contributing to instability in the market (in this case the bandwagon traders). Chapter 3.2 concludes that the short-term bandwagon traders create more destabilizing demand than the ones having a wider time horizon. The idea is to implement a new tax that would "punish" the fast, speculative traders, and provide an incentive to think in longer terms.

Conventional taxes (i.e. a flat tax on trades) affect all traders the same way, and consequently do not favor any particular way of trading. The tax on a hundred trades in a day would amount to the same as the tax on a hundred trades made in ten years, assuming the price level and traded volumes are the same. This type of tax does not contribute to stability like the one about to be discussed.

The idea behind the progressive tax is this: The amount of time passed between buying and selling a stock determines the transaction tax level. Fundamentalists and other long-term traders would be charged with little or no taxes. A trader who buys and sells within minutes will incur a relatively high tax level of, say, 20 or 30%. An example is shown in figure 3.11.

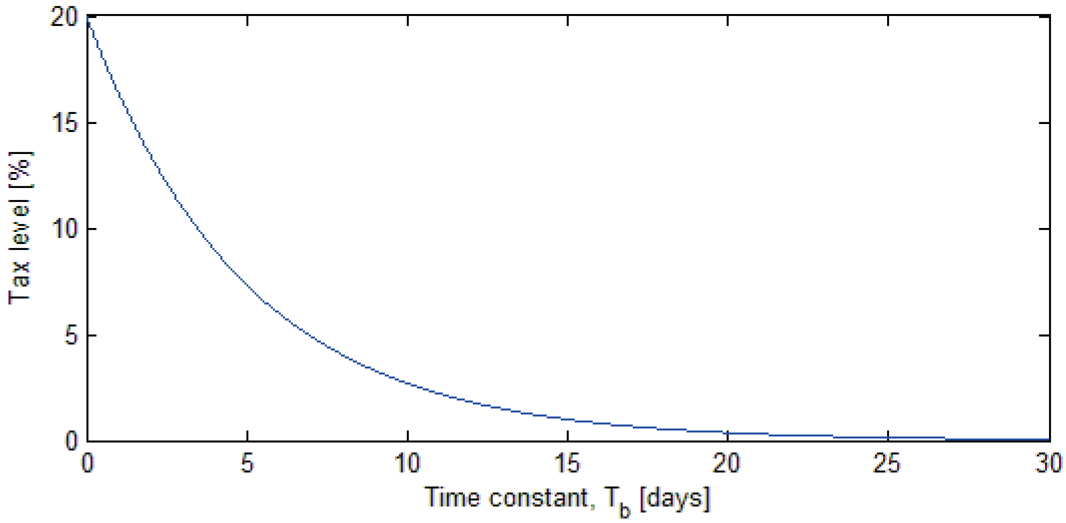

Figure 3.11 - An example of a progressive transaction tax.

A bandwagon trader looks T_b days back in time to decide how he thinks the stock price will change in the future (implemented using a low-pass filter in the Simulink model). If the trend is positive, he will buy. He then assumes the same trend will continue, and hopes to sell his stocks T_b days later with a profit (figure 3.12).

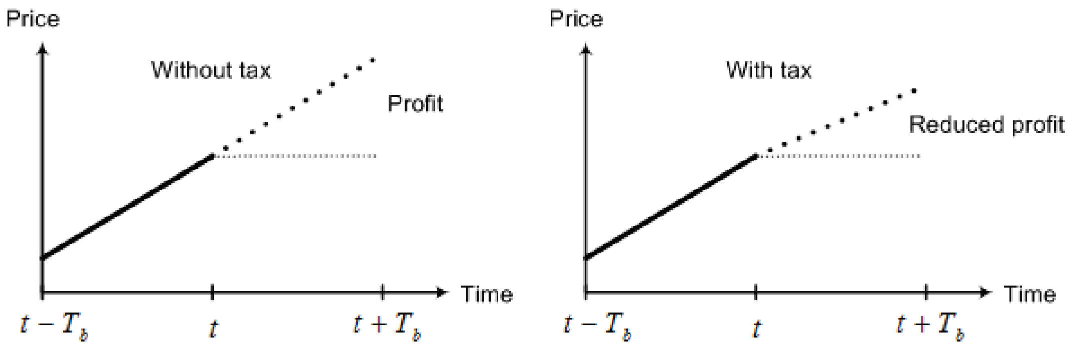

Figure 3.12 - The bandwagon trader at time t looks t-T_b days back in time to determine the price trend (solid lines). He then projects the same trend into the future (dotted lines), hoping to sell at t+T_b with a profit (left). The transaction tax reduces the profit potential seen in the future (right).

The mentioned tax will shrink the potential profit on each stock, and thereby reduce the number of purchased stocks accordingly. The reason for this is simple: The potential profit on each stock is assumed to be the driving force behind the purchase in the first place (chapter 2.2). This can also be illustrated with the Simulink diagram (figure 3.13). The low-pass filter determines the trend, and thereby the profit potential available T_b days later. This potential is then reduced by the progressive tax accordingly. The speculative strength (K_b) translates the remaining profit potential into actual demand (n_b).

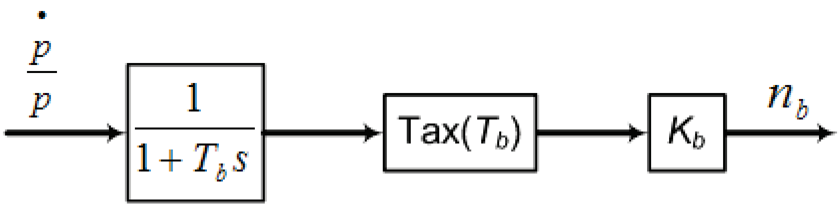

Figure 3.13 – Shows how the tax influences bandwagon demand. The filter produces the trend and profit potential, the tax reduces the profit potential, and the remaining profit potential is turned into demand by the speculative strength.

The effects of the tax can be seen as a reduction in speculative strength. As an example, let's assume a tax level of 20% for a particular trader. The tax equals reducing K_b with 20%, and it is not difficult to see how this affects the stability of the market. Some traders may even be convinced to think in longer terms due to the incentives provided by the progressive tax.

Will a progressive transaction tax be possible to implement in real life? All stocks would then have to be time-stamped on purchase, so that the correct tax could be determined when they are sold etc.

4 Conclusion

This paper is based on a model of the stock market with two types of traders: The rational and the speculative. It is made clear that speculative action has the potential to destabilize the market and cause increased volatility and extreme price movements, as seen in the real world. New dynamics were implemented in the model, allowing the market to become occasionally unstable due to the mentioned speculation. The resulting model is capable of producing simulations with periodic bursts and increased volatility in the stock price.

Furthermore, short-term speculation is, in the context of this model, experienced to cause the most damage in the market. The progressive transaction tax discussed at the end of this paper could be used as an instrument for market stabilization. Such a tax will reduce attractiveness of short-term speculation, and provide incentives to abandon this kind of behavior. The result is found to be a more robust and stabile stock market.

5 Further work

It could be useful to implement several types of speculation to see how they affect the market together. Is it possible that a speculative way of trading will have a canceling effect on another (Pagano, 1989)?

The ability to determine if a particular way of trading generates a profit or not, and where the profit comes from (fundamentalists, other speculative traders etc.), could be interesting features. This will require larger changes in the modeling. Individual traders and money flows would have to be included.

6 References

Andresen, Trond. Working paper. “Overvaluation – not volatility – is the main danger in stock markets”. The Norwegian University of Science and Technology.

Arthur, W. B., J. H. Holland, B. LeBaron, R. Palmer, and P. Tayler. **1996**. “Asset Pricing Under Endogenous Expectations in an Artificial Stockmarket”. Santa Fe Institute.

De Long, J. Bradford, A. Shleifer, L. H. Summers, and R. J. Waldmann. **1990**. “The Survival of Noise Traders in Financial Markets”.

Frølich, Steffen and Geir Linløkken. **2001**. “Teknisk Aksjeanalyse” (Technical trading) (in Norwegian).

Harrison, P. **1998**. “Similarities in the Distribution of Stock Market Price Changes between the Eighteenth and Twentieth Centuries”, Journal of Business 71.

Kusch, M. G. and B. Erik Ydstie. **1994**. “Drift Instabilities and Chaos in Forecasting and Adaptive Decision Theory”. Physica D 72, 309-323.

Lucas, R. E. **1978**. “Asset Prices in an Exchange Economy”. Econometrica, 46, 1429-1445.

Lux, Thomas and Marchesi, Michele. **1998**. “Volatility Clustering in Financial Markets: A Microsimulation of Interacting Agents”. International Journal of Theoretical and Applied Finance.

OSE, Oslo Stock Exchange. **2008** statistics from www.oslobors.no.

Pagano, M. **1989**. “Trading Volume and Asset Liquidity”. Quarterly Journal of Echonomics 104 (May): 255-74.

Shiller, Robert J. **2001**. “Irrational Exuberance”. United Kingdom, Princeton University Press.

Sørum, Kjetil. **2009**. Article in Dagens Næringsliv 13th of July 2009: “Blikkstille på børs” (in Norwegian).